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BAYESIAN INTEGRATION of internal and external views IN FORECASTING PROJECT PERFORMANCE

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ABSTRACT

This paper focuses on the project control process and aims at improving the accuracy of the Estimate at Completion at Time Now, both in terms of cost and time. This objective requires the use of all the available information, in particular the information related to the actual performance of the current project, corresponding to the "internal view", and the information related to the cluster of similar projects completed in the past, corresponding to the "external view". In order to integrate both types of information, a Bayesian model has been developed, allowing for the updating of a prior estimate based on the external view by means of the data records collected during the progress of the current project, in order to obtain a posterior estimate of the final cost and duration of the project. This approach allows for the mitigation of possible biases which can affect the project control process, particularly at the early stage of the project. The Bayesian model has been applied to three cases in the Oil and Gas industry. Notwithstanding the great difference between the projects, the integration of the internal and external views in the Bayesian model resulted in a better accuracy compared to the traditional formulas used in the Earned Value Management approach and, moreover, a better stability of the estimates from the early stage along the entire life cycle of the project.

INTRODUCTION

Project management comprises a set of processes, techniques, tools and knowledge aimed at planning and controlling a unique, temporary and multidisciplinary task *(Kleim & Ludin, 1998)*. The PMI *(2008)* has identified the following project management processes: initiation, planning, monitoring/execution, control and close-out.

This paper focuses on the control phase, in which, at every specific time "t" *(time now)*, two distinct views emerge. One concerns the work already done, "WC" *(work completed)*, whilst the second deals with the remaining part of the work, "WR" *(work remaining)*. The control phase not only evaluates the past performance related to the work already done *(WC)*, but also aims at forecasting the performance expected for the work remaining *(WR)*, by analyzing current trends and future events which could possibly affect the evolution of the project. In the context of Earned Management System *(Stevens, 1986; Barraza et al., 2000; Kim and Reinschmidt, 2010; Marshall, 2008)*, this forecasting process allows for the estimation of the final cost "EAC" *(estimate at completion)* and the final duration "TAC" *(time at completion)*. Obviously, the control phase can only influence the remaining work of the project, taking corrective measures in case EAC and TAC differ significantly from the planned baseline. This approach corresponds to a feed-forward type control loop, in which forecasting and re-planning processes are strictly interrelated.

Even though effective project management systems have been put in place, project failures in meeting planned objectives are common, in particular in large engineering and construction projects such as in the oil & gas industry, causing budget overruns and completion delays *(Merrow, 2011)*. In this regard, it remains an open question whether these failures are due to variances in project efficiency during execution or to a lack of forecasting capability during the planning phase. In the former case, both positive and negative deviations from the baseline should be expected, depending on the evolution of the project. On the contrary, a systematic overrun in terms of cost and time should be explained as a weakness of the planning process at the project outset.

Kahneman and Tversky's studies *(Kahneman and Tversky, 1977; Kahneman and Tversky, 1979; Kahneman and Tversky, 2007)* show that a major source of planning failure, which influences the accuracy of final cost and duration estimates, seems to be related to an exclusively "internal" view approach, i.e., based only on data records or experts' judgments related to the current project. Consequently, the research focus has moved to the psychological and political factors causing a bias in the planning process *(Lovallo and Kahneman, 1993; Lovallo and Kahneman, 2003)*, and, in particular, two main sources of bias have been identified *(Flyvbjerg, 2006)*.

Firstly, the cognitive illusions, entailing two major aspects: over-optimism, i.e., the common attitude to assess future projects with greater optimism than is justified by the actual previous experience, and anchoring, i.e., the attitude to deal with complex decisions selecting an initial reference point *(e.g., the anchor stemming from past experience)* and anchoring the estimate on it *(Amabile, 1985; Bar-Hillel, 1973; Buehler and Griffin, 2003; Buehler et al., 1994; Kutsh et al., 2011; McGraw and McCullers, 1979; Eroglu and Croxton, 2010; Evand et al., 2003; Roy et al., 2005; Slovic et al., 2004; Taylor and Brown, 1994; Walter et al., 2006; Coget and Keller, 2010; Weick and Guinote, 2010; Ying et al., 2007)*.

Secondly, the strategic and political pressures that may typically emerge during proposal preparation. Indeed, the selection of a project presupposes a competition involving different proposals, which often causes a voluntary underestimation of cost and duration by the project proposers in order to make their own proposal as attractive as possible. As a consequence, the contribution of the external view may be significant in improving the planning process and minimizing any bias *(Birgit, 2011; Flyvbjerg et al., 2002; Flyvbjerg, 2004; Flyvbjerg, 2005; Flyvbjerg, 2009a; Flyvbjerg, 2009b; Flyvbjerg et al., 2009)*.

