Improving the Forecasting Process in Project Control

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INTRODUCTION

Among the typical project management processes, forecasting plays a decisive role in reducing a project's uncertainty. Since uncertainty arises from a lack of knowledge, it is strictly linked to the inability of the project team to exploit all the available knowledge in order to anticipate the future development of the project (Williams & Samset, 2010; Williams et al., 2009).

In fact, planning represents a forecasting exercise (Soderholm, 2008). Developing a project plan is strictly related to making assumptions about the near and long term future, since the project plan reflects a summary of the assumptions taken about the future (Dvir & Lechler, 2004). Planning and forecasting are interrelated since they allow us, for instance, to fix milestones, e.g. critical dates for the project's stakeholders, in order to coordinate material/services delivery, provided that forecasting lead times are consistent with delivery lead times. In particular, planning is necessary for each supplier in order to deliver the required contribution to the project in a timely way (Kleim & Ludin, 1998).

Forecasting capability remains at the heart of project control. At a specific Time-Now (TN), a part of the work is completed (WC) and a part of the work, the work remaining (WR), still has to be done. Based on the Earned Value Management System (EVMS) (Fleming, 1992), the two components of the estimate at completion (EAC) are given by the Actual Cost AC of the WC and the Estimate To Complete (ETC) concerning the Work Remaining (WR). Analogous considerations may be applied to the estimate of Time at Completion

(TAC). It should be noted that in the project control process the role of ETC is critical, since the only way to influence the overall project performance is to take actions affecting the WR. The information drawn from the ETC may highlight the possible need for corrective actions that may adjust the project plan (Anbari, 2003; Christensen, 1996). This approach corresponds to a *feed-forward* type control loop (see Figure 1).

As a consequence, during the project control process, the project manager plays a twofold role: the "historian," attempting to grasp the drivers that have determined the past evolution of the project, and the "wizard," attempting to grasp the future evolution of the project and to exploit all the lessons learned from the past (Makridakis & Taleb, 2009; Makridakis et al., 2009).

This chapter will address the question of identifying the possible knowledge sources and integrate their different contribution in order to improve the forecasting capability during the project control process.

BACKGROUND

As Project Management Institute (2008) stated, the main processes involved in project management are: initiating, planning, executing, monitoring, controlling and closing. In particular, Earned Value Management (EVM) represents an effective way of addressing the project control process. EVM is an efficient performance measurement and reporting technique for estimating cost and time at completion (PMI, 2011; Marshall et al., 2008). The following basic parameters are used in EVM,

Figure 1. Estimation at completion at Time Now (internal view)
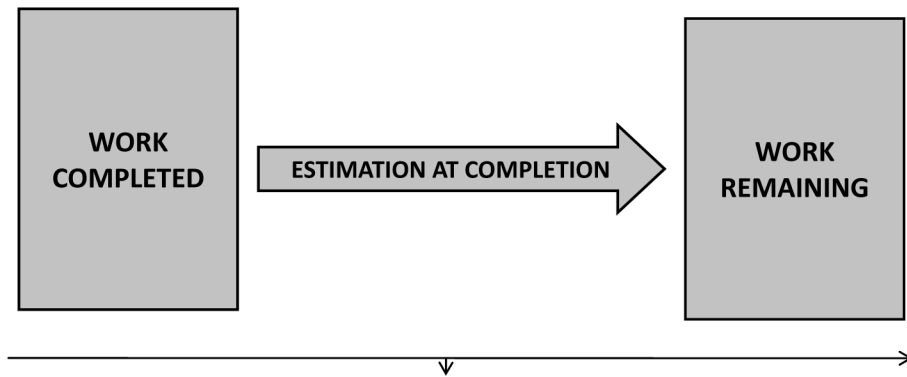
where TN indicates Time Now, i.e. the time along the project life cycle at which the control process is implemented:

- **Planned Value (PV):** The budget cost of work scheduled at TN;
- **Earned Value (EV):** The budget cost of work completed at TN;
- **Actual Cost (AC):** The actual cost of work completed at TN.

EVM was improved by Lipke (2002a; 2000b; 2003), who introduced the concept of Earned Schedule (ES) for measuring schedule performance in time units and overcoming the flaws associated with a Schedule Performance Index SPI defined as the ratio between EV and PV, expressed in monetary terms. Earned Schedule is the time at which the EV value achieved at TN should have been obtained according to the project baseline. The new Schedule Performance Index SPI(t) at TN, defined as the ratio between ES and TN, represents a more effective approach, since it avoids the problem of the convergence of the EV and PV values toward BAC, i.e. Budget At Completion, as the project reaches completion (Lipke, 2006a; Lipke, 2006b).

The above three parameters and the ES value allow for the calculation of a set of indices and variances at TN. The most important of these are:

- **Cost Performance Index:** $CPI = EV / AC$;
- **Cost Variance:** $CV = EV - AC$;
- **Schedule Performance Index:** $SPI_{(t)} = ES / TN$;
- **Schedule Variance:** $SV_{(t)} = ES - TN$;
- **Schedule Cost Index:** $SCI_{(t)} = CPI * SPI_{(t)}$.

Variances CV and SV(t) summarize the project's past performance during WC, while indexes CPI and SPI(t) may be used in order to highlight current trends and estimate the future performance during WR (Anbari, 2003).

Many Estimate at Completion formulas have been proposed during almost 50 years of EVM applications but none of them has proved to be always more accurate than any other one (Christensen, 1993). In the standard approach, the estimations of final cost (i.e. EAC) and final duration (i.e. TAC, Time at Completion) are based on the following equations:

$$EAC = AC + (BAC - EV)/ CPI_f \qquad (1)$$

where:

AC = Actual Cost at TN

BAC = Budget at Completion

EV = Earned Value at TN

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