An Information-based Forecasting Model for Project Progress and Completion Using Bayesian Inference

Wi Sung Yoo* · Fabian C. Hadipriono**

Abstract

In the past, several construction projects have exceeded their schedule resulting in financial losses to the owners; at present there are very few methods available to accurately forecast the completion date of a project. These may be because of unforeseen outcomes that cannot be accounted for earlier and because of deficiency of proper tools to forecast completion date of said project. To overcome these difficulties, project managers may need a tool to predict the completion date at the early stage of project development. Bayesian Inference introduced in this paper is one such tool that can be employed to forecast project progress at all construction stages. Using this inference, project managers can combine an initially planned project progress (growth curve) with reported information from ongoing projects during the development, and in addition, dynamically revise this initial plan and quantify the uncertainty of completion date. This study introduces a theoretical model and proposes a mathematically information-based framework to forecast a project completion date that corresponds with the actual progress data and to monitor the modified uncertainties using Bayesian Inference.

Keywords : Bayesian Inference, changed uncertainties, completion date, future progress, information-based model

1. INTRODUCTION

In today's construction industry, forecasting future outcomes of a construction project is an important part of managing a successful project. Many large construction projects may be complex, unique and different from other projects in terms of design, purpose, cost, and time. Generally, a construction project has an initial progress plan and completion date, but in many cases the project is required to follow a plan that varies significantly from the initial plan due to unpredictable conditions during project development. In such cases, forecasting future project progress at early execution periods, based upon actual reported progress, is crucial to assist project managers and construction contractors to complete their projects on time.

Earned Value (EV) management system has assessed the performance of an ongoing construction project and achieved the predictions of project completion in terms of monetary terms. Hence, this system provides one way to monitor the future progress and completion date (Fleming and Koppelman, 2002). However, the system is deterministic and difficult to reflect the impacts of the past performance to the future progress and completion against time. The goal of this study is to introduce a theoretical model for forecasting a project completion date based upon Bayesian approach and updating the predicted completion date resulted from actual reported project progress over time periods. The study is

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concerned with a construction project in which the progress is timely reported and objectively assessed.

This study proposes an effective decision-making framework for evaluating and forecasting a future project progress and completion date on the basis of planned information and reported progress data with a consistent confidence level. Such predictions and evaluations can be accomplished by revising the initial desired project growth at each time period using Bayesian Inference and three types of S-shaped growth curves (Gompertz, Logistic, and Reverse-Gompertz curves). The S-shaped curves have been widely employed for cost-effectively technological growth forecasts in animal science during a short-term period (Franses, 1994; Meade, 1985). For a challenge toward construction industry, the model introduced in this paper uses Bayesian inference and growth curves. Thus, these approaches provide the forecasts according to timely reported information defined as actual progress data. One of important objectives of Bayesian Inference is to compute updated probability distributions of main parameters determining the planned project growth curve to revise and to predict the future project progress and completion date. Once revised distributions are estimated, confidence intervals are placed around the forecasts to assess the confidence the project managers have in the forecast. The error in fitting initial project progress curve is introduced as a "noise" and also it is interpreted with the sum of the squares of the deviations (SSD). This approach theoretically represents a common fact that when information related to project development is increasing, the uncertainties are decreasing (Ramgopal, 2003). Bayesian Inference in the study appropriately expresses this fundamental fact by continuously modifying the growth curve of ongoing project corresponding to the reported progress data over project execution. Therefore, the information-based forecasting model introduced in this paper is constructed on the basis of Bayesian Inference. This model will demonstrate that the amount of uncertainties on completion date is reduced when more reported information is available, such that it merges to zero at the completion of the project.

2. FORECASTING METHODS

Over the years construction projects have become larger and more complex, and so they often cost millions of dollars spent over a period of several years. Owners who invest millions of dollars expect suitable rate of return over a period of time. This rate may depend on timely completion of projects. Furthermore, inaccurate forecasts of completion date due to unpredictable events during project development may cause financial losses for the owners (Ford and Sterman, 2003).

With so much at stake in construction projects, owners and contractors alike must know a more defined status of project schedule throughout project progress and completion date. The forecasts for progress and completion date are useful if they are made at the early stages of the project development (Joglekar and Ford, 2005). If predictions are made at the beginning stages of a project, then project manager could have the opportunity to arrange for more resources when the project is behind schedule. Moreover, contractors can allocate resources elsewhere and earn a bonus if the project is completed ahead of schedule.

This study introduces an information-based model for use in evaluating and forecasting progresses and completion date at any time using the Bayesian Inference and three different types of growth functions determined by the characteristics of projects. The following section addresses the completion date described in this paper, application of S-shaped growth curves (Gompertz, Logistic, and Reverse-Gompertz curve) as a good representation of project development, and prior information of the main parameters ("a" and "b") that determine the project growth pattern. These present a few fundamental rules in modifying the project growth curve, forecasting the completion date, and updating it at any stage of project period when progress data is obtained.