The "external view" corresponds to the knowledge related to similar projects developed in the past *(Flyvbjerg, 2006)*. In fact, it may be assumed that the current project belongs to a cluster of similar projects completed in the past. Note that the selection of the cluster of similar projects will be a subjective judgment since it depends on the weight assigned to the similarity criteria adopted *(product, risks, customer, geographical area, site, contract, etc.)*. Some cases, in fact, may express strong ambiguity. For example, if a company has to estimate the costs of an investment in a new technology and in an unfamiliar technological domain, should it take into account the set of highly innovative projects developed in different technological domains or the set of barely innovative projects but belonging to the same technological domain? Neither the former nor the latter option may be the best solution but both should be considered *(Kahneman and Tversky, 1979)* and the choice of the cluster of similar projects requires a subjective judgment from the project team.

Besides similarity criteria, the subjective assessment should also consider the trade-off between a large number of projects, leading to the risk of including projects substantially different from the current one, and a small number of projects, leading to a substantial loss of statistic significance. It should be noted that in general when dealing with Large Engineering Projects the number of past similar projects is small, since Large Engineering Projects developed by a single company are necessarily few and moreover the differences between the projects in terms of technology, stakeholders, environment, etc. may be significant.

Firstly, this paper aims at exploiting all the knowledge sources available for project planning and, in particular, integrating the "internal view" and the "external view" by means of a Bayesian statistical model. The model allows for updating a prior estimate derived from the "external view", i.e., from the cluster of similar past projects through the data records collected during the progress of the current project, in order to

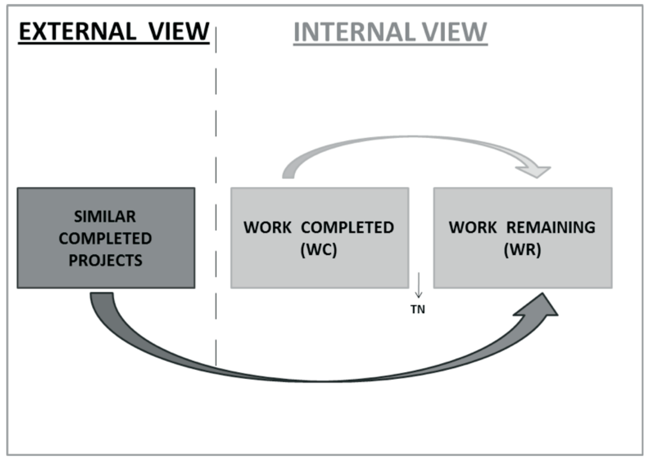

FIGURE 1. *External view and internal view.*

obtain a posterior estimate of the final cost and duration required to accomplish the project *(Gardoni et al., 2007; Kim and Reinschmidt, 2009)*. **Figure 1** shows the integration of the two knowledge components in order to improve the forecasting accuracy: the knowledge related to similar previous projects *(external view)* and the knowledge related to the work completed in the current project *(internal view)*.

Secondly, the Bayesian approach has been extended to the overall project life cycle, i.e., to each Time Now from the project outset to the project completion, in order to improve not only the initial planning process but also the control *(i.e., re-planning)* process during the project execution *(Koole and Spijker, 2000; Goodwin, 2005)*. In fact, an episodic trend at time now, either negative or positive, may influence the estimate to complete, unless the "external view" mitigates the bias.

The first section introduces the Bayesian model and the second section describes the application of the model to three oil & gas cases in order to test its effectiveness in comparison with the traditional EVM approach, based on the linear extrapolation of the current performance trend. Eventually, some final conclusions are given.

1. A Bayesian approach

Subjective probability is defined as the degree of belief in the occurrence of an event, by a given person at a given time and with a given set of information *(Galavotti, 1991; Nau, 2001)*. The subjective probability of an event may be interpreted as the price that a person is willing to pay for a lottery ticket that yields one unit of money if the event occurs and nothing if it does not *(De Finetti, 1974)*. The concept of probability, from this point of view, is strictly related to the set of available information *(D'Agostini, 1999; Suppes, 2007; Lavine, 2007)*.

In this context, the "Bayes Theorem" allows us to obtain the posterior probability density function of the parameter to be estimated by updating the prior probability density function, which expresses the experts' opinion, by means of the likelihood function, namely, the probability density function of the actually observed experimental data.

