ABSTRACT

Title of Dissertation: ESTIMATING THE IMPACT OF BUILDING INFORMATION MODELING (BIM) UTILIZATION ON BUILDING PROJECT PERFORMANCE

Kiavash Parvan, Doctor of Philosophy, 2012

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Many benefits of utilizing the Building Information Modeling (BIM) technology have been recognized and reported in the Architectural, Engineering and Construction (AEC) industry literature. However, it seems that the construction industry still hesitates to fully adopt BIM. As some researchers suggest, the root cause may be in the lack of understanding of whether and how BIM improves project outcomes. This research aims to shed some light on this matter by studying the impact of BIM utilization on building project performance.

This research follows a model-based approach as opposed to statistically analyzing the project outcomes with and without BIM utilization. The construction project supply chain is modeled at the design and construction activity level to represent the project behavior in terms of cost over time. As traditional project management tools as well as statistical methods are not able to consider the dynamic nature of the projects such as feedbacks, time delays and non-linear relationships, this research uses system dynamics methodology to model the project supply chain. The project supply chain model is calibrated with two sets of the projects; with BIM and without BIM. The two calibrated models, Non-BIM and BIM-utilized, are used to estimate the outcomes of a hypothetical set of the projects. The outcomes are compared in terms of the project performance indexes to analyze the BIM impact on the project performance.

Since relatively few projects that utilized BIM were found, this research employs expert elicitation (EE) technique to capture the required knowledge from the industry to estimate the parameters of the BIM-utilized model. The EE is used to build a causal model to capture the impact of BIM utilization on the Non-BIM project model parameters in the absence of sufficient BIM-utilized project data.

Keywords: Building Information Model (BIM), Project Supply Chain, System Dynamics, Expert Elicitation, Information Technology (IT), Construction, Project Management

ESTIMATING THE IMPACT OF BUILDING INFORMATION MODELING (BIM) UTILIZATION ON BUILDING PROJECT PERFORMANCE

By

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

To my Mom and Dad, with all my heart, for their constant support and encouragement.

"This achievement is the result of your true love and generous cares"

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List of Abbreviations

A/E	Architectural/Engineering
AEC	Architectural, engineering and construction
BIM	Building information model
BIM-ICM	BIM impact causal model
CAD	Computer-aided design
CI	Construction industry
DOE	Degree of expertise
EE	Expert elicitation
EP	Error percentage
FIC	Facility information council
GSA	General Services Administration
IT	Information technology
MEP	Mechanical / Electrical / Plumbing
NIBS	National Institute of Building Sciences
OO	Object-oriented
PI	Performance index
RFI	Request for information
SD	System dynamics

Chapter 1. Introduction

1.1. Definition of BIM

Information technology (IT) is one of the promising tools which have been constantly deemed as a solution to save construction projects. Among those, computer-aided design (CAD) software applications have been playing the leading role for more than three decades in the construction industry (CI). BIM-supported software applications are the new generation of those CAD software applications.

BIM stands for Building Information Model. BIM is known as a shared digital representation of the physical and functional characteristics of the facility in the Architectural, Engineering and Construction (AEC) industry. The basic premise of BIM is to improve collaboration and interoperability among the stakeholders of the facility during its lifecycle. The 3D visualization is the basic essential feature of BIM. However, BIM is not just a 3D CAD. It is more than the elaborated 3D renderings. Also, it is more than delivering the project documentation in the electronic version. It is about information use, reuse, and exchange, of which the digital format is just one part.

BIM has been practiced by many companies and organizations. They have their own definitions of BIM. The General Services Administration (GSA) is an independent agency of the United States government, established in 1949 to help manage and support the basic functioning of federal agencies. GSA, with almost 7,800 buildings and 261 million square feet of space under its management, is the nation's largest property manager. GSA ran nine pilot projects to examine the implications of BIM. GSA estimated that the cost savings on just one of the nine pilot projects offset the cost of conducting the two-year pilot program. That set the stage for the agency in November 2006 to mandate BIM on all its new projects.

