



Construction Industry Institute®

Improving the Accuracy and Timeliness of Project Outcome Predictions

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Construction Industry Institute

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IMPROVING THE ACCURACY AND TIMELINESS
OF PROJECT OUTCOME PREDICTIONS

by

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A Report to
Construction Industry Institute
The University of Texas at Austin

Under the Guidance of
CII Research Team 291
Improving the Predictability of Accurate Project Outcomes

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EXECUTIVE SUMMARY

The research effort undertaken by RT 291 provides strong evidence that predictability can enable project teams to address project performance proactively and in a timely manner, through proper management decisions, and thus increase value to the stakeholder organizations. There are numerous examples where project stakeholders put their trust in a project outcome prediction that proves to be in error, often significantly so, to the strong detriment of the project, organization, and the reputation of the managers involved. As such, RT 291 analyzed and recommended forecasting practices in the construction industry by conducting statistical analyses, multiple surveys, and workshops with subject matter experts. The major findings are summarized below:

- Predictability, the condition to produce early and accurate forecasts for cost and schedule measures at completion, is actually influenced by factors across multiple core competencies intrinsic to the delivery of capital projects.
- Predictability enables project teams to address project performance proactively and in a timely manner, through proper management decisions, and thus increase value to the organization.
- There are distinct and identifiable practices between effective and ineffective projects with respect to their ability to forecast final cost and schedule outcomes.
- Project team performance needs to be evaluated based on the team's ability to mitigate cost and schedule deviations through the early and accurate prediction of cost and schedule outcomes, as opposed to the prevalent evaluation of a team's performance based solely on the magnitude of such deviations at project completion.
- The disruptive nature of change on owner and contractor project performance presents itself in varied form, frequency, and intensity.

The research insights that led to such findings are presented in this Research Report, which summarizes an investigation that involved more than 100 individuals and 20 organizations.

LIST OF ABBREVIATIONS AND SYMBOLS

Y	Actual value
Ω_t	All information available at time t
df	Degrees of freedom: number of values free to vary after certain restrictions have
Δ	Delta
$E()$	Expected value
χ^2	Chi square
$\hat{Y}$	Forecast
h	Forecast horizon
U	Forecast error
τ	Kendall's Tau-b coefficient
α	Level of significance
p	Probability associated with the occurrence under the null hypothesis of a value
$R_{-/ +}$	Rank (negative/positive)
RR	Relative risk
SD	Standard Deviation
SE	Standard Error
$\Pi(x)$	"Success" Probability
Σ	Sum
t	Time

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1. INTRODUCTION

There are numerous examples where project stakeholders put their trust in a project outcome prediction that proves to be in error, often significantly so, to the strong detriment of the project, organization, and the reputation of the managers involved. Owners and contractors alike base key strategic decisions on their project forecasts and typically ask project teams to refine cost and schedule predictions continually, with a goal toward providing management with valid, timely, and reliable information. However, the ability to accurately predict project outcomes is highly varied within the industry, sometimes even within an organization itself, resulting in many member companies experiencing “surprises” or unexpected negative consequences late in the project execution process.

The ability to forecast in a timely and accurate manner should be regarded as a fundamental competency within an industry characterized by the cost and schedule deviations. Such deviations have become inherent to the delivery of its capital projects. CII has recently reported that nearly 70% of 975 owner projects suffered actual cost and schedule deviations exceeding +/- 10% from their baseline or authorized values (Mulva and Dai, 2012). Oil and gas industry projects were reported with cost overruns and schedule delays exceeding +/- 10% from their authorized or baseline values in 40% of the investigated projects (McKenna, Wilcznski, and VanderSchee, 2006). Many others (United States Government Accountability Office (GAO), 2007; McKenna, Wilcznski, and VanderSchee, 2006; GAO, 2005; Bordat, McCullouch, Sinha, and Labi, 2004; and GAO, 2003) have reported similar cost and schedule deviations across industry sectors, organizations, project scale, or geographic location. Thus, predictability, the condition that enables the generation of early and accurate forecasts at completion, should be regarded as a fundamental competency to ascertain total installed costs and completion times early in the delivery process, and hence facilitate informed and proper decisions at both project and organization levels.

In short, getting to the correct outcome sooner, whatever that outcome might actually be, is much better than being surprised later when no mitigation actions are possible. This ability to be proactive, rather than reactive, can significantly improve the team's ability to minimize the deviation between predicted and actual outcomes. For example, the early recognition that the baseline cost has been significantly underestimated cannot guarantee meeting such cost target at project completion, but enables the project team to proactively and timely address and improve cost performance. Also, in an opposite scenario, the early recognition that the baseline cost has been significantly overestimated enables organizations to timely invest the overcommitted funds to other financial endeavors in order to fulfill the expected rate of return. A timely and proactive response to external events leads to an early and more accurate prediction of project outcomes. Indeed, predictability enables project teams to improve project performance and thus increases value. It should not be expected for a project team to eliminate all surprises, but teams can actually mitigate the potential negative effect of such surprises with early recognition and early provision of corresponding data. External events, either in quantity or magnitude, can always be properly managed with the right people, processes, and behaviors.

Despite the inherent volatility to real world conditions, project teams are consistently asked to incrementally predict accurate future project outcomes at regular intervals. Indeed, the predictions need to have a high degree of accuracy and reliability in order to have meaningful benefit to the sponsoring organizations. Predictions set expectations of project outcomes, provide the basis for important financial adjustments across a portfolio of projects and for the execution of individual projects, and drive decision making processes. With this end in mind, RT 291 was commissioned to identify forecasting practices that can render early and accurate project predictions. In doing so, the team sought answer to questions of primary importance to industry organizations, such as: What are the underlying drivers, events, or conditional issues that impact the accuracy of project outcome predictions?; What practices that can effectively improve the transparency and accuracy of predicted project outcomes in a timely manner?; How

should forecasting practices be applied to cost and schedule measures of project performance?
Can high value and high impact tools and recommended practices that can be widely adopted
by CII member companies be identified?

An answer to these and similar questions can contribute significantly to enhance predictability as an effective management tool by industry organizations. The remaining chapters of this report discusses the nature of this research, the conceptual framework that supported this study, the purpose and scope of the research endeavor, the research design, the data collection instruments, the analyses techniques, and, finally, a discussion on the findings and their practical and academic merit.

2. LITERATURE REVIEW

This chapter summarizes the current state of knowledge in cost and schedule forecasting practices and techniques. Throughout this chapter and in the present study, predictability and forecasting terms are indistinctly used.