For example, if μ is the parameter to be estimated and $y=(y_1, ..., y_n)$ is the vector corresponding to the *n* independent and identically distributed experimental observations, conditional on the parameter μ, the Bayes Theorem may be formulated as shown in equation 1:

$$f(\mu|y_1, \dots, y_n) \quad \frac{\prod_{i=1}^{n} f(y_i|\mu)\cdot f(\mu)}{\int \prod_{i=1}^{n} f(y_i|\mu)\cdot f(\mu)\cdot d\mu} \qquad (1)$$

In equation 1, the following four components may be identified:

- $f(\mu|y_1, ..., y_n)$: posterior probability density function of the parameter μ, given the sample *y* of experimental data;
- $\prod_{i=1}^{n} f(y_i|\mu)$: probability density function of the vector $(y_1, ..., y_n)$ conditional on the parameter μ, i.e., the likelihood function;
- $f(\mu)$: prior probability density function of the parameter μ ;
- $\int \prod_{i=1}^{n} f(y_i|\mu) \cdot d\mu$: marginal density function of *y* .

Equation 1 describes a formal method to update the prior estimate $f(\mu)$, taking into account the experimental observations y_i, i=1,n, related to the current project. A simpler and intuitive manner to formulate the previous equation is shown in equation 2, where the denominator is not considered since it represents just a normalization factor:

$$f(\mu|y_1, \dots, y_n) \propto f(y_1, \dots, y_n|\mu) \cdot f(\mu) \qquad (2)$$

The Bayesian model as proposed in this paper is described by the following two distributions. The first one is related to the likelihood function and the second one to the prior distribution. The two distributions are assumed Gaussian; note that deviations may assume both positive and negative values, i.e., indicate both overrun and underrun. The two distributions are formulated by equations 3 and 6, respectively:

$$\frac{x(t)}{K(t)} \sim N\,(Z\,;\,\sigma_x) \qquad (3)$$

where:

- $K(t)$: physical progress percentage at time now;
- $x(t)$: overrun percentage cumulated at time now;
- $\frac{x(t)}{K(t)}$: overrun percentage extrapolated to the end of the project;
- Z : true value, to be estimated, of the final overrun percentage;
- σ_x: standard deviation of the observation $\frac{x(t)}{K(t)}$.

Note that in the model the likelihood function used to update the prior distribution is based on a single observation $\frac{x(t)}{K(t)}$ obtained at time now, where $\frac{x(t)}{K(t)}$ represents the observed value affected by error of the true value Z of the final overrun percentage. The project's physical progress percentage *K(t)* at time now may be defined as the ratio between the amount of work already done, i.e., WC, and the overall amount of work to be done, i.e., WC+WR. In the following, the quantity *x(t)* may indicate both cost overrun and time overrun percentages at time now, depending on the type of estimate required, as shown by equations 4 and 5.

Equation 4 is used in order to obtain the cost overrun percentage cumulated at time now:

$$x_C(t) = \frac{AC(t)-EV(t)}{BAC} \qquad (4)$$

where:

- *AC(t)*: Actual Cost at time *t*
- *EV(t)*: Earned Value at time *t*
- *BAC*: Budget At Completion

Regarding the time overrun percentage cumulated at time now, equation 5 is used:

$$x_T(t) = \frac{t-ES(t)}{PAC} \qquad (5)$$

where:

- *t*: Time Now
- *ES(t)*: Earned Schedule
- PAC: Planned At Completion, i.e. planned duration of the project

The standard deviation σ_x expresses the decision maker's degree of belief in the observation at time now $\frac{x(t)}{K(t)}$ as a good predictor of the final actual value, namely, how much he/she believes that the final actual value may deviate from $\frac{x(t)}{K(t)}$.

The prior distribution on Z is given by:

$$Z \sim N\,(\theta; \sigma_{rc}) \qquad (6)$$

where:

- *Z*: parameter to be estimated: overrun percentage at the end of the project;
- θ: expected value of the parameter to be estimated;
- σ_{rc}: standard deviation of the parameter to be estimated.

The standard deviation σ_{rc} describes the dispersion of the parameter Z related to the cluster of similar past projects. If σ_{rc} assumes a high value, it denotes that the outcomes of similar past projects in terms of cost/ time overrun are dispersed over a wide range; otherwise, it suggests a concentration around the central value.

The two distributions *(equation 3 and 6)* are assumed Gaussian. Obviously, this assumption about the normality of both distributions must be verified by analyzing the experimental data gathered during project progress.

Furthermore, the Gaussian prior distribution *(equation 6)* is conjugated with respect to the Gaussian model *(equation 3)*, hence allowing to obtain a Gaussian distribution as posterior distribution.