GSA defines BIM as:

"Building Information Modeling is the development and use of a multi-faceted computer software data model not to only document a building design, but to simulate the construction and operation of a new capital facility or a recapitalized (modernized) facility. The resulting Building Information Model is a data-rich, object-based, intelligent and parametric digital representation of the facility, from which views appropriate to various users' needs can be extracted and analyzed to generate feedback and improvement of the facility design."

The National Institute of Building Sciences (NIBS) is a non-profit, private organization dedicated to bring together government, professionals, building products manufacturers, construction labor, and the end consumer to identify and resolve the current and potential problems that disrupt the ability to design and build safe and economical private, public, and institutional structures throughout the United States.

According to NIBS it is best to think of BIM as:

"A digital representation of physical and functional characteristics of a facility. As such it serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its lifecycle from inception onward. (defined as existing from earliest conception to demolition)"

Also Facility Information Council (FIC) which is the council chartered under the NIBS defines BIM as:

"A computable representation of the physical and functional characteristics of a facility and its related project/life-cycle information using open industry standards to inform business decision making for realizing better value. BIM can integrate all the relevant aspects into a coherent organization of data that computer applications can access, modify and/or add to, if authorized to do so."

1.2. BIM Versus Traditional CAD

To better understand what BIM is, it is worth comparing BIM versus the traditional CAD concept. BIM software can be broken down to three essential underlying technologies (Figure 1): 1) the 3D CAD technology, 2) the object-oriented technology, and 3) the parametric design technology. Combining these three technologies creates an excellent platform that provides better information management, better change management and better interoperability for the BIM software users.

The original 3D CAD technology basically creates an interactive virtual environment based on the 3D geometrical coordination system. In this technology, the virtual model elements are the drawing objects. However, based on the object-oriented technology the drawing objects no longer exist. They are encapsulated into the Architectural/engineering (A/E) objects such as the walls, windows, beams, pipes, etc. The A/E objects are the substitute of the drawing objects in the virtual model as the result of the object-oriented (OO) technology. The parametric design is the key technology that makes the 3D OO virtual environment work. As the A/E virtual models in normal construction projects are very complex in terms of the number of elements and their connection, reviving the model integrity is extremely difficult during the changes and it requires an extensive amount of effort. The parametric design technology guarantees the integrity of the model during the changes. It employs parametric equations to enforce the elements' connections. These equations are called constraints. For example, if the wall moves or gets extended the other elements connected to the wall, such as the ceiling and the floor are adjusted to sustain the 3D geometry integrity.