2.1 Prevalent Cost and Schedule Deviations

Recent studies show that both cost overruns and delays are prevalent among industry projects. The Department of Energy (DOE) reported that 8 of 12 projects investigated (with a total installed cost of \$27 billion) showed deviations ranging from \$79.0 million to \$7.9 billion, and that 9 of the 12 projects were behind schedule by 9 months to more than 11 years [United States Government Accountability Office (GAO), 2007]. Oil and gas industry projects were reported with cost overruns and schedule delays exceeding +/- 10% from their authorized or baseline values in 40% of the investigated projects (McKenna, Wilcznski, and VanderSchee, 2006). In a study of 78 courthouse facilities with an aggregate installed cost of \$4.5 billion and completed between 1993 and 2005, cost overruns for design and construction were, on average, 17% and 5%, respectively (GAO, 2005). The Indiana Department of Transportation (INDOT) incurred approximately in \$17 million in cost overruns, an equivalent aggregate deviation of 9% for the total installed cost in the year of 2001 (Bordat, McCullouch, Sinha, and Labi, 2004). Another study by the DOE reported that 23 of 30 highway and bridge infrastructures with an authorized cost of \$100 million suffered from overruns between 2% and 211%, and that such overruns were above 25% for 15 of the projects (GAO, 2003).

As clearly demonstrated in a recent study, such deviations, either overruns (negative) or underruns (positive), negatively affect the net present value of the project, and hence the financial and cash flow situation of the stakeholder organizations (Mulva and Dai, 2012). In such study, nearly 70% of 975 owner projects investigated reported cost and schedule deviations exceeding +/- 10% from their baseline values (Mulva and Dai, 2012). Thus, based on such

prevalent occurrence of cost and schedule deviations, forecasting is a critical to predict outcomes at completion in a timely and accurate manner, and hence enable informed decision making processes. The rest of this Chapter discusses forecasting as a fundamental management practice to facilitate project success.

2.2 Forecasting as a Prediction Mechanism

Traditionally, the basic definitions of forecasting have been taken from business, economics, and finance disciplines. Makridakis et al. (1998) actually indicates that quantitative and statistical forecasting techniques are widely used in these disciplines. According to Armstrong (2001) and Makridakis, Wheelwright, and Hyndman (1998), forecasting aims at ascertaining future outcomes affected by uncontrollable, varying, or uncertain events. As generally defined, a forecast generated at time t for an outcome projected in an interval of time h [$\hat{Y}_{t+h}$] is a conditional expectation based on all the information available at time t [$E(Y_{t+h}|\Omega_t)$]. Equation 2.1 and Equation 2.2 below explain this definition.

$$\hat{Y}_{t+h} = E(Y_{t+h}|\Omega_t) \quad \text{Equation (2.1)}$$

$\hat{Y}_{t+h} \rightarrow$ expected outcome at time $t + h$

$$Y_{t+h} = E(Y_{t+h}|\Omega_t) + U_{t+h} \quad \text{Equation (2.2)}$$

$Y_{t+h} \rightarrow$ actual outcome at time $t + h$

$\Omega_t \rightarrow$ information available at time t

$U_{t+h} \rightarrow$ forecast error at time $t + h$

According to this general definition, the components of a quantitative or statistical forecasting model are the past outcomes of a subject of interest, the forecasting errors, the timeline of prediction, and the relation with the factors or events of influence (see Figure 1).

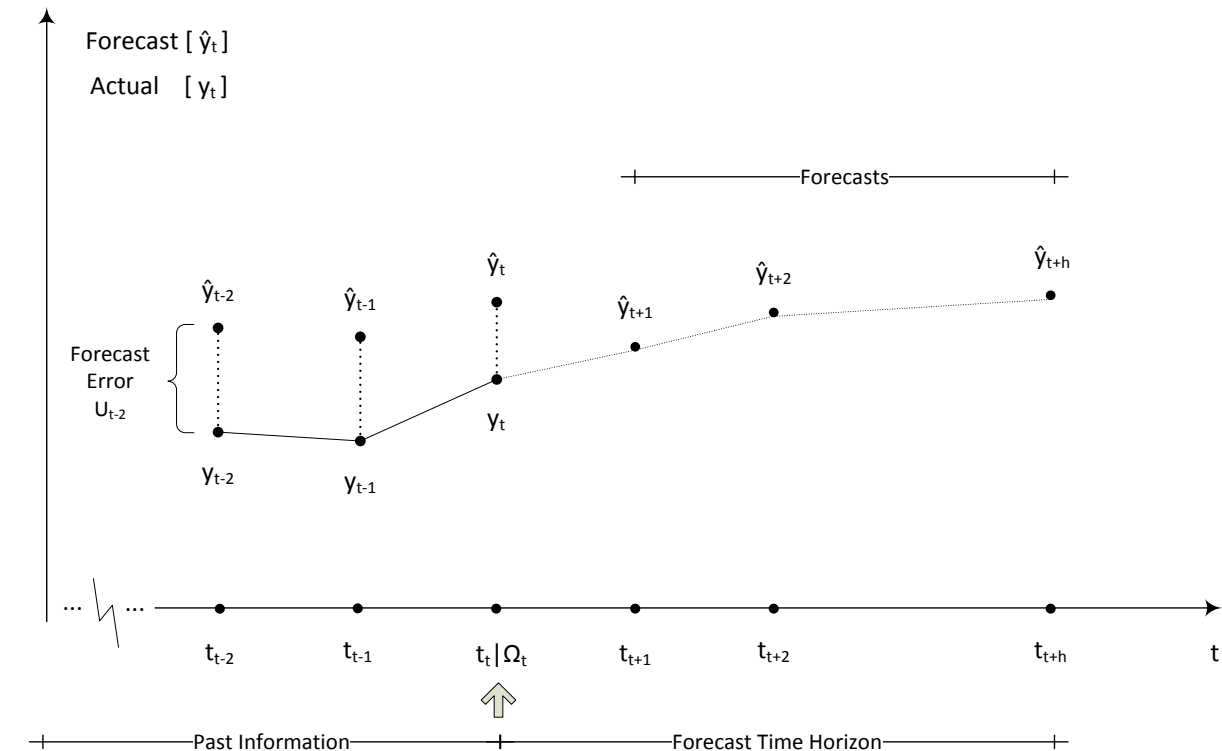


Figure 1. Forecasting components.