From equation 2, equation 7 may be obtained.

$$f(Z|\tfrac{x(t)}{K(t)}) \propto f(\tfrac{x(t)}{K(t)}|Z) \cdot f(Z) \qquad (7)$$

As shown in equation 7, the *posterior* probability density function of the parameter *Z* to be estimated is obtained by a combination between the prior probability density function given by equation 8:

$$f(Z) = \frac{1}{\sqrt{2\pi}\,\sigma_{rc}} \exp\left[-\frac{1}{2}\left(\frac{Z-\theta}{\sigma_{rc}}\right)^2\right] \qquad (8)$$

and the probability density function of the experimental data, i.e., the likelihood function, given by equation 9:

$$f\left(\frac{x(t)}{K(t)}\Big|Z\right) = \frac{1}{\sqrt{2\pi}\,\sigma_x} \exp\left[-\frac{1}{2\,\sigma_x^2}\left(\frac{x(t)}{K(t)} - Z\right)^2\right] \qquad (9)$$

These two distributions are to be combined in order to obtain the posterior distribution, as given by equation 10.

$$f(Z|\tfrac{x(t)}{K(t)}) \propto \exp\left[-\frac{1}{2}\left(\frac{Z-\theta}{\sigma_{rc}}\right)^2 - \frac{1}{2\,\sigma_x^2}\left(Z - \frac{x(t)}{K(t)}\right)^2\right] \qquad (10)$$

Through some mathematical transformation the following equation is eventually obtained:

$$f(Z|\tfrac{x(t)}{K(t)}) \propto \exp\left[-\frac{1}{2}\left(\frac{\sigma_{rc}^2+\sigma_x^2}{\sigma_{rc}^2\cdot\sigma_x^2}\right)\cdot\left\{Z - \left(\frac{\theta\,\sigma_x^2 + \frac{x(t)}{K(t)}\,\sigma_{rc}^2}{\sigma_{rc}^2+\sigma_x^2}\right)\right\}^2\right] \qquad (11)$$

i.e., Z has a Gaussian posterior distribution with mean and variance shown in equations 12 and 13, respectively. It should be noted that the posterior mean in Equation 12 represents the estimate of Z obtained through the Bayesian model.

$$E((Z|x(t)/K(t)) = \frac{\theta\,\sigma_x^2 + \frac{x(t)}{K(t)}\,\sigma_{rc}^2}{\sigma_{rc}^2+\sigma_x^2} = \frac{\theta\,\sigma_{rc}^{-2} + \frac{x(t)}{K(t)}\,\sigma_x^{-2}}{\sigma_{rc}^{-2}+\sigma_x^{-2}} \qquad (12)$$

$$V((Z|x(t)/K(t)) = \frac{\sigma_{rc}^2\cdot\sigma_x^2}{\sigma_{rc}^2+\sigma_x^2} = \frac{1}{\sigma_{rc}^{-2}+\sigma_x^{-2}} \qquad (13)$$

In equation 12, the *posterior* mean appears to be based on a weighted average of the *prior* mean of Z, i.e., θ, and the experimental observation at time now $\frac{x(t)}{K(t)}$. The weights are given by the reciprocal of the variances σ^2_{rc} and σ^2_x, respectively.

If we put $\sigma^{-2}_{rc} = w_e$ *(where the footnote "e" refers to the external view)* and $\sigma^{-2}_x = w_i$ *(where the footnote "i" refers to the internal view)* equation 12 can be formulated as follows:

$$E(Z) = \frac{\theta\,w_e + \frac{x(t)}{K(t)}\,w_i}{w_e + w_i} \qquad (14)$$

and equation 13 can be written as follows:

$$V(Z) = \frac{1}{w_e + w_i} \quad (15)$$

where wi and we indicate the weight of the internal view and the external view, respectively. Along the project life cycle, an increase of wi is expected, due to the increasing level of knowledge made available by the project progress, corresponding to a decreasing value of σ_x.

2. Three case studies in the oil & gas industry

The Bayesian model has been tested on three industrial projects, each associated to one of three different clusters of similar projects completed in the past, in order to test its forecasting effectiveness compared to the traditional approach typical of the Earned Value Management System *(EVMS) (El Sabban, 1973; McKinney, 1991; Anbari, 2003; Christensen, 1996; Christensen, 1998; Demenlemeester and Herroelen, 2002; Lipke, 2003; Marshall et al., 2008; Project Management Institute, 2011).*

The company, representing the owner of the projects, operates in the oil and gas industry, covering the entire exploration, development and production cycle, from exploring oilfields to extracting, producing, refining and distributing refined oil to final customers. In this context, the typical project entails a sequence of phases:

- Evaluation: carrying out the feasibility study of the project;
- Concept selection: developing technical and economical alternatives and choosing the alternative which maximizes the project value;
- Concept definition: designing and planning the selected project;
- Execution: executing the project;
- Commissioning, Start-up and Performance Test: preparing for the final test representing the prerequisite for the start up of the operation phase (i.e., first oil).

When closing out a phase, there is gate, which represents a mandatory check point, giving the green light to proceed to the next phase, otherwise the project is to be closed.