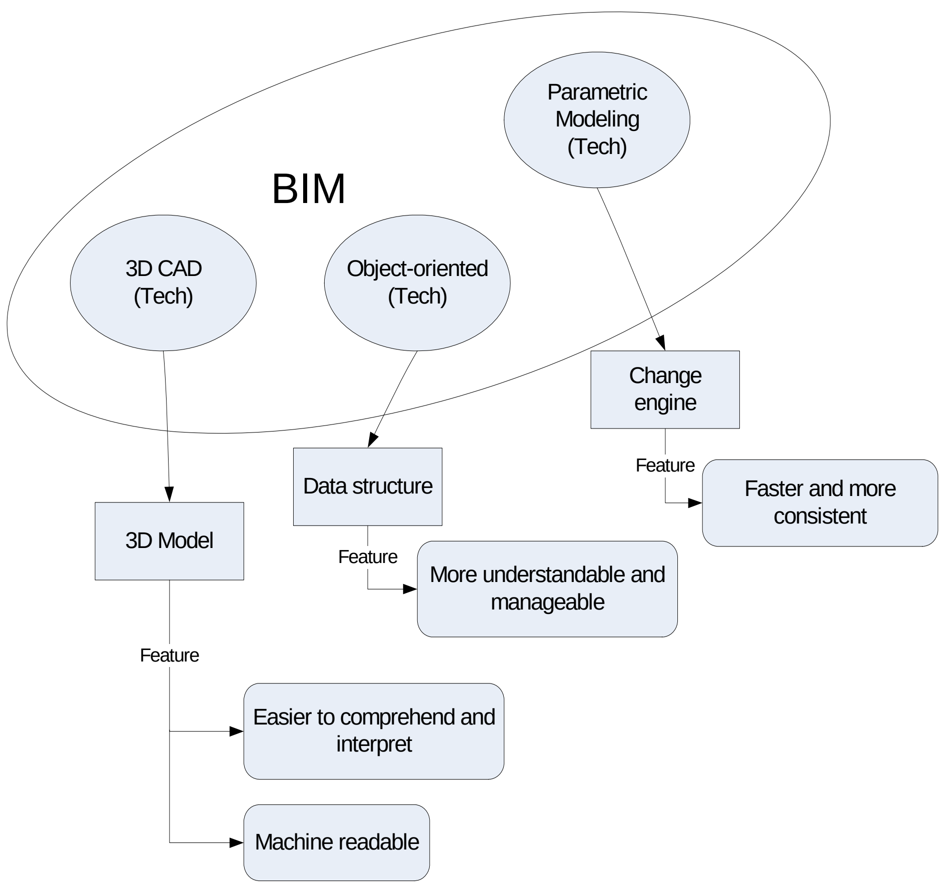


Figure 1: Functional decomposition diagram of the BIM underlying technologies

Moreover, in the original 3D CAD concept, the virtual model is the 3D geometry representation of the A/E model. However the geometry is only one of the information sets that should be delivered by the design process. There are other information sets, called design-specific information, that are crucial in the A/E design process. For instance, the room space information is required to perform the energy and illumination analyses. However, the original 3D CAD concept is not able to restore this information as part of the virtual model because it does not exist as the distinct drawing object. Each discipline has its own design-specific information. Also, they have their own A/E objects. This is the reason that there is no single BIM software application which fits all A/E design purposes, similar to what original CAD software applications did in the last 3 decades. As a result, the family of the BIM software applications is usually marketed in a bundle of software.

1.3. BIM Perceived Benefits

BIM stores all relevant information of the building in an integrated, reliable and quickly accessible database. The accessibility of data facilitates the design analyses such as illumination analysis, energy analysis, etc. Besides, it reduces the accidental user mistakes due to the multiple data entries. BIM features such as automated 2D view generation, automated schedule and material take-off and automated change managements improves the drafting as well. Detecting the spatial interferences is another important feature of BIM that helps to detect the inter-disciplinary conflicts in the drawings. As a result, error is reduced, design intent is maintained, quality control is streamlined, and communication is speeded up. The time saving and error reduction are the main results of BIM utilization. The following is the short list of the BIM benefits perceived in the AEC industry (Fischer et al (2003), Eastman et al (2003) and Sacks (2004)):

1. Shortening design duration
2. Extra analyses which are otherwise impossible or difficult because of lack of the digital data exchange capability
3. Reviewing more design alternatives
4. Reducing engineering lead-time to production
5. Reducing direct engineering design and drafting costs
6. Reducing engineering work not only off-site but labor input on-site
7. Accelerating the construction process by performing part of the work off-site simultaneously
8. Improving construction quality by better controlled production of the prefabricated elements
9. Enhancing design errors

1.4. Problem Statement

BIM is a new technology which has been blooming in AEC industry with lots of jargons in the last few years. "BIM is a huge buzzword in AEC" as Chuck Eastman says (http://bim.arch.gatech.edu/?id=402). Many benefits of BIM technology have been identified and reported in the literature. However, the AEC industry still hesitates to adopt BIM. The construction industry is a very competitive industry and the best companies are in constant search for the proven technologies that offer a competitive advantage (O'Connor and Yang 2004). However, the construction industry is conservative to adopt new IT technologies. Andresen et al. (2000) and Bjork (2003) provide a clue to this matter. They report the hesitance of the construction industry to adopt IT as a result of the low level of the perceived benefits. Mitropoulos and Tatum (2000) also state two major reasons: (1) uncertain competitive advantage from using new technologies and, (2) lack of information regarding technology benefits that are the main causes of the company reluctance to incorporate new technologies. In many construction companies, at any point in time there is only limited capital available for investment and IT investment must compete with other demands on capital. If the expected benefits of the IT advancement are not clear enough for the company decision makers, it gets off the table. Hampson and Tatum (1997) discuss that managers need a way to measure the expected benefits of IT to invest in technology. The quantitative analysis methods that subjectively study the effects of IT technologies on project outcomes facilitate the decision making process in the companies. Kumashiro (1999) calls out quantitative analyses to guide IT implementations and argues that firms would be better able to make technology decisions in the presence of such quantitative analysis.