Consistent with the previous definition but specific to the construction engineering and management discipline, forecasting represents the set of techniques or processes to estimate the expected cost or schedule outcomes at completion [Jarnagan, 2009; Lukas, 2008; Project Management Institute (PMI), 2011]. Forecasting is a core competency and is intimately intertwined with planning, risk management, and controls (Kim, 2008; PMI, 2008). In planning, forecasting is used to estimate the project cost and schedule outcomes at completion. In risk management, the forecasting is used for evaluating the impact of the identified risk factors. In controls, forecasting is used to estimate cost and schedule current status versus planned or forecasted outcomes. Thus, forecasting plays an important prediction role that requires proper knowledge, experience, and judgment for the reliable generation and interpretation of project predictions (Jarnagan, 2009; PMI, 2011). Figure 2 represents the forecasting components specific to the construction industry.

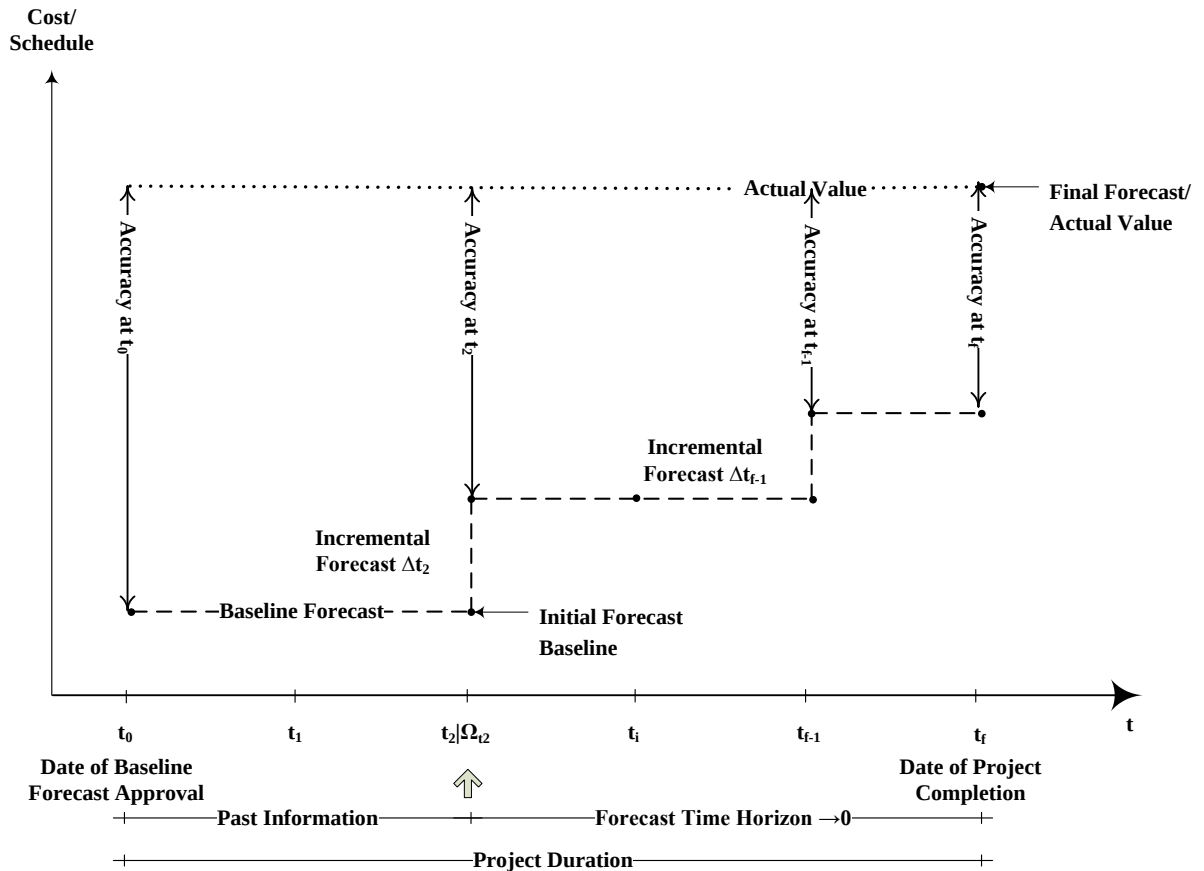


Figure 2. Components of construction forecasting

2.3 Forecasting as a Control Function

As a function of controls, forecasting interrelates with the processes of tracking, assessment, and adjustment of expected cost and schedule outcomes (Kerzner, 2009; PMI, 2008). In fact, a forecasting mechanism estimates the outcome of cost, schedule, and resources required to fulfill the project scope (O'Brien et. al 2009). For this reason, the function of forecasting plays an important role since the controls function requires early and accurate estimates of the project cost and schedule outcomes at completion. The importance of forecasting in controls relies on its ability to generate and report accurate and timely outcomes, so that managers can make effective and well-informed decisions (Alarcon and Ashley, 1996; Kerzner, 2009; PMI, 2008). Such decisions indeed rely on the promptly and reliable report of

deviations from the cost and schedule baseline values, and result on critical financial decisions and cash flow projections (Wideman, 1989). Despite such importance, a recent study has reported that forecasting currently faces a lack of both guidance or a set of standard practices and integration with other project management processes (O'Brien et. al 2009). Such limitations can jeopardize the decision-making processes so that rely on inaccurate or late forecasting projections.

There is no consensus on the standard framework to control the performance of projects. Some researchers refer to three traditional indicators: cost, time, and quality (De Marco and Rafele, 2009; Wang, El-Gafy, and Zha, 2010). Others refer to four indicators: cost, schedule, quality, and safety (Bassioni, Price, and Hassan, 2004; Grau, Back, and Prince, 2011); or cost-growth, schedule-growth, incidents, and rework (Shields, Tucker, and Thomas, 2003). Even more, there are researchers that account for more than four performance measures (KPI Working Group, 2000; Lee, Thomas, and Tucker, 2005). Although the set of project performance indicators is broad and varied, undoubtedly cost and schedule at completion have been prevalently used, and are nearly always considered to evaluate the performance of a project (Barraza et al., 2004; Chan, Scott, and Lam, 2002).

2.4 Earned Value Method

Monitoring and controlling cost and schedule requires tracking, managing, and reporting the status of a project with respect to the baseline or authorized values. The report of the project status must include progress measurements and forecasts at completion. The most common forecasting techniques are earned value methodology (EVM) to monitor cost and schedule, and the critical path methodology (CPM) to monitor schedule (Kerzner, 2009; PMI, 2008). In addition, Monte Carlo stochastic approaches are used to add a probabilistic component to evaluate the impact of uncertainty in the prediction of cost and time outcomes (Kim, 2007). Due to its prevalent use in construction, EVM is discussed in the paragraphs below.