(1) Earned Value (EV) Management

Earned Value (EV) provides one way to measure work accomplished by integrating cost and schedule performance in monetary terms, such that this helps evaluate project progress and predicts completion date. One of major objectives in EV management is to allow project managers to monitor the current project progress for predicting the future progress and completion date (Fleming and Koppelman, 2002). Throughout this paper, project costs are defined as budgeted cost of work as scheduled (BCWS) and budgeted cost of work as performed (BCWP). Commonly, if the schedule performance index (SPI) is less than one, then a project is behind schedule. The estimated date at completion (EDAC) is obtained when the BCWP equals the budget at completion (BAC). This study forecasts the EDAC with a consistent confidence level, based upon reported progress data at a certain period.

(2) Growth curves (S-shaped) and project development

Construction projects may often start slowly at the beginning and tend to progress quickly. This means that the rate of project growth, represented by the slope in growth curve, is accelerating when projects are 100% complete. Hence, this point leads the application of a growth curve (S-shaped curve) to represent how projects actually go through their development (Meade, 1985; Stukel, 1988). As a construction project progresses, works can be categorized into two parts such as "work-done (WD)" and "work to be done (WTD)". The project is completed through the process of transferring the works from the WTD to the WD, and if all the WTD is totally transferred to WD, then the project is finally completed.

(3) Logistic and Gompertz growth curves

The evaluation of project progress is shown as a cumulative WD as a function of time. There are three possible types of project growth curves on the basis of the rate of progress over time. For instance, if a project development is slow at the early stage and it is speedily completed in the middle or final stages, the progress rate starts from small to large. In this case, the distribution of progress growth rate over time is skewed to the right (e.g. Reverse-Gompertz curve). Figure 1 presents three typical types of growth rate of construction projects against time period (Franses, 1994).

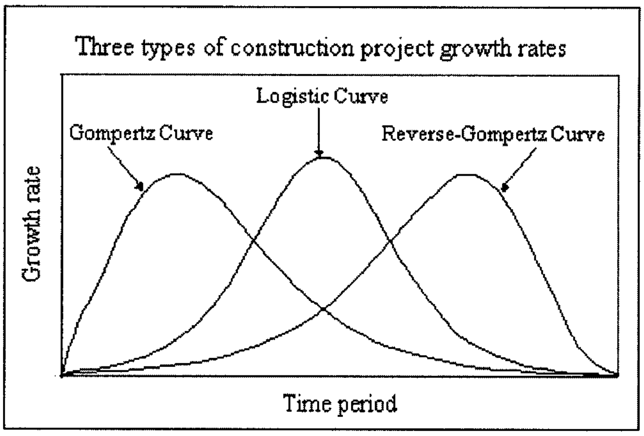


Figure 1 Three typical types of construction project growth rates

Logistic growth curve; symmetric growth rate:

$$BCWP(t) = \frac{S}{(1 + a \times e^{-bt})}$$

Gompertz growth curve; growth rate skewed to the left side:

$$BCWP(t) = S \times e^{-a \times e^{-bt}}$$

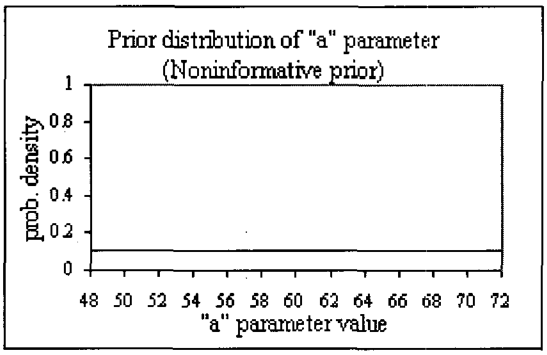
Reverse-Gompertz growth curve; growth rate skewed to the right side:

$$BCWP(t) = S \times (1 - e^{-a \times e^{bt}})$$

In the above equations, the a parameter is a shift parameter. It is a constant of integration that shifts the curve along the time axis. Each curve is calculated differently. The b parameter controls the slope of the growth curve and thus it represents the amount of the resource allocated. As the amount of resources increases, the value of this parameter increases and vice versa. Hence, the slope of the growth curve increases and the project is completed ahead of schedule. In fact, the actual amount of resources used depends on the amount of planned work to be done in each time period. "S" is an upper asymptote of the BCWS.