The lack of analytical studies on the BIM competitive advantages may be the cause of the AEC industry hesitance. It is common to find articles in journals and magazines saying that: "*BIM has many benefits to the project stakeholders. BIM reduces the cost and time of construction. BIM reduces the project cost X%*". However, none of those articles explains the association between the BIM capabilities and the perceived benefits. Many questions still have been left open such as "How does BIM reduce cost and time?", "Which one of the BIM features plays the crucial role?", "How does BIM improve design versus construction?" and others. These might be the questions which make the AEC industry stop to adopt BIM.

BIM as a software package is used by different disciplines and activities of the project. BIM impacts the activities in terms of the time saving and the error reduction. Since each activity's influence on the project supply chain is different, saving time and reducing error in each activity, resulted by the BIM utilization, has a different influence on the project outcomes. The impact of BIM capabilities on project outcomes has not been studied yet. The project supply chain model is an essential key to this study.

The well-developed traditional tools available in project management such as work break down structure, Gantt chart, PERT/CPM networks are based on two simplifying assumptions. First, they assume the project goes as planned and are not able to consider reworks. Second, they assume the project activities are independent. These assumptions ignore two important dynamic natures of the project: rework and activity inter-relations. Statistical techniques such as multivariate analysis, regression analysis and analysis of variance (ANOVA) are pervasive throughout the literature of studying the impact of IT advancements on the construction industry. Those techniques are not quite adequate to model the project supply chain. The statistical methods are not able to take the dynamic features of the projects such as feedback, time delay and non-linear relations into account.

Using project performance metrics as a framework to measure the impact of technology on the projects has been noted by researchers (Kang, O'Brien, Thomas, and Chapman; 2008). O'Connor and Yang (2003) highlight the necessity to improve the tools to analyze the impact of technology on the project/construction firm's performance.

1.5. Research Objective and Motivation

This research aims to measure the impact of BIM utilization on building project performance using a system dynamics (SD) modeling approach. SD is used to model the project supply chain process at the design and construction activity level. The SD capabilities to consider feedbacks, non-linear relations and time delays make it as an appropriate tool for this research. This research attempts to:

1. Identify the BIM features that affect project outcomes
2. Measure the impact of the BIM utilization on the project performance
3. Analyze the significance of the impacts of the BIM features on the project performance

This is a model-based approach to measure the impact of BIM utilization as opposed to the regression models and ANOVA analysis. To the best of the author's knowledge, there is no model-based or causality analysis research to analyze the impact of BIM utilization on project outcomes. No research was found in the literature that has broken down the BIM black box into its features and functionalities to clarify and address the association between the BIM features and its benefits perceived on project outcomes. This research is the first attempt to open the black box. The main purpose of this study is to improve the causal understanding of the associations between the BIM features and the BIM utilization benefits.

1.6. Research Methodology

This research is performed in the 4 steps. Figure 2 shows the overview of those steps.

A system dynamics (SD) project model is developed in step (1). The project model basically is the project supply chain at the design and construction level, interpreted in the SD modeling concept. The project model represents the building project behavior in terms of the cost over time during the design and construction phase. In steps

(2) and (3), the model parameters are calibrated with two sets of the projects: Non-BIM projects and BIM-utilized projects, respectively. This yields two structurally identical models with two sets of the parameters, Non-BIM and BIM-utilized. A hypothetical set of projects is analyzed with these two models and the outcomes are compared in terms of the project performance indices to analyze the impact of BIM on project performance.