Indeed, EVM is the most commonly used approach to predict cost and schedule outcomes (Chen and Zhang, 2012; Kim, Wells, and Duffy, 2003). EVM represents a quantitative technique that involves variance analysis and the assessment of performance indexes—cost performance index and schedule performance index—to identify deviations and their effect on cost and schedule outcomes (Jarnagan, 2009; Kim et al., 2003; Lukas, 2008; PMI, 2008, 2011). Thus, EVM measures cost and schedule performance, determines deviations against the baseline, identifies causes of variations, provides both a trend analysis and an evaluation of estimated completion values, and hence becomes the support to make critical decisions, such as to define corrective actions to performance (PMI, 2008; PMI, 2011). According to past research, the EVM can produce information and predict the outcomes of projects in a reliable manner so that managers can undertake corrective actions when deviations are forecasted (Lavingia, 2004; Putz et al., 2007). However, the EVM approach cannot prevent the overly optimistic or bias behaviors of those in charge of the forecasting process, so that unreliable forecasts can be nonetheless produced with EVM or any other forecasting technique (Chen and Zhang, 2012; Kim et al., 2003; Vargas, 2003). In the same line of thought, additional efforts have suggested the integration of cost and schedule performance at work package level with approaches to mitigate issues related to overly optimistic or biased judgments in order to mitigate forecasting accuracy (Howes, 2000; Rasdorf and Abudayyeh, 1991; Ruskin, 2004). As such, EVM cannot prevent adverse cost and schedule deviations, it can only serve as an early warning mechanism (Jarnagan, 2009). That EVM lacks the interpretation of workflow and value generation has been pointed out as another limitation intrinsic to EVM (Kim and Ballard, 2002). Despite the value of EVM as a prediction tool, these previous research efforts indicate that there is still a noticeable need to find methodologies that can reliably report the state of the project at completion as accurately and early as possible.

2.5 Deterministic and Probabilistic Approaches to Forecast

The literature indicates a preference for the use of probabilistic forecasting approaches rather than deterministic approaches (Back and Bell, 1995; Back, Boles, and Fry, 2000; Barraza, Back, and Mata, 2000; Kim and Reinschmidt, 2010). Probabilistic approaches result in a more accurate interpretation of the variability and uncertainty typically inherent to capital delivery processes (Bowen and Edwards, 1985; PMI, 2008). While deterministic approaches aim at estimating the most likely and unique outcome at completion, probabilistic approaches result in continuous intervals of possible outcomes in order to consider the uncertainty associated with internal and external events (Al-Bahar and Crandall, 1990; Kim and Reinschmidt, 2011). For instance, Barraza, Back, and Mata (2004) proposed a probabilistic forecasting approach based on S curves. The stochastic S curves technique measures the possible variability of cost and schedule in a project for a given executed work quantity.

2.6 Accuracy

Traditionally, the performance assessment of forecasts at completion has relied on the accuracy of the above quantitative or statistical models. Technically, the prediction error or accuracy error is the difference between the actual project cost (or schedule) at completion and its equivalent forecast at time t during the delivery of a project. Additionally, a practical connotation of accuracy might refer to the aggregate deviation (cost overrun or schedule delay), which is the difference between the actual project cost at completion and the authorized value or baseline. This practical connotation might indicate the efficacy of the forecasting warnings related to the expected cost and schedule at completion (see Figure 3).

Accuracy is also regarded as a measure of the prediction error associated with the forecasting method, which has technical and practical connotations (Armstrong, 2001; Carbone and Armstrong, 1982; Makridakis et al., 1998; Mahmoud, 1984; Walden, 1996; Wilson and Keating, 2002). According to Makridakis et al. (1998), the technical connotation of accuracy is related to a quantitative measure that indicates how well a prediction model reproduces an

actual real-world process or event. Complementary, Makridakis et al. argues that the practical connotation is related to the actual effect of the prediction on decision making processes.

In conclusion, the performance of construction forecasting has relied on the accuracy or reliability of cost and schedule outcomes (Bowen and Edwards, 1985; Park et al., 2005). As such, the current measure of forecasting accuracy informs little or nothing on how early deviations were identified. Indeed, this study is to adopt a predictability approach to evaluate and assess the early generation of reliable outcome predictions.

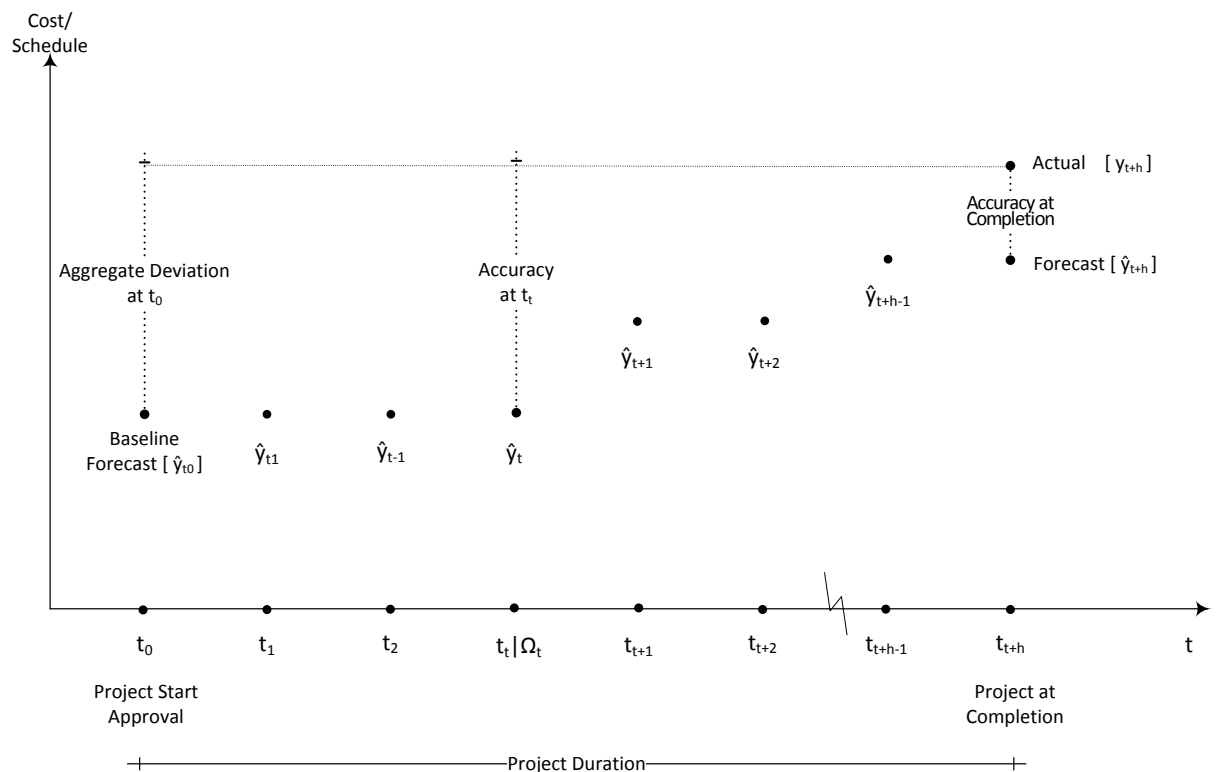


Figure 3. Forecasting accuracy of outcomes at completion.