(4) Prior information

Project managers set up the values of two parameters (a and b) that determine the BCWS growth curve. Initial best estimates are obtained from the fitted growth curve to the BCWS curve. The prior distributions of these parameters depend on project managers' degree of belief in the various potential outcomes. These distributions are categorized into three kinds of prior information, such as noninformative prior, informative prior, and subjective judgment with manually entered value. For instance, if they have no information about the estimated parameter values, prior information is defined as a noninformative prior. This means that project managers show no preference for any particular values. However, when there is available information, based upon their experience and historical data, informative prior is appropriate. Moreover, if they have fuzzy or vague belief for those values, the belief is represented with manually scaled value (e.g. lowest belief = 1 and highest belief = 10) considering the potential outcomes. Noninformative prior can be commonly presented with uniform probability distribution, and informative prior can be shown with any specific probability distribution (e.g. normal distribution). This study employs noninformative prior distribution for more universal considerations.



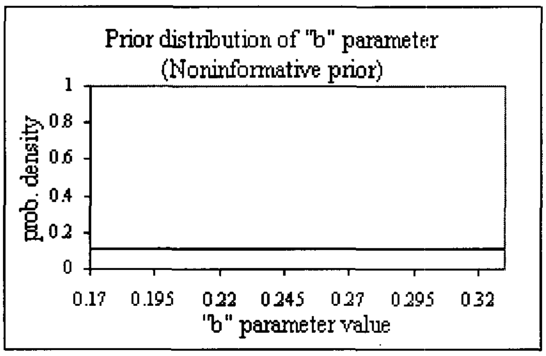


Figure 2 Initial probability distributions of "a" and "b" parameters

3. PREDICTING A PROJECT PROGRESS AND COMPLETION USING BAYESIAN INFERENCE

Project managers may be constantly looking forward to seeking indicators to provide them an early warning of how well their projects are going and how accurate the completion date of projects are predicted. In most cases, the maximum use of information generated by the project itself must be made to successfully forecast future outcomes. The classical Earned Value (EV) analysis presents simple rules for forecasting the completion date shown as a single-point estimate. This is typically linear extrapolation supposing that the project's schedule performance index (SPI) changed in the past will not impact that of the future. The critical path method (CPM) predicts the time at completion given a delay in critical path activities, but typically, delays affected past activities will not affect future ones. These traditional forecasting methods to predict the project completion date are commonly made on the basis of single-point estimates and deterministic approaches; but Bayesian Inference provides the confidence intervals on such forecasts. Furthermore, this modifies the intervals considering the affect of reported progress data to project development by re-computing the predictions of completion date with the data.

Prior to developing a project, the manager can firstly obtain from the project plan the values of the budget cost of work scheduled (BCWS) distributed over time, as determined by the resource-allocation schedule for the project under considerations. In fact, other patterns of project growth (e.g. completion percentage) can be used, but in this study, the BCWS is employed because it is substituted by any progress relation that is monotonically non-decreasing. As well, it is efficient to approximate the set of planned values (BCWS) by fitting any growth function to the points. The Logistic and Gompertz functions are introduced in this paper as project growth curves because they can be manipulated into linear forms by taking the logarithm; and so, they are suitable for fitting by simple linear regression. These growth functions satisfactorily fit and approximate the BCWS plan by computing their minimum sum of squares of the deviations. The satisfactory level of approximation and goodness-of-fit depends upon project manager's experience and attitude. The closeness of fitted functions to the BCWS plan is measured by the square root of the sum of the squares of the error terms; it can also be judged visually (Franses, 1994). Construction projects have frequently shown that most projects follow the S-shaped curve, but the individual shapes vary and thus, no universal growth curve function to fit all projects can be found. If a growth curve function fits the planned BCWS to an acceptable degree, the budgeted cost of work performed (BCWP) follows the same functional group of the BCWS with different parameters, depending on the degree to which an actual progress matches the plan. Parameter values are changeable for the forecasted progress curve compared to the (BCWS), but they are constant over a specific time period.

If actual project progress deviates from the plan, project managers may wish to change the parameter values and try to restore it to the planned condition. Based upon reported progress data, Bayesian Inference is applied to identify such changes. Prior to applying Bayesian Inference, parameters obtained by fitting the selected growth curve to the BCWS can be used as initial parameters of the BCWP curve. Since any progress data on the past BCWP is reported at a specific period, it is used to modify the Bayesian estimates of the parameters of the fitted approximation. Any deviation of the actual progress from the planned process shows up as a deviation of the forecasted BCWP curve from the planned BCWS. This deviation is used to predict the estimated date at completion (EDAC) from the original schedule. Bayesian Inference allows project managers to control the inferencing process by stipulating their own opinions through the probability distributions of main parameters (a and b) that determine the S-shaped functions described in this paper. The following section involves the way to find the best-fitted curve to the BCWS, to build the inference for generating the posterior distributions, and to create the confidence interval around the forecasted completion date.