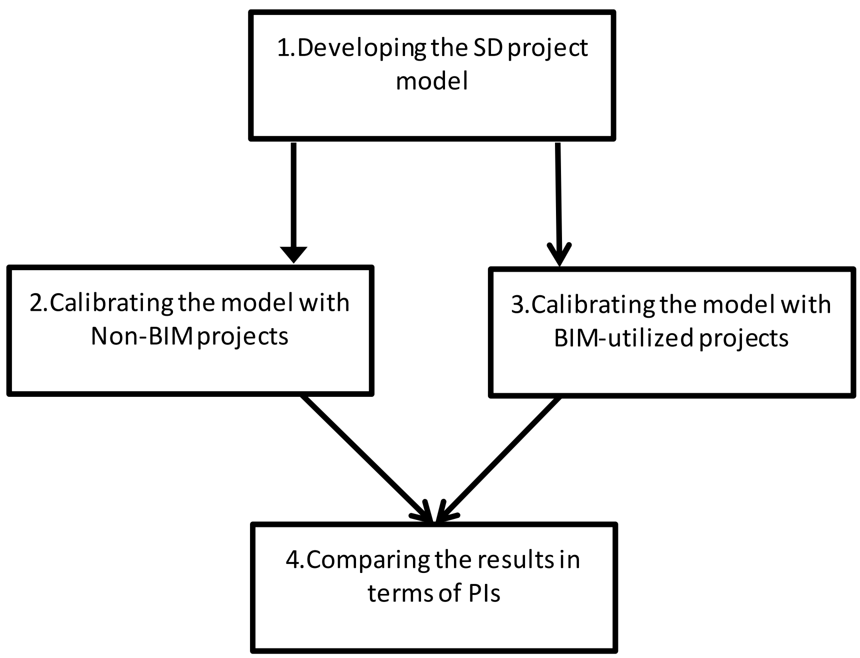


Figure 2: Research methodology diagram

Since relatively few BIM-utilized projects were found, the expert elicitation (EE) technique is used to capture the required knowledge from the industry. EE is employed to build a causal model, called BIM Impact Causal Model (BIM-ICM). BIM-ICM aims to capture the impact of BIM utilization on the Non-BIM project model parameters. Figure 3 depicts the updated research methodology diagram.

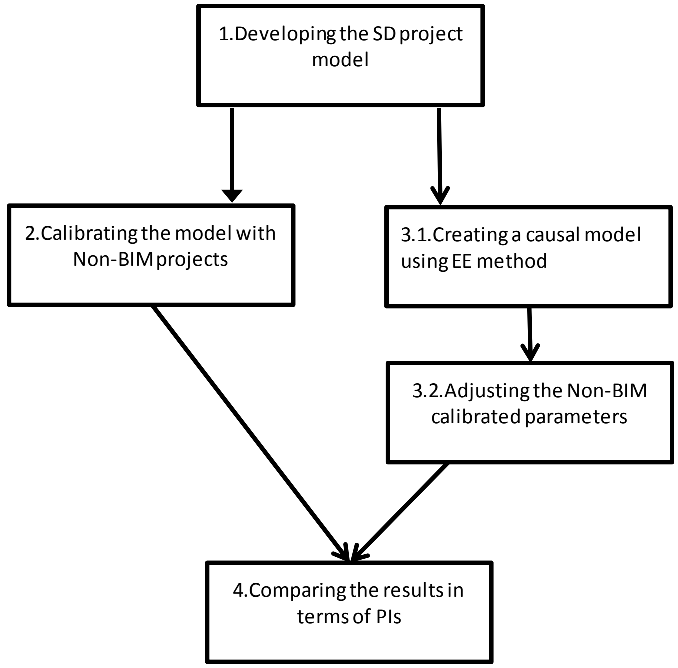


Figure 3: Research methodology diagram in details

1.7. Contributions

This research developed a new model-based methodology in the area of IT construction studies as an alternative to statistical analysis. The methodology employs a project supply chain model to represent project dynamic behaviors. This model combined with a customized causal model can be used to analyze the impact of any IT advancement in the construction industry. The author believes this methodology can help researchers in improving the causal understandings of the IT dynamics impacting construction industry. Besides, this methodology has the capability to be used easily to study the impact of other IT advancements such as web-based applications, tablet computers and RFID tags in the construction industry. This study introduced a system dynamics application to model the project supply chain at the detailed level of activities. The author believes that this concept has the potential to be used as a new powerful tool in project management studies upon further improvements.

This research improved the causal understanding between BIM features and project benefits. It clarifies how BIM, not as a black box anymore, affects project activities and sub-activities and how this impact is projected on the project performance metrics.