2.7 Predictability

In addition to accuracy, timeliness is a critical factor for successful predictability. Indeed, the literature evidences a noticeable lack of research on predictability, although, according to Bröchner, Josephson, and Alte (2005), project controls and uncertainty are among the five top

trends in construction research. There is a strong relationship between timely forecasts, effective decision-making processes, and the implementation of prompt corrective actions (Baar and Jacobson, 2004). Timely forecasts are important to communicate issues and trends prior or right after to the occurrence of events, so that management teams minimize and/or avoid impacts on cost and schedule (Hamilton, 2004). Thus, for the last decade, researchers have sought new concepts of forecasting assessment that involve time measurements or indicators in addition to quantitative errors in accuracy. For instance, Teicholz (1996) proposed accuracy, timing, and consistency as the criteria to assess forecasts. For Teicholz, accuracy is the area enveloped between the actual final cost and the forecasts of cost at completion through the project duration, while timeliness is related to the accuracy error at 50% project completion, and consistency is a dispersion measure of the forecasts computed with the square of the deviations from the final cost. Kim (2008) based the performance evaluation of forecasting on accuracy, timeliness, and reliability. Anjaneyulu (2009) proposed a new assessment approach based on a practical connotation of the forecasting accuracy. Similarly, Alarcon and Ashley (1996) recognized the relevance of any forecasting system within a construction project control because of the capability of generating and providing accurate and timely information on the actual project status.

Several critical problems arise when controls functions tardily and/or erroneously detect potential deviations related to cost and schedule performance (Backes and Ibbs, 1994; Oberlender and Trost, 2001). Therefore, predictability as a performance indicator for a project that takes into account the forecast's timeliness, its accuracy, and its impact on cost and schedule at completion, can become an alternative approach to identify the factors that influence cost and schedule deviations in a project. In consequence, achieving admissible cost and schedule deviations at completion partially relies on predictability, and, at the same time, predictability relies on timeliness and accuracy. While the next chapter presents the research

objectives and methodology, Chapter 4 introduces a novel predictability measure to assess the accuracy and timeliness of project outcomes predictions.

3. RESEARCH PROBLEM, OBJECTIVES, AND METHODOLOGY

This chapter states the problem investigated in this study. Then, the objectives within the problem statement and the scope of this research work are defined. Finally, the research methodology undertaken to achieve the proposed objectives is also explained.

3.1 Problem Statement

In spite of valuable research efforts on uncertainty and project controls over the last two decades (Bröchner et al., 2005), the literature shows gaps in the forecasting assessment methodologies (Anjaneyulu, 2009; Kim, 2008; Teicholz, 1996). Current methodologies result in insufficient information to warn of potential problems in an easy, fast, and reliable manner. The construction industry lacks predictability tools that can quickly diagnose likely deviations of cost and schedule outcomes at completion, in a promptly, accurate, and reliable manner. Due to this lack of predictability, the construction industry still faces difficulties in avoiding adverse deviations. Hence, this study adopted a predictability approach to address this prevalent issue.

3.2 Research Aim

To address the problem stated above, this study aimed to measure the predictability of the cost and schedule outcomes at completion and to analyze its nature. The study specifically measures the performance of predictability based on the timeliness and the accuracy of the generated forecasts. Additionally, the present study identifies the relevant factors that influence these measures of predictability. With this research aim, this study can offer project management teams valuable insights to diagnose adverse deviations, in a timely and accurate manner.

3.2.1 Specific Objectives

The specific objectives of this study were defined to:

1. Identify and analyze underlying drivers, events, or conditional issues that impact the accuracy of project outcome predictions.
2. Propose prediction practices that can effectively improve the transparency and accuracy of predicted project outcomes in a timely manner.
3. Evaluate whether forecasting practices should change based on the stage of completion during project execution.
4. Explain how forecasting practices should be applied to cost and schedule measures of project performance.
5. Develop high value and high impact tools and recommended practices that can be widely adopted by CII member companies.

3.2.2 Research Scope

Being aware of the complexity of the problem, this study delimited its scope based on the following four considerations: proper implementation of front-end planning (FEP) practices, cost and schedule predictability, project timeline between authorization and completion, and consideration of forecasting as a management process rather than a set of forecasting techniques alone. First, this study assumed that projects properly implement front-end planning practices. Although the ineffective implementation of FEP practices will certainly influence the predictability of every project performance measure, FEP have been investigated and detailed by numerous CII research teams. As such, the investigation of FEP practices is not considered within the scope of this work, even though their influence on predictability was indeed statistically investigated and assessed.

Second, this study specifically investigated the cost and schedule predictability measures based on their actual outcomes at project completion. Other project outcome measures such as safety, quality, operability, or stakeholder satisfaction were acknowledged but not included in the scope of this study. Several of these measures were not included due to their qualitative nature, and hence required subjective assessment. Safety only admissible forecast at any moment during the project delivery process corresponds to zero accidents, and

for such reason was not included since there is not a safety measure to project. Overall, this study investigated cost and schedule predictability measures.

Third, this study analyzed the performance of cost and schedule predictability from authorization to project completion. Previous to the authorization date, there is a noticeable variability of project definition and consequently of the expected accuracy of projected cost and schedule outcomes at completion. A large variability in project and schedule outcomes predictions at early project stages is admissible and, frequently, expected. Therefore, this study analyzed the performance of predictability after the release of project funds, when predictions are already produced with the expectation to be reliable and accurate.

Finally, this study investigated predictability as a comprehensive management process as opposed to a set of quantitative forecasting techniques alone. Quantitative forecasting techniques have been studied and reported in the literature considerably (Back and Bell, 1995; Back et al., 2000; Barraza et al., 2000; Kim and Reinschmidt, 2010). Nevertheless, the prediction of cost and schedule outcomes at completion is considered in this study as a management process that requires an understanding beyond the deterministic and stochastic approaches to generate the forecasts, even though their influence on predictability is indeed considered in this study.