(1) Finding the best-fitted growth curve to the BCWS

The goal of Bayesian approach in this study is not to make a perfect forecast but to create an early warning system. An approximate prediction of project completion date in early project development is valuable to project managers, and may lead to an early warning for deviations of the BCWP from the BCWS plan. Although this approach is slightly more complicated and probably less familiar to users as compared with the traditional methods, it may efficiently represent the reduction of uncertainties on completion date when more progress information becomes available. This point is one of advantages of using Bayesian analysis for project managers to make better decision. As mentioned earlier, because a growth curve is non-linear, it is necessary to linearize the S-shaped curves by performing some mathematical manipulations with the natural logarithms to seek the best-fitted curve to the BCWS. For instance, the linearization process of Logistic function is presented in the below, and the values of parameters are calculated from the fitted linear line.

$$y(t) = \frac{S}{(1 + a \times e^{-bt})}$$

$$\frac{S - y(t)}{y(t)} = a \times e^{-bt}$$

$$\ln\left(\frac{S - y(t)}{y(t)}\right) = \ln(a) - bt$$

$$Y(t) = \beta_0 + \beta_1 t$$

,where ln[(S-y(t))/y(t)], ln(a), and-b with Y(t), β_0, and β_0, respectively. Finding this best-fitted curve is critical to generate a reliable forecast and to reproduce the growth curve using any reported data. Statistically, the minimum sum of the squares of the deviations (SSD) is one effective indicator to determine the best-fitted curve.

$$SSD = \sum_{i=1}^{n} \{y(t_i) - \hat{y}(t_i)\}^2 \text{ ....Eq. (1)}$$

where t_i=1 and t_i=n are the first and final periods, respectively. For computing the values of "a" and "b" parameters in fitting initial growth curve, one effective method called linear regression analysis is used because it is familiar to most engineers and managers, and hence, it provides the confidence intervals around the forecasts.

(2) Bayesian Inference for project forecasting

As mentioned in the previous, a growth curve is an effective representation of how a construction project progresses through its development. This S-shaped curve has beginning, middle, and end stages. The speed of work is slow initially, but it picks up in the middle stages and again slows down at the end. As an actual progress data is reported on the BCWP, Bayesian Inference evaluates whether the data properly support the initial values of two parameters, in which case project managers believe that the progress is on schedule. This inference also evaluates whether the data support some other values of the parameters, in which case the project managers need to change their belief, particularly if the actual progress is behind schedule. A posterior distribution of parameters is computed by a likelihood function and a prior distribution. The probability of observing the actual data conditional on the parameters is called the likelihood function. Given that the parameters have values $a=a_i$ and $b=b_j$, the likelihood that the actual data BCWP(t) will be observed is P{BCWP(t) | $a=a_i$ and $b=b_j$}. The following presents the relationship among a prior, a posterior, and a likelihood function, and addresses the formula to compute the posterior probability distribution with Bayes' Rule.

$$Posterior\ distribution = \frac{(Likelihood) \times (prior\ distribution)}{Integration\ of\ likelihood}$$

$$\Pr(``a_i" \text{ and } ``b_j" | BCWP(t)) = \frac{\Pr(BCWP(t) | ``a_i" \text{ and } ``b_j")\Pr(``a_i" \text{ and } ``b_j")}{\sum_{i=-\infty}^{\infty}\sum_{j=-\infty}^{\infty}\Pr(BCWP(t) | ``a_i" \text{ and } ``b_j")} \quad \text{......Eq. (2)}$$

Here, $\sum_{i=-\infty}^{\infty}\sum_{j=-\infty}^{\infty}\Pr(BCWP(t) | ``a_i" \text{ and } ``b_j") = 1$

The progress and completion date predicted at time period t may not exactly match on the plan. This means that there is some error in measuring the reported BCWP. The measurement errors are distributed normally with N (0, σ^2) around the growth curve, where the mean error is zero and so the errors are not biased up or down. This principle is commonly used in a typical regression analysis. The progress of the growth curve with parameters a and b is y(t_i"a" and "b"). Their deviation is represented like the below.

$$Deviation = y(t | ``a_i" \text{ and } ``b_j") - BCWP(t) \quad \text{......Eq. (3)}$$

The likelihood as to how large this deviation is observed is determined by computing the normal probability density function using the normal distribution, N (0, σ^2), for the error. Thus, the likelihood is computed, and a posterior distribution over all pairs of parameters at each reporting period t is also obtained through Eq. (2). Then, the expected values of parameters are inferred and used to generate a growth curve to represent the best forecast of the BCWP curve.

(3) Creating confidence intervals

In either the Logistic or Gompertz growth curve, the parameter b represents the length of S-shaped curve called project duration. By plotting the distribution of b parameter from the posterior probabilities for each b_j, the confidence bounds on b parameter is estimated at desired confidence levels. The mean and standard deviation values of b parameter are computed based upon the posterior distribution. Hence, they are used to generate a modified growth curve that represents the best prediction of the future BCWP curve. As project managers are also interested in the confidence band for the predictions of BCWP, an estimate of the confidence bounds on b is obtained by plotting histogram of the probability density distribution of b from the posterior probabilities for each b value. The normal probability distribution table is used to assign confidence bands on the expected completion date at the desired confidence levels.