In particular, the Bayesian model proposed in this paper covers the execution phase, namely, from the end of the concept definition phase to the performance test. The parameters to be estimated by the model are the mean and the variance of the final overrun percentage, both in terms of cost and time. The use of the percentage value allows for a direct comparison of different similar projects, notwithstanding a different size.

The clusters of similar projects considered in the case study are the following:

- Subsea projects (wellheads and pipeline installation under the sea);
- Offshore projects (facilities construction and oil extraction in the sea);
- Onshore projects (facilities and pipelines construction on land).

Once these reference clusters had been identified, the final overrun percentages in terms of cost and time were calculated for each single project included in a cluster. Based on this data, the prior distribution related to each cluster was derived *(see equation 6)*, assuming a Gaussian distribution with mean and variance equal to the sample mean and variance of the cluster data. The prior distribution deriving from each cluster was used for improving the control process of a current similar project.

Before obtaining the three prior distributions, the following points had to be checked:

- Identification of potential “outliers” (values considered to be anomalous for the distribution and possibly discarded);
- Test of normality of the prior distribution.

The normality test and the outlier elimination concerning the sub-sea and the onshore project clusters gave a positive result confirming both normality and absence of outliers. The analysis of normality was carried out by means of the Anderson Darling test, using Minitab software. In both cases, a P-Value was obtained, i.e., the minimum significance value for which the normality hypothesis would be rejected *(Gibbons and Prat, 1975)*. A figure for the P-Value higher than 0.05 allows the normality hypothesis to be accepted. In order to identify potential outliers in these two clusters, the Box-and-Whiskers graph was considered to be the appropriate methodology, indicating the absence of outliers for both clusters respectively.

A different situation emerged in the offshore cluster. The preliminary normality test showed negative results for both cost and time overrun percentages. This can be discerned from the P-Value which is lower than 0.05 in the Anderson Darling test, as shown in **Figure 2**.

In order to identify potential outliers, the Box-and-Whiskers graph was applied, as in the previous cases.

A potential outlier was identified, corresponding to the project in the upper right sector of the graphs in **Figure 2**. After an analysis of the cause of the anomalous result, it was decided to eliminate it from the distribution. It appeared that the project had undergone, during the execution phase, an unpredictable disruption creating both a budget overrun and a completion delay. After having eliminated this outlier, a further normality test was performed, obtaining a positive result.

After having tested the normality of the distributions and eliminated the potential outliers, the prior distributions *(see equation 6)* were obtained for each reference cluster, whose mean θ and standard deviation σ_{rc} values are shown in **Table 1**.

It can be seen that the three clusters are characterized by a different behavior in terms of cost performance and a similar behavior in terms of schedule performance. In particular, in **Table 1** the subsea cluster is characterized by the lowest values of cost overrun percentage and related dispersion, while the onshore cluster presents the highest values.

- The following characteristics explain the behavior of the subsea cluster;
- More standard technologies;
- Larger contingency used to cover unforeseen events;
- Long term partnership with a small number of specialized suppliers;
- Highly skilled workforce.

On the other hand, the onshore cluster is characterized by greater values of cost overrun percentage and related dispersion, mainly due to the different geographic areas where the company operates, often requiring different technologies and numerous interfaces with local stakeholders which may adversely influence the project performance.

After having identified the reference clusters of projects, a single project currently in progress was chosen for each cluster in order to test the accuracy of the forecasting model.

Note that the model requires the calculation of EV*(t) (Earned Value)*, which indicates the budget cost of the work completed at time now *(see equation 4)*. In the same way, the calculation is required of ES*(t) (Earned Schedule)*, i.e., the planned time corresponding to the actual physical progress achieved at time now *(see equation 5) (Lipke, 2003)*.

Based on EV*(t)* and ES*(t)*, the observation x*(t)* required by the model at time now, i.e., the overrun percentage at time now, can be calculated for the current project, for cost *(equation 4)* and time *(equation 5)* respectively. Then, dividing the results obtained by the physical progress percentage at time now K*(t)*, the forecast at the end of the project, in terms of both cost and time final overrun percentage, i.e., $\frac{x(t)}{K(t)}$, can be obtained.

It should be noted that the standard deviation σ_x, which represents the decision maker's confidence at time now in the estimating accuracy of $\frac{x(t)}{K(t)}$ as a predictor of the final overrun percentage, depends mainly on the physical progress of the project. For instance, the estimate of the final overrun percentage obtained at 10% of physical progress deserves less confidence than the same estimate obtained at 90% of physical progress, since in the latter case the amount of work completed and information available is larger. So the standard deviation σ_x decreases with the increasing progress of the project. In the three oil & gas case studies an empirical relationship based on experience has been adopted between the physical progress K*(t)* and the standard deviation σ_x, for cost and time respectively *(see* **Table 2***)*.