3.3 Research Methodology

To fulfill the research objectives, the appropriate sequence of research methods was designed and rigorously implemented in four key steps —see Figure 4. These four steps were: 1) identification and categorization of both factors of influence on predictability and change reasons; 2) conceptualization of a reliable, yet practical predictability measure; 3) identification, impact assessment, and substantiation of practices for effective predictability; and 4) impact assessment of change reasons on cost and schedule predictability and deviations. Required

research tasks not explicitly identified in Figure 4, such as data collection or data analyses, were rigorously performed and are described in this Report.

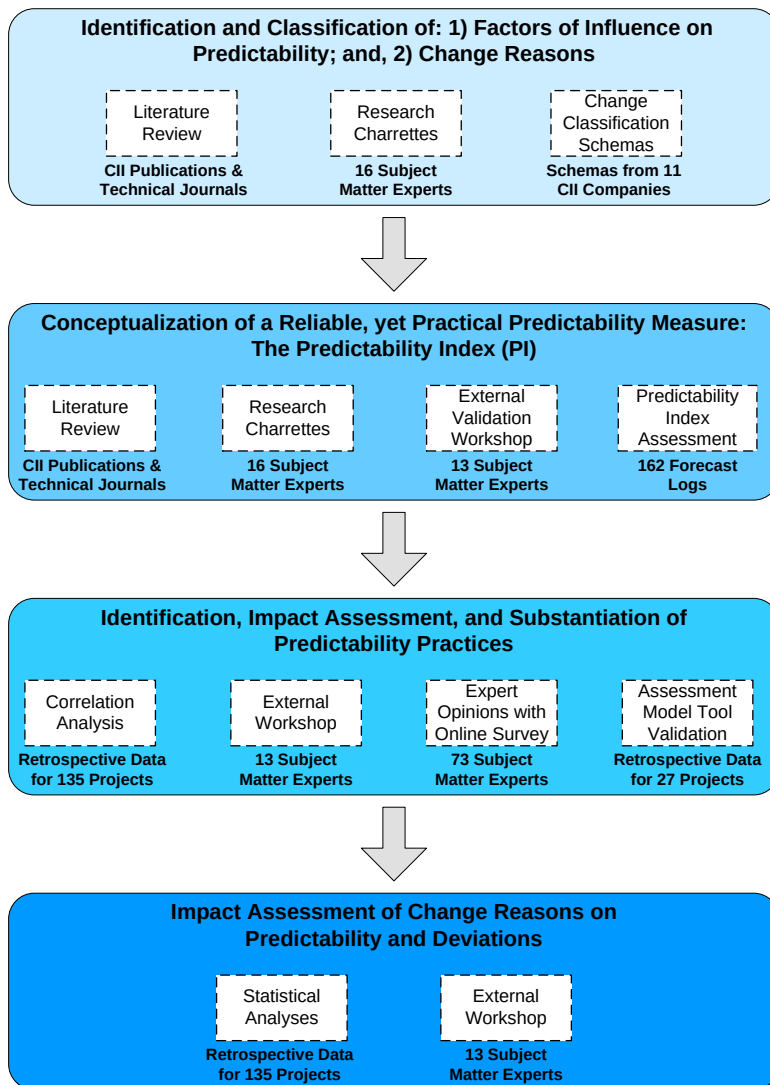


Figure 4. Methodology

In total, 18 CII member companies participated, from within or outside the team, during the research. Detailed retrospective data was collected for 135 completed projects to sustain the Four-Casting model for predictability practices, while the Four-Casting assessment tool was validated with data from additional 27 completed projects. Overall, the findings were validated

and substantiated through one or more of the following mechanisms: statistical analyses, research charrettes, workshops, and/or survey inquiries.

3.3.1 Identification of influencing factors and change reasons

The identification and categorization of both factors with a potential influence on predictability and change reasons was accomplished through an extensive literature review, and input from both subject matter experts and CII member companies. The identification and categorization process included three face-to-face meetings and multiple phone meetings. The research methods used to assess the influencing factors and change reasons are detailed Chapter 6 and Chapter 7.

Influencing Factors

An initial list of factors with an influence on predictability was developed based on an extensive review of literature. Based on the findings, research charrettes with the subject matter experts in the team were utilized during three face to face meetings to further identify and group the influencing factors. Research charrettes encompass a dynamic, creative generation and sharing of a large amount of information in a short amount of time. The team typically worked in small subgroups, which reported the conclusions of their charrette sessions back to the entire team for further discussion and elicitation. Example of core factors included alignment, transparency, forecasting methods, reporting, information issues, risk, or changes, among others. Based on the identified factors, a total of 72 inquiries (most of them with a predefined set of answers) were framed with the purpose to collect retrospective project data by means of a facilitated survey. Even though a very few inquiries related to specific factors alone (such as project size or industry sector), most inquiries were framed around the corresponding influencing factor through industry practices. As an example, inquiries were framed around the utilization of performance based fee adjustments, integration of project management and control

information, or forecast reporting frequency. Overall, inquiries were grouped in 4 categories: 1) human behavior and organizational culture; 2) project characteristics; 3) forecasting practices; and 4) management processes.

Change Reasons

An extensive review of CII literature and technical journals led to a preliminary definition of the type of cost and schedule changes that can typically arise during project execution. This preliminary list was complemented with the change classification schemas used by 11 CII member companies. Five owner, four contractor, and two service companies provided their detailed change log classification, for a total of 310 individual change reasons. The collected data provided evidence regarding the industry perspective on change reasons, and revealed that the methods to document them are very diverse. While some companies catalogue changes through multiple individual reasons that are grouped in key types of change, some other companies choose to catalogue changes through the definition of a few primary reasons. Reported change reasons also reflected the different business aspects among the distinct industry sectors. Differences were also observed between owner and contractor organizations, for instance in the controllability assessment for changes in scope. Thus, in an effort to provide a categorization of changes that could fulfill the purpose of this research, the team sequentially reduced the initial list of 310 change reasons to 36 distinct change reasons grouped in 10 types of change: A) scope changes; B) standard, regulatory, and legal requirements; C) engineering design; D) work planning and execution; E) commissioning and startup; F) control functions; G) vendor/supplier and procurement; H) economic conditions; I) legal and social conditions; and J) force majeure.