1.8. Data Collection

Data plays a critical role in quantitative analysis researches. In this research, data is used to build, calibrate and validate the model. Gathering data in the construction industry is cumbersome, time consuming and costly. Since project information is considered as business sensitive information in the AEC industry, construction companies are not interested to reveal any project information that includes the dollar values even when the names and specifications of the projects are concealed.

Some organizations have been established to address this issue. Construction Industry Institute (CII) is one of these. They have more than 1600 project records from more than 500 companies over the past 15 years. Since these databases are created to gather construction industry data for general purposes, they contain very high level industry data which is suitable for the purpose of this research. Also all industry-wide databases are based on cross-sectional data gathering methods. They do not include data in temporal order which is required for the system dynamics modeling purpose. On top of that, the membership for using those databases is expensive and cost a couple of thousand dollars!

Several databases were investigated in terms of accessibility, compatibility, reliability, affordability and sufficiency in the level of detail. The archive of the capital projects department at the University of the Maryland was found as a very rich library of construction projects. In an agreement, a dataset of 33 projects was retrieved from the archive. Table 1 depicts the statistical properties of the 33 gathered projects. The histograms of the design estimated duration (D_T_0), ratio of design actual duration to design estimated duration (D_T/T_0), design estimated cost (D_C_0), ratio of design actual cost to design estimated cost (D_C/C_0) are shown in Figure 4. Figure 5 contains the same information for the construction stage of the 33 gathered projects.

Table 1: Statistical properties of the dataset

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
D_T0	33	1.9	47.2	10.867	9.0332	81.599
D_W0	33	69000	4416480	1230997.52	1380266.263	1.905E12
D_T_2_T0	33	.943	2.072	1.21648	.294548	.087
D_W_2_W0	33	.351	2.188	1.21294	.318793	.102
C_T0	33	2.5	24.8	13.236	7.0085	49.119
C_W0	33	348316	55056526	14698535.76	16976977.90	2.882E14
C_T_2_T0	33	.680	1.409	.97909	.139671	.020
C_W_2_W0	33	.525	1.827	1.05203	.239046	.057
Valid N (listwise)	33					

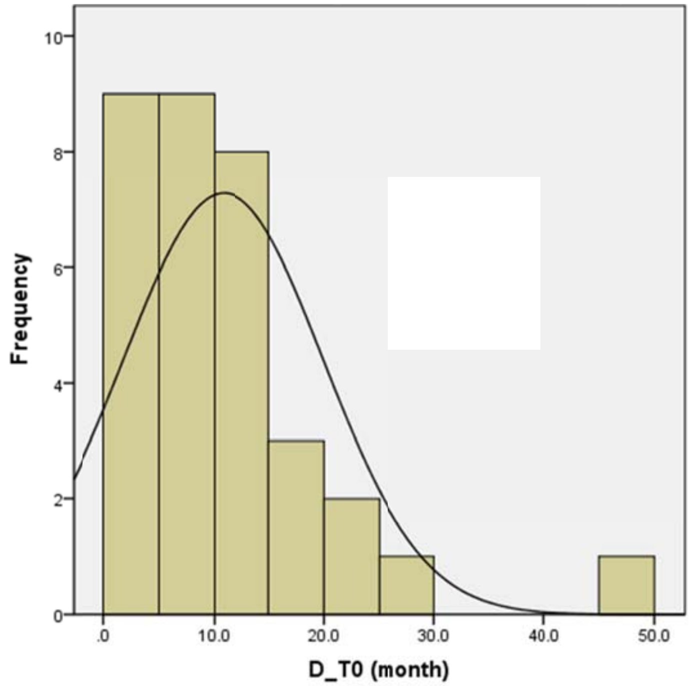


Figure 4.1: The histogram of design estimated duration (T0), Mean=10.87, StDev=9.03, N=33