4. TESTS AND VALIDATIONS OF MODEL

For illustration purposes, a small construction project was considered, and its budgeted at completion (BAC) was $9,500,000. The project was scheduled to complete in 28 weeks; however, this was actually executed in 38 weeks. This construction project was developed and delayed (about 10 weeks). Figure 3 shows the project plan or BCWS, and Table 1 presents the BCWS data at each time period t.

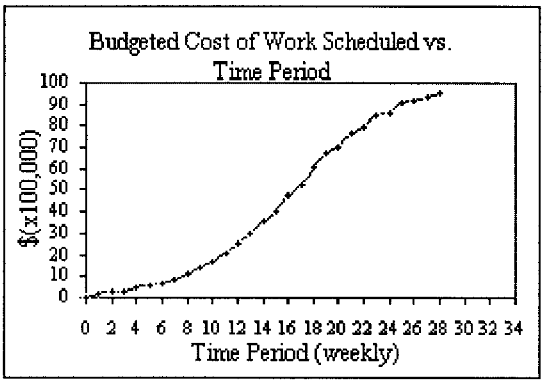


Figure 3 Planned project growth curve, BCWS(t) plan

Table 1 Estimated project progress data of BCWS plan

Time period	Planned BCWS (x$100,000)	Time period	Planned BCWS (x$100,000)
0	0	20	70
1	2	21	77
2	3	22	79
3	3	23	85
4	5	24	86
5	5.5	25	91
6	7	26	92
7	8	27	93
8	11	28	95
9	14	29	
10	17	30	
11	21	31	
12	25	32	
13	30	33	
14	35.5	34	
15	40	35	
16	48	36	
17	52	37	
18	61	38	
19	67	39	

Firstly, it is necessary to determine the best-fitted growth curve representing the BCWS(t) plan. By comparing between the BCWS(t) and the fitted S-shaped curves resulted from each growth curve and by computing the SSD, the best-fitted growth curve is established.

As seen in Figure 4, for this project and by calculating the SSD, the Logistic growth curve is more fitted than that of Gompertz. The optimal values of a and b

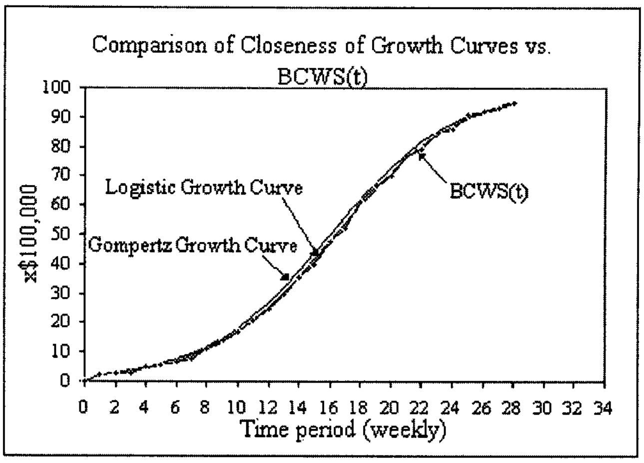


Figure 4 Fitted growth curves to BCWS(t) plan

parameters in minimizing the SSD are obtained by using nonlinear optimization procedures. In this study the linear regression analysis is used because it is familiar to most engineers and managers. The analysis yields the values a=60 and b=0.25. The SSD of the linearized function of the Logistic growth curve is computed as about 18.6, while that of the Gompertz growth curve is about 83.45. In the application of Bayesian Inference, it is clear that parameter a and b are continuous variables, and there are mathematical methods available to handle Bayesian inferencing problems using continuous variables. However, the discrete values of two parameters are used to validate the models in this study because such discretization is a common practice in construction projects. Also the nature of the process is constant and unchangeable over any specific time period. The values of a and b that fall outside the initially determined range are considered to have a probability value of zero. Here, its range is extended far enough to protect excluding real possible outcomes. The given project was tested for the proposed Bayesian Inference to show how well the forecasts based upon the reported data during early project stages (8 time periods) predict the actual full progress and completion date. For instance, the actual BCWP ($150,000) at time period 1 was less than the BCWS data. As shown in Figures 5 and 6, the posterior distributions of parameters are estimated, and hence the fitted Logistic function growth curve, where a=60 and b=0.25, is modified based upon these distributions.