In **Table 2** the standard deviation values related to time are lower than those related to cost since for oil & gas projects meeting the schedule deadlines, i.e., the outset date of the operation phase, is typically a more binding constraint than meeting the budget cost. In **Table 2**, a ratio equal to 5 has been adopted between σ_x cost and σ_x schedule, along the project life cycle. The assumptions used in **Table 2** seem to be robust, since a sensitivity analysis has demonstrated that variations of the ratio do not significantly change the results given by the model.

After obtaining the prior probability density function *(see* **Table 1***)* and the likelihood function *(see equation 9)* based on $\frac{x(t)}{K(t)}$ and σ_x, mean and variance of the posterior probability density function can be calculated by means of the Bayes Theorem *(equation 13 and 14, respectively)*.

Considering the above mentioned three cases, i.e,. A *(subsea)*, B *(offshore)* and C *(onshore)* respectively, for each project, **Table 3** indicates three different values of physical progress, at which the observation x*(t)* has been collected *(see K(t)* column) and the corresponding estimate, based on the Bayesian model, of the final cost of the project *(see EAC Bayesian column)*. Furthermore, the initial budget *(see BAC column)* and the final actual cost *(see the last column)* are reported. In particular, the data related to cases A and C, i.e., the cost baseline, the actual cost curve and the corresponding monthly expenditures, are given in Figures 3 and 4 respectively.

Analogous parameters are given for the project duration *(***Table 4***)*, where PAC indicates Planned at Completion, i.e., the planned project duration, and TAC indicates Time at Completion, i.e., the estimated project duration at time now. Furthermore, the final actual duration *(see the last column)* is reported.

For each case and for each value of physical progress, further estimates of the final actual cost and duration have been determined using two traditional formulas applied in EVMS *(Earned Value Management System) (equations 16 and 17)*, as shown in **Table 3** and **Table 4**, for cost and time respectively:

$$EAC = AC(t) + [(BAC-EV(t))/CPIf] \quad (16)$$

$$TAC = t + [(PAC-ES(t))/SPIf] \quad (17)$$

These formulas represent a benchmark for evaluating the performance of the Bayesian model. Two cases have been considered for CPI*f (cost performance index future)* and SPI*f (schedule performance index future)*, respectively:

- CPIf = CPIp, (SPIf = SPIp), i.e., the future performance of the project, related to WR, will correspond to the past performance, related to WC (see the fourth column in Table 3 and Table 4);
- CPIf = 1, (SPIf = 1), i.e., the future performance of the project will correspond to the initially planned performance (see the fifth column in Table 3 and Table 4).

As shown in **Table 3**, the Bayesian model generally gives better results than the EVMS formulas, in particular at the project outset, when the available information is scant and significant decisions are to be made. These results confirm that an overconfidence on the internal view at the project outset, without the balancing effect of the external view, may lead to a forecasting error.

For example, focusing on the forecast in case A, at 12.06% of physical progress in February 2010 *(see figure 3)*, the exclusive use of the “internal view”, based on the observation at time now of $\frac{x(t)}{K(t)}$ = -1.09, corresponding to an underrun, would give an over optimistic estimation of the final cost