3.3.2 The Predictability Index (PI) – a Predictability Measure

To differentiate between good and poor project predictors, the research team conceptualized and assessed the validity of the *Predictability Index (PI)*. The PI is a quantitative

measure to determine the predictability performance for completed projects. For a given project, the lower the PI is, the better the predictability performance. It should be used to both assess and benchmark the predictability of completed projects. The PI is detailed and explained in Chapter 5.

3.3.3 Data Collection

A facilitated survey approach was designed to collect retrospective project data on: 1) predictability practices; 2) the actual predictability associated with the cost and schedule forecasts; and 3) change reasons. This retrospective data collection effort was particularly comprehensive, included both qualitative and quantitative responses, and addressed specific project characteristics and outcomes, forecasting practices utilized, management processes employed, and detailed information regarding project team behaviors, organizational issues, and company culture. First, four survey sections, corresponding to the four categories of influence, contained the 72 inquiries previously developed. As earlier stated, inquiries were framed around the corresponding influencing factor and related to industry practices, with a pre-defined set of responses, and with an open response option. For instance, to the question of whether contract incentives or performance based fee adjustments had been used in a project, the following responses were available: positive incentives; negative incentives; both positive and negative incentives; and none. The open response captured comments and insights from the subject matter experts regarding the issue of inquiry.

Second, in order to evaluate the predictability of the completed projects, the actual forecast log for both cost and schedule predictions along the project completion timeline were requested. The researchers requested the original authorization values or estimates for cost and schedule. This represented the baseline condition or the original commitment / plan as approved by the project sponsor. Incremental adjustments or revisions to project forecasts are nearly always made during project execution and this historical forecasting log was requested.

Final cost and schedule values at completion were also requested. Finally, the impact (if any) for each of the 36 change reasons on the deviations at completion for both cost and schedule were separately gathered through an impact scale from 1-10, and with no recognition of timing within the project timeline. Once pilot tested, the survey was distributed among CII member companies. In all, 135 surveys (data for individual projects) were collected. This data collection effort is detailed in Chapter 4.

Further data collection efforts to satisfy the research objectives included an online survey, workshops, research charrettes, and the collection of retrospective project data to validate the *Four*-Casting Assessment tool. These data collection efforts are detailed throughout the rest of this Research Report.

3.3.4 Predictability Practices

The 135 completed projects in the database were segregated by quartiles based on their predictability performance –measured with the Predictability Index. This allowed practices from ***first quartile or very good predictors*** (early and accurate predictors) to be contrasted with ***fourth quartile or very poor predictors*** (late and inaccurate predictors). Threshold PI values that segregate the predictability performance among the four quartiles of predictability (first quartile, Q1, or very good; second quartile, Q2, or good; third quartile, Q3, or poor; and fourth quartile, Q4, or very poor) were determined. Through statistical analyses, numerous patterns between the previously identified queries, which were based on both influencing factors and industry practices, and predictability performance were identified. Queries conceptually close to each other, when possible, were further grouped together for the elicitation of a general set of practices. In total, 43 distinct practices with a marked influence on predictability were identified —25 of them were actually determined to have a statistically significant correlation with predictability. Chapter 7 presents such practices grouped by categories and subcategories, and indicates whether or not each practice was statistically correlated with predictability.

The data analysis was conducted in three basic steps. First, a descriptive analysis described the characteristics of the investigated variables. The study described the variables involved in the PI and its components by measures such range, and quartiles. Thus, projects were divided in the 4 quartiles of predictability performance: very good, good, poor, and very poor. Such division of predictability measures was fundamental to the data analysis explained below. Also, the change reason variables were explained in terms of their frequencies and impact on predictability. Finally, the influencing factors were analyzed by their frequency of occurrence within each of the 4 predictability performance quartiles.

Second, this study determined how well the collected sample data fit the hypothesized relationships of predictability. A bivariate and categorical correlation analysis was undertaken. These statistical analysis techniques allowed finding evidences of association between variables rather than evidences of causality, because of the non-experimental nature of this research (Pedhazur and Schmelkin, 1991). Overall, the study accomplished a test of the fit for the proposed index of predictability. On the one hand, this study used a Spearman's rank correlation coefficient ρ (p) that is a nonparametric measure of association between two variables to test the significance of predictability association for each change reason. This coefficient assesses how well the relationship between two variables can be established between +1 and -1 (Agresti, 2010). On the other hand, the study identified the significant and relevant relationships between the list of potential influencing factors and the index of predictability. At the significance level $\alpha = 0.05$, this study used the Goodman and Kruskal's gamma coefficient as a measure of rank correlation of ordinal data, which takes into account the similarity of the orderings of the data. The strength of association is indicated as in the Pearson coefficient, where the values range from -1, a negative association or perfect inversion, to +1, a positive association or perfect agreement. The value of zero indicates the absence of association. The Goodman and Kruskal's gamma coefficient (γ) was specifically selected for this study because gamma is a symmetric measure of association between two ordinal variables

that ranges between -1 and 1 and its interpretation is similar to that of the Pearson's correlation. Consequently, this research adopted this coefficient because the similarity of interpretation with the Pearson coefficient (Agresti, 2010). For the strength of association, this study utilized the effect sizes given by De Vaus (2001). A coefficient between 0.90 and 0.99 indicates a very strong relationship; a coefficient between 0.70 and 0.89, a strong relationship; a coefficient between 0.50 and 0.69, a substantial relationship; a coefficient between 0.30 and 0.49, a moderate relationship; a coefficient between 0.10 and 0.29, a low relationship; and finally, a coefficient between 0.01 and 0.09 indicates a trivial relationship.

Based on the statistical results, observations, and expert opinions collected throughout the study, the Four-Casting model was developed and documented. The model proposes and supports the implementation of practices for early and accurate predictability. Such model and its complementary Four-Casting assessment tool are detailed in IR 291-2. The tool is conceived as a continuous assessment mechanism to evaluate the effectiveness of forecasting processes, and hence refers back to the practices defined within the Four-Casting model. The Four-Casting assessment tool was externally validated through its correlation with the PI measure. Data was collected for 27 completed projects –such projects were in addition to and hence different from the 135 previously analyzed– with both the Four-Casting assessment and PI tools. For those 27 projects, a strong correlation between the outcomes of the Four-Casting assessment tool and the PI tool was determined. In other words, for a given project, the assessment of predictability practices with the Four-Casting assessment tool proves to be proportional to its actual predictability performance. Such evidence validates the tool. Discussion on such validation effort is provided in Chapter 9.