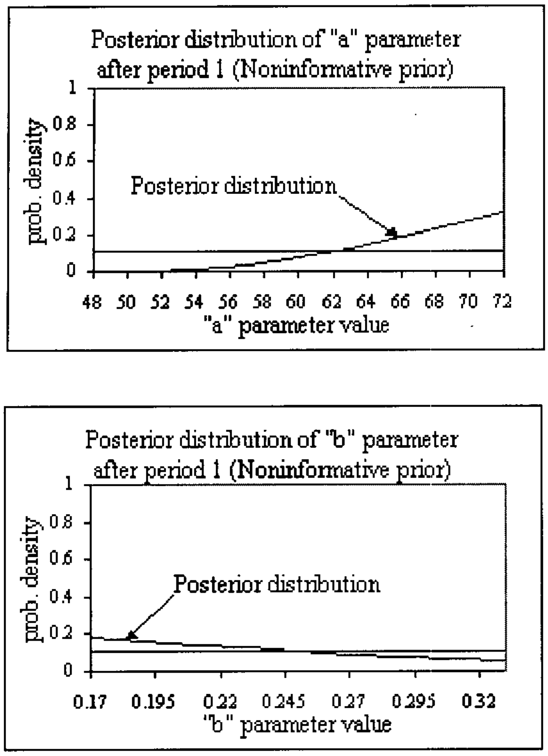


Figure 5 Posterior distributions of parameters after 1 Period

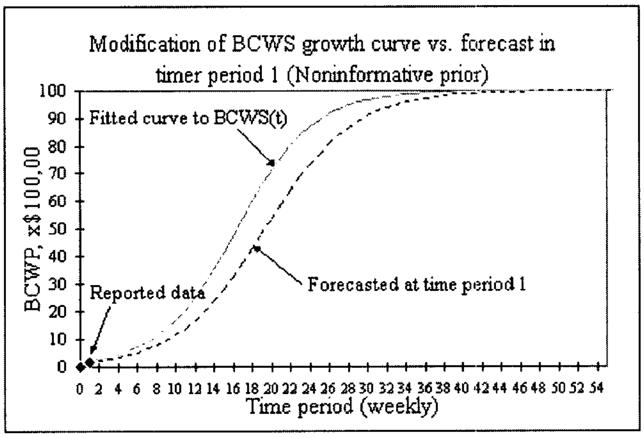


Figure 6 Modification of the initial growth curve after 1 Period

Since time Period 1, project progress was behind schedule. Project manager has to be concerned with this delay and try to re-predict the project completion date. Figure 7 shows that the probability distribution for completion date is moving to the right side with the slightly smaller width than the initial one, which means the expected completion is far from the scheduled date. On the other hand, the uncertainty on completion date is reduced due to obtained information known as the

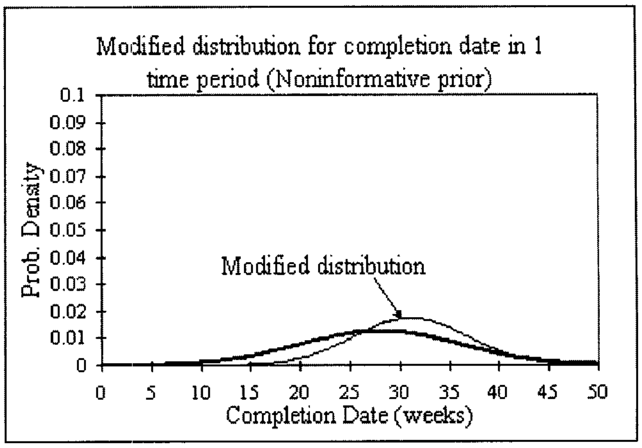


Figure 7 Modification of prior probability distribution on completion date at time period 1

reported progress data. The initial probability that the project would be completed within 28 weeks is about 50%. After project was developed during Period 1, the probability is re-calculated with a result of about 31.5%. This can provide the manager an early warning and help him or her to consider some strategic management and to successfully achieve the project schedule. If 30% of planned project duration is about 8 weeks, project manager re-predicts the estimated date at completion (EDAC) with each reported data during 8 time periods.