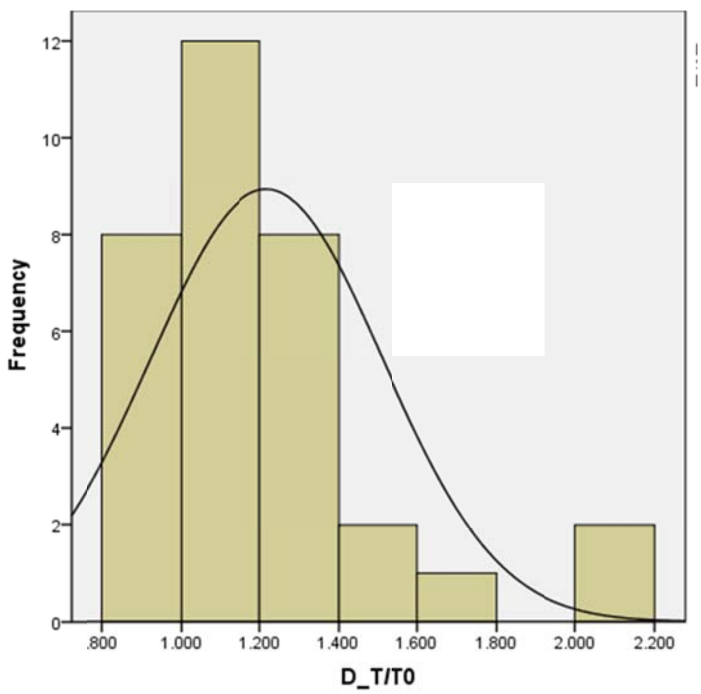


Figure 4.2: The histogram of ratio of design actual duration (T) to design estimated duration (T0), Mean=1.22, StDev=0.29, N=33

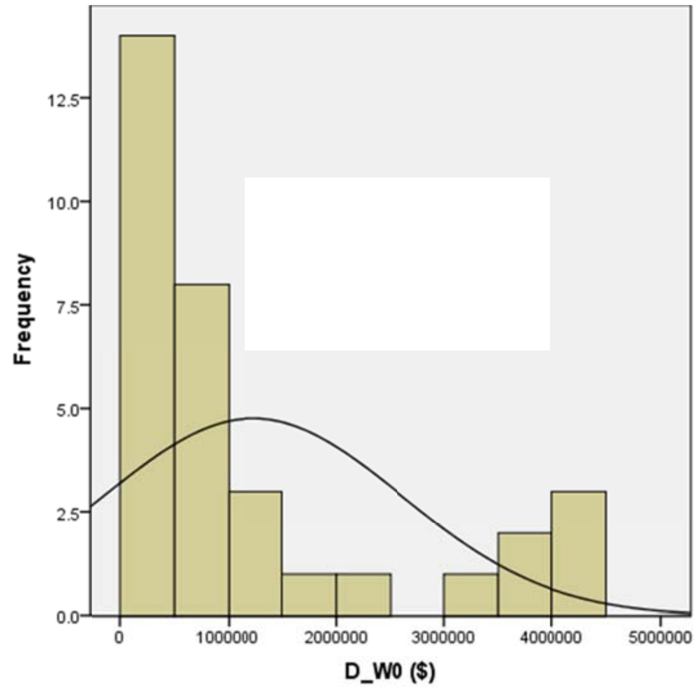


Figure 4.3: The histogram of design estimated cost (W0), Mean=$1.23M, StDev=$1.38M, N=33

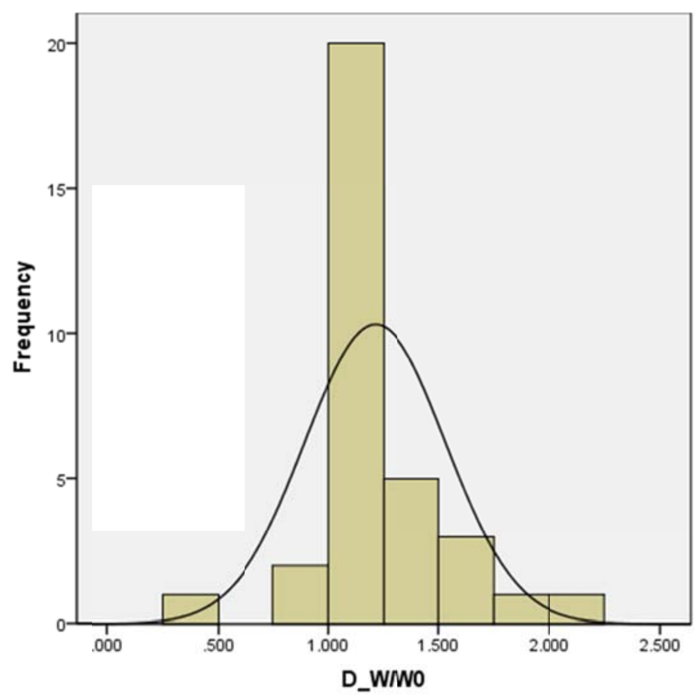


Figure 4.4: The histogram of ration of design actual cost (W) to design estimated cost (W0), Mean=1.21, StDev=0.32, N=33