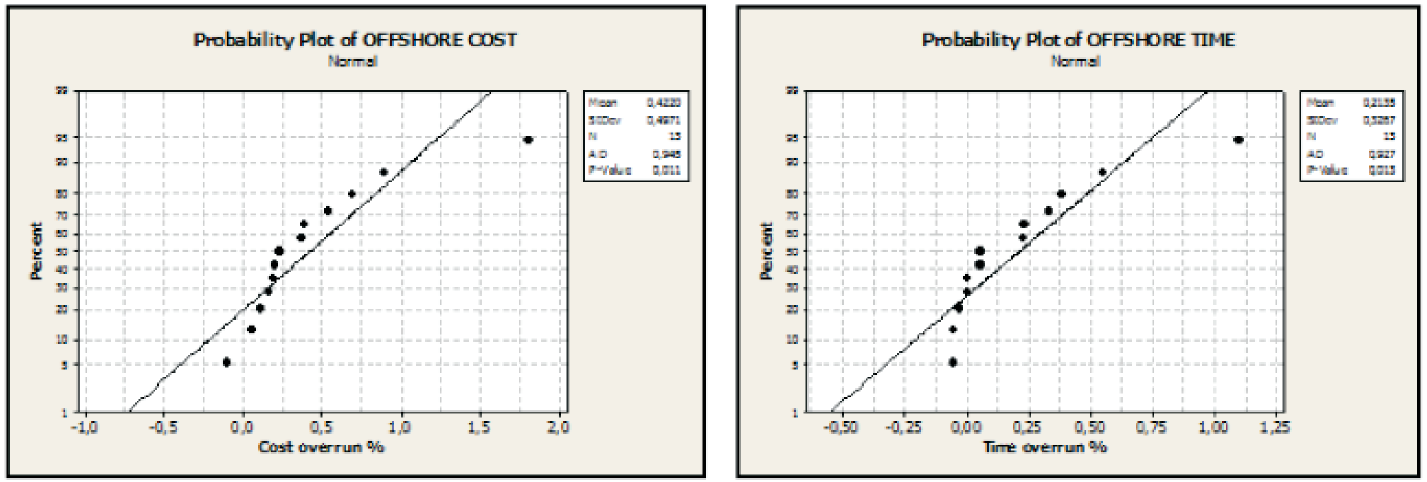

FIGURE 2. *Anderson Darling Test offshore projects.*

	Mean cost overrun %	Standard deviation cost overrun %	Mean time overrun %	Standard deviation time overrun %
CLUSTER SUBSEA	0.08175	0.163	0.2374	0.2149
CLUSTER OFFSHORE	0.03065	0.2833	0.1399	0.199
CLUSTER ONSHORE	0.6344	0.5159	0.1966	0.2397

TABLE 1. *Means and standard deviations of prior distributions.*

corresponding to -47 million *(obviously impossible)*. Thanks to the integration with the external view, at this early stage of the project, the final cost estimation becomes 509 million, which is close to the 523 million actual cost at completion. At 50% progress the estimate given by the model becomes even more accurate.

The case A reveals a high efficiency at the outset but the gap between the actual cost *(grey line)* and the baseline *(black line)* decreased during the project life cycle meeting the budget requirements at the end of the project *(see* **Figure 3***)*.

Notwithstanding the initial high performance leading to an over optimistic forecast, the integration of internal and external view for the subsea project, provides an estimated value of final cost close to the actual value, registering only 2.7% of forecasting error since the project outset.

Obviously, the influence of the prior distribution, corresponding to the external view, will be lower at a higher physical progress percentage, according to the decreasing values of standard deviation σ_x along the project life cycle *(see* **Table 2***)*. This behavior of σ_x, i.e., the degree of belief in the estimate provided at time now, makes sense since the closer the observation $\frac{x(t)}{K(t)}$ to the completion date of the project, the greater the amount of work completed and the fewer the degrees of freedom for corrective actions. Similar considerations about the performance of the forecasting model may be extended to the estimations obtained in case B.

A lower forecasting accuracy occurred in case C with reference to the first two observations. This forecast inaccuracy was mainly due to an unforeseen situation that occurred after the second observation, due to a change of contractor, causing a severe disruption in the construction process. This event may be considered a very low probability and very high impact risk *(Caron, 2013)*. In fact, a sharp increase in the actual cost *(grey line)* compared to the budget cost *(black line)* is shown in **Figure 4** in June 2009, due to the work disruption stemming from the change of contractor, that neither the Bayesian model nor the traditional EVMS formulas could have been able to foresee. Notwithstanding the unforeseen situation, the Bayesian model gives overall better results than the EVMS formulas, particularly at the project outset.

As shown in **Table 4**, where the values are expressed in months, the estimations of the project duration, obtained by the Bayesian model, are on average more accurate than the EVMS estimations. Nevertheless, as shown in **Table 4**, a loss of accuracy in case C occurred, due to the unforeseen problem.

The results achieved by the Bayesian model do not only show a greater accuracy compared to the traditional EVMS formulas at the outset of the project, but they also indicate a greater stability of the forecast along the project life cycle. Indeed, the results achieved by the traditional EVMS formulas feature a greater volatility along the project life cycle, as shown in **Tables 3** and **4**. It should be noted that the cases considered in the paper are challenging from the forecasting point of view, in particular case A *(initial exceptional performance)* and case C *(unforeseen disruption in the middle of the execution phase)*. In the Bayesian model, the stability has been obtained by means of the contribution of the external view, which, in general, represents a stabilization factor for the internal view, particularly in the early phase of the project.