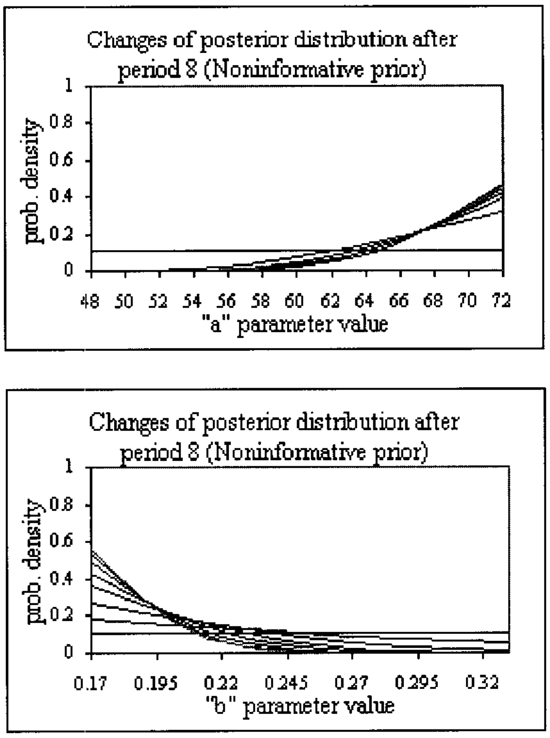


Figure 8 Changes of posterior probability distributions of parameters

Figure 8 presents the changes of posterior probability distributions of the parameters. The distributions become more specific when the progress data during the development is reported. As a result, this indicates that the uncertainty related to each parameter is decreasing due to increasing information. This appearance appropriately reflects the fundamental principle of Bayesian Inference. Modifications of progress growth curve are tracked during 8 time periods, and changes of probability distributions of completion date are shown in Figure 9. The initial distribution is moving to the right direction with the different degrees. However, the width of each distribution also becomes narrow corresponding to more reported data. Project managers can compute and quantify the probability that the project will be completed within schedule and within any specific date.

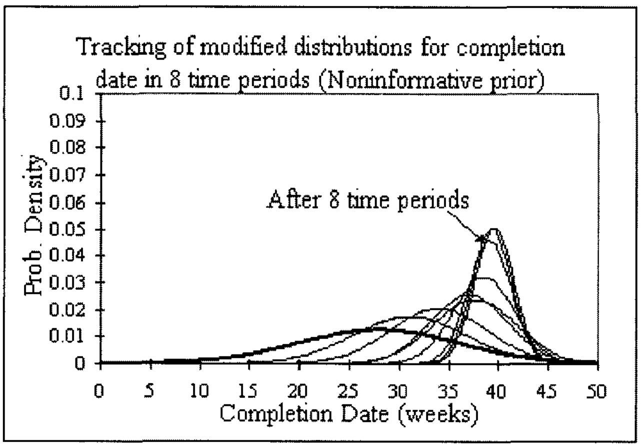


Figure 9 Modifications of probability distribution on completion date during 8 Periods

Table 2 Comparison between planned BCWS and actual BCWP at project completion

Time period	Planned BCWS (x$100,000)	Actual BCWP (x$100,000)	Time period	Planned BCWS (x$100,000)	Actual BCWP (x$100,000)
0	0	0	20	70	41.5
1	2	1.5	21	77	56
2	3	1.8	22	79	57
3	3	2	23	85	57.5
4	5	2.4	24	86	58
5	5.5	2.5	25	91	64
6	7	3	26	92	75
7	8	4.5	27	93	78
8	11	6	28	95	78.5
9	14	8	29		78.9
10	17	8.5	30		79.3
11	21	8.9	31		87
12	25	10	32		87.5
13	30	10.5	33		91.5
14	35.5	14	34		92
15	40	14.5	35		93
16	48	28	36		94
17	52	31	37		94.5
18	61	40	38		95
19	67	41	39		

In the application of Bayesian Inference, it is another important step to evaluate how properly the forecast at about 30% completion of project development fits the actual final project progress and completion date. Therefore, the full actual data of this project that was completed in 38 time periods (weeks) was compared with this early forecast. Hence, their assessment is presented in Figures 10 and 11 resulted from noninformative and informative prior, respectively. In both Figures, the early forecasts fit well with the actual progress data. However, the result from the informative prior follows the path of the actual progress as shown in Figure 11. This is because the informative prior involves more information for two parameters relative to the noninformative prior at the start.

As a result, the forecasted growth curves from different prior information after 8 time periods are close to the actual completion date. This fact assists in helping project managers recognize the realistic completion date at the

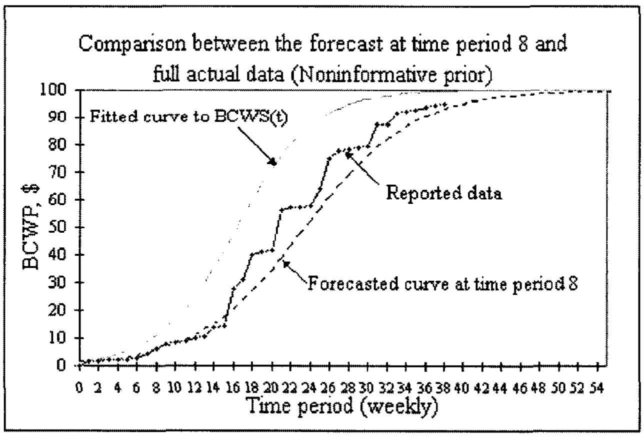


Figure 10 Actual progress and forecast after 8 Periods (Noninformative prior)