3.3.5 Change Reasons Impact Assessment

For each of the 36 individual change reasons within the 10 change types previously identified, the research team determined its frequency of occurrence, its average impact or level

of severity –in a scale of increasing impact from 1 to 10, and the average impact effect of the change on actual cost and schedule deviations. Such average impact effect was computed through the sum, for each project, of the product of its impact value times the project cost or schedule deviation. Thus, the research team was ultimately able to identify the changes that are, for both owners and contractors and for both cost and schedule, most frequent *and* impactful in the capital project environment on predictability. For owners, changes associated with scope and work planning and execution disrupt predictability the most. For contractors, changes associated with scope and control functions were statistically found to be the most disruptive. The impact of change reasons on predictability is detailed in Chapter 6.

3.3.6 Further Validation and Substantiation

The research findings were further validated, in addition to the statistical and quantitative analyses previously described, by conducting a detailed external evaluation. First, an external workshop was conducted where the findings were evaluated and critiqued by subject matter experts, who had not been previously associated with this research. Their expert analysis and insight benefitted the research process and provided valuable perspective with respect to the interpretation of the findings and the formulation of recommendations. Second, another rigorous approach to further validate the research findings and recommendations was accomplished by means of collecting the perception and opinion from a wide number of CII subject matters experts in forecasting. Thus, a second survey data collection initiative was distributed in the format of an online instrument. Each respondent was asked to evaluate the likelihood of occurrence and the probable severity, or level of negative impact, for each of the inquiries or practices identified in the earlier phase of the research. The response to this survey inquiry was facilitated by 73 subject matter experts *external* to the project team, with 1,686 years of total industry experience. Such validation effort is presented in Chapter 8. Third, additional research charrettes with the subject matter experts in the team were used to critique,

explain, and substantiate the findings throughout the research. Finally, the key insights from this study were compiled and summarized, and this Research Report, RS 291-1, IR 291-2, and IR 291-3.

4. DATA COLLECTION

This chapter describes the instrument and procedures used for the data collection effort. A definition of the variables used in the study is discussed. Also, this chapter describes the sample data and the data screening procedure undertaken before conducting the statistical and quantitative data analyses described in the following chapters.

4.1 Data Collection Instrument and Procedure

A structured questionnaire collected relevant information regarding the actual project forecasts, the change reasons, and the factors likely to influence predictability performance, factors that were determined through a definition process with a panel of experts. Three face-to-face meetings and several phone-call conferences, scheduled along a 7-month period, determined the procedure to collect the relevant data and discussed and approved the design of the questionnaire.

Regarding the actual project forecasts, the survey instrument was designed to request data about the original authorization estimates for cost and schedule measures. The authorization values represent the baseline condition as approved by the project sponsor(s). Incremental adjustments to project forecasts are nearly always made during project execution and these historical data was requested through the survey instrument. The survey instrument was also designed to request final cost and schedule values at completion. Once collected, such numerical cost and schedule data were normalized in percentage, which is explained in the next section within this chapter, for all projects in the database in order to facilitate their comparison and statistical analysis as part of the research process to account for differences in scale and magnitude.

An extensive review of CII literature and technical journals led to a preliminary definition of the type of cost and schedule changes that can typically arise during project execution. This

preliminary list was complemented with the change classification schemas used by 11 CII member companies. Five owner, four contractor, and two service companies provided their detailed change log classification, for a total of 310 individual change reasons. Thus, in an effort to provide a categorization of changes that could fulfill the purpose of this research, the team sequentially reduced the initial list of 310 change reasons to 36 distinct change reasons grouped in 10 types of change: A) scope changes; B) standard, regulatory, and legal requirements; C) engineering design; D) work planning and execution; E) commissioning and startup; F) control functions; G) vendor/supplier and procurement; H) economic conditions; I) legal and social conditions; and J) force majeure. Similarly, a process of identification of influencing factors ended in over 60 potential factors, grouped in four sections: A) project characteristics; B) forecasting practices; C) management processes; and D) human factors.

Finally, the panel of experts rigorously designed a survey instrument with six sections and over multiple structured questions. The electronic version was designed on a Microsoft® Excel® version 2010 spreadsheet with the use of developer tools to create the data collection forms (Etheridge, 2010). The digital form enabled a greater feasibility of collecting information; thus, filling the form was provided to be relatively simple. The rigorous survey design process met standards of good practice, see, and carefully avoided ambiguity or bias in the survey questions (Pedhazur and Schmelkin 1991). A pilot test of the survey design included the participation of seven experts over a month period. After 1 month of revision and discussion upon the pilot version, the final version had four qualitative sections and two quantitative sections. The qualitative sections included a) project characteristics, b) forecasting practices, c) management practices, and d) human factors (i.e., information regarding project team behaviors, organizational issues, and company culture). The quantitative section included project cost forecasts and project schedule forecasts with their associated change reasons. Table 1 summarizes the questions per survey section while Appendix A shows the form of each section of the questionnaire.

Table 1. Sections and Questions of the Questionnaire

Section	Aim	Related to	No Questions	Type of Response
Project characteristics (17 questions)	To collect data on potential underlying factors (Specific Objective 3)	Type of company	3	Qualitative
		Type of project	9	Qualitative (7) & Quantitative (2)
		Type of contract	5	Qualitative
Forecasting practices (20 questions)	To collect data on potential underlying factors (Specific Objective 3)	Team	6	Qualitative
		Information	2	Qualitative
		Process	6	Qualitative
		Interrelations	5	Qualitative
Management processes (20 questions)	To collect data on potential underlying factors (Specific Objective 3)	Project planning	6	Qualitative (5) & Quantitative (1)
		Information management	4	Qualitative
		Change management	2	Qualitative
		Risk management	4	Qualitative (2) & Quantitative (2)
		Project control	2	Quantitative
		Execution practices	2	Qualitative
Human factors (15 questions)	To collect data on potential underlying factors (Specific Objective 3)	Explicit influences	4	Qualitative
		Implicit influences	4	Qualitative
		Reactions	3	Qualitative
		Work climate & culture	2	Qualitative
Cost forecast deviations	To collect data on authorized forecast deviations (Specific Objective 1)	Authorized change	Logs	Quantitative
Schedule forecast deviations		Authorized change	Logs	Quantitative
Change reasons (36 reasons)	To collect data on the change reasons of authorized forecast deviations (Specific Objective 2)	Owner/Scope change	5	Quantitative
		Legal requirements	4	Quantitative
		Engineering design	3	Quantitative
		Work planning/execution	5	Quantitative
		Startup/commissioning	1	Quantitative
		Control System	6	Quantitative
		Suppliers/Procurement	5	Quantitative
		Economic conditions	3	Quantitative
		Legal/Social conditions	3	Quantitative
		Natural threat	1	Quantitative