3. Conclusion

In this paper a Bayesian model for estimating the final cost and duration of a project at time now has been developed, based on the integration of the internal view concerning the current project and the external view, related to knowledge deriving from previous similar projects. The model may be applied at each time now along the project life cycle and allows for mitigating the possible forecasting

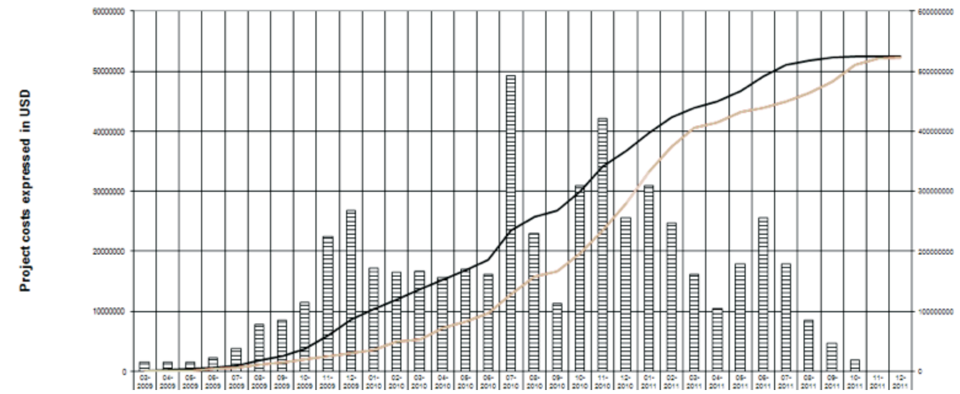

FIGURE 3. *Actual cost curve vs. planned cost curve (case A).*

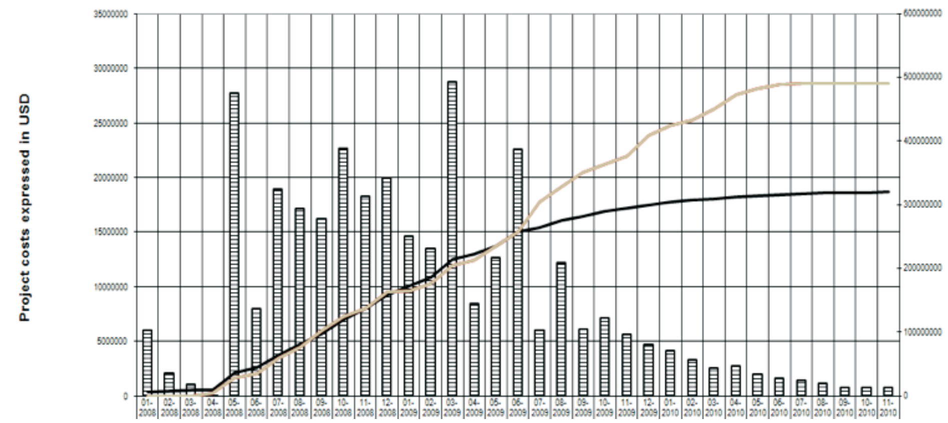

FIGURE 4. *Actual cost curve vs. planned cost curve (case C).*

k(t)	(0-40)%	(41-80)%	(81-100)%
σ_x COST	0.5	0.3	0.1
σ_x SCHEDULE	0.1	0.06	0.02

TABLE 2. *Standard deviation σ_x as a function of physical progress.*

	K(t)	BAC	EAC Bayesian	EVMS (CPIf=CPIp)	EVMS (CPIf=1)	FINAL ACTUAL COST
CASE A (subsea)	12.06		509	218	456	523
	58.8		523	380	435	
	86.7		530	516	517	
CASE B (offshore)	6.83	81	103	95	82	89
	62.2		90	71	75	
	80.6		91	90	82	
CASE C (onshore)	20.08	320	416	314	319	491
	68.1		385	338	332	
	89.57		473	470	455	

TABLE 3. *Output of the Bayesian model vs. EVMS formulas vs. actual results (COST).*

	K(t)	PAC	TAC Bayesian	EVMS (SPIf=SPIp)	EVMS (SPIf=1)	FINAL ACTUAL COST
CASE A (subsea)	12.06	35	34	32	32	33
	58.8		33	33	32	
	86.7		33	33	33	
CASE B (offshore)	6.83	32	38	38	32	37
	62.2		35	35	34	
	80.6		37	35	34	
CASE C (onshore)	20.08	31	32	32	31	35
	68.1		33	33	36	
	89.57		35	35	35	

TABLE 4. *Output of the Bayesian model vs. EVMS formulas vs. actual results (SCHEDULE).*

bias causing excessively optimistic *(or pessimistic)* estimates, particularly at the project outset when available information is scant and significant decisions are to be made. An explorative analysis was conducted in order to test the model accuracy in three projects belonging to three separate clusters of similar projects related to the Oil and Gas industry. The model allowed for an improvement of the forecasting accuracy in comparison with the traditional formulas used in the Earned Value Management System framework.The estimations given by the proposed model showed a better performance from the project outset and a good stability along the life cycle of the project.

An extensive industrial application of the model is required in order to confirm the effectiveness of the proposed approach. Moreover, a further research development could be the improvement of the internal view by integrating data records and experts' judgment through a Bayesian approach.

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