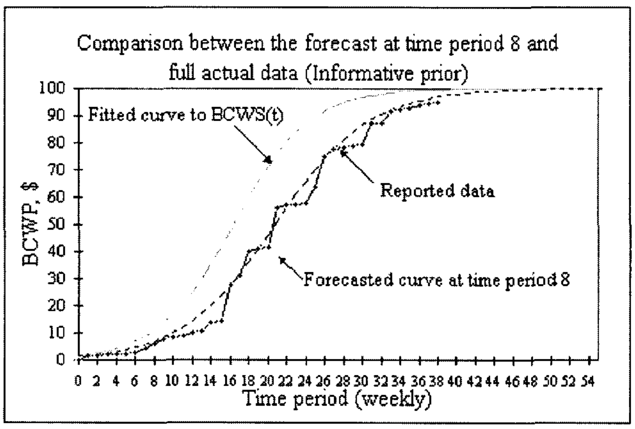


Figure 11 Actual progress and forecast after 8 Periods (Informative prior)

early development and aids in avoiding the delay with an early warning signal.

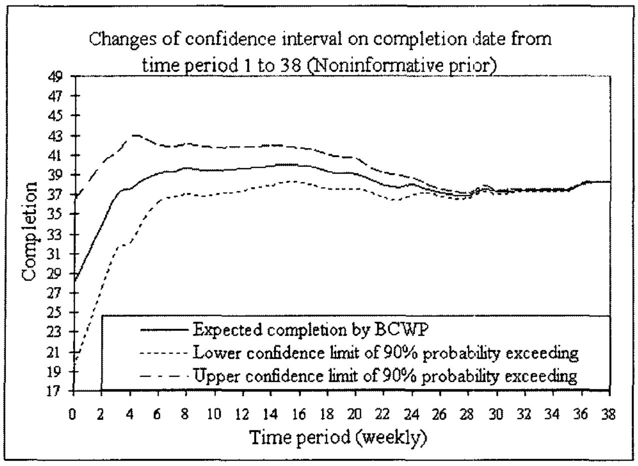


Figure 12 Changes of 90% confidence intervals on completion date until the completion (Noninformative prior)

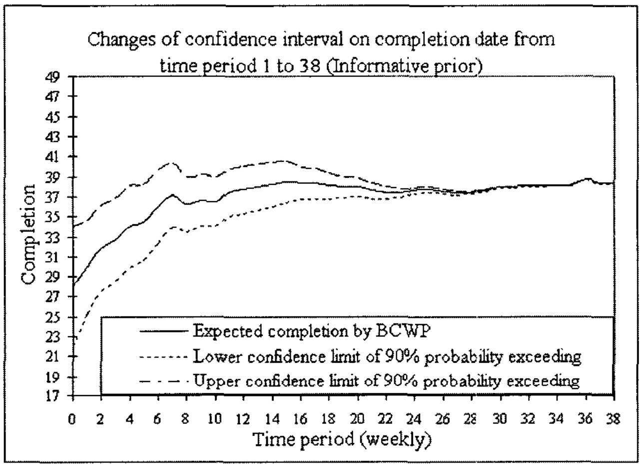


Figure 13 Changes of 90% confidence intervals on completion date until the completion (Informative prior)

If the probability distribution on the completion date is modified until the project is totally completed, the 90% confidence intervals on the forecasts are merged to a specific date as shown in Figures 12 and 13. This is due to the fact that when the project is completed, the uncertainty no longer exists. In turn, with the absence of this uncertainty, the confidence intervals merge to about 37.8 weeks, which is very close to the real completion date (38 weeks).

5. CONCLUSIONS

This study proposes one decision-making framework for evaluating and forecasting project progresses and completion date based upon the planned development information and reported progress data. Bayesian Inference and three types of growth curves were introduced to perform the modifications of the initial project growth curve at the early stages of the project development. Furthermore, Bayesian Inference was employed to update probability distributions of two parameters that determine the forecasted project growth. Hence, the forecasts of the project progress and completion date were achieved. The application of the theoretical model introduced in this paper has resulted in that the forecast of about 30% construction project completion (8 periods of the 28-week schedule) is close to the actual project progress and completion time.

When project managers identify problems with resources and estimate the probabilities of the respective resource parameters, they start to make some corrective changes of these parameters for successful project completion. They assess the ongoing project progress and quantify the uncertainty on completion date at any specific period. As a result, the completion date at early implementation stages follows the track represented by the actual growth curve and completion date. By using the model introduced in this paper, project managers are able to employ the actual progress data, such that the outcomes are obtained in the form of the forecasted growth curve and completion probability distribution.

In conclusion, the theoretical model described in this study modifies the forecast that depends upon the reported progress information at a consistent confidence level during the development. Hence, Bayesian Inference shown here has the potential to be used as a tool for early warning system. In addition, the model provides users indicators for evaluating how well projects are developing and for helping them make a better decision for completion date. However, in the further study it is a challenge to generate a universal project growth curve and to employ a nonlinear optimization procedure for the best fitted curve.

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논문제출일: 2007.03.06
심사완료일: 2007.04.26