Figure 4: The histogram of some properties of the project design activity

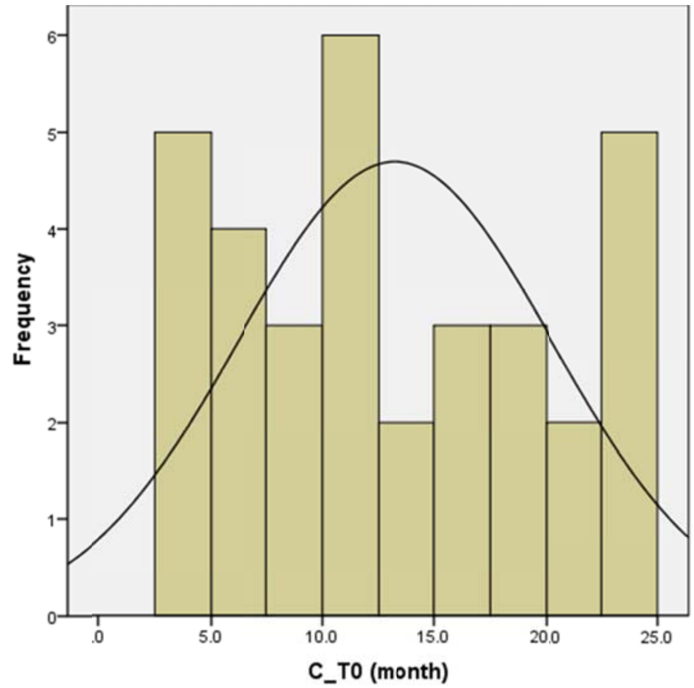


Figure 5.1: The histogram of construction estimated duration (T0), Mean=13.24, StDev=7.01, N=33

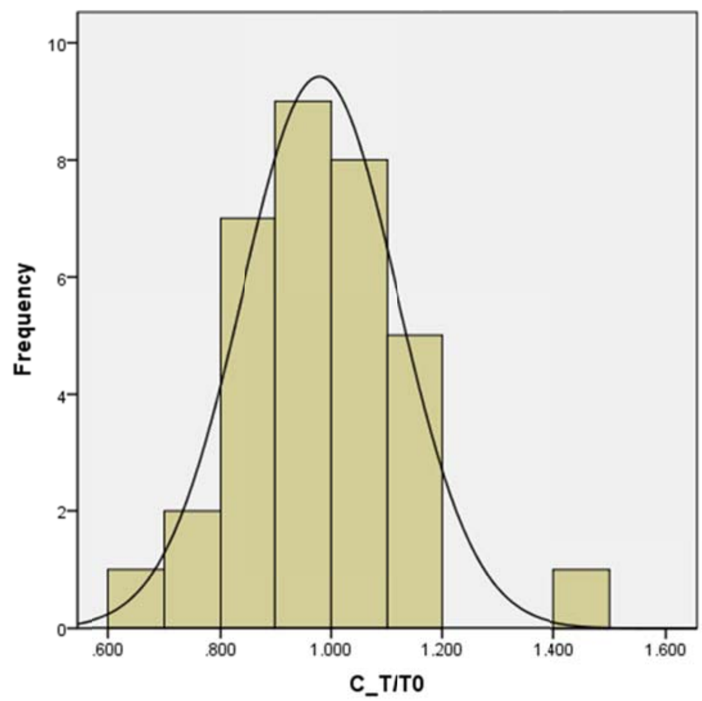


Figure 5.2: The histogram of ratio of construction actual duration (T) to construction estimated duration (T0), Mean=0.98, StDev=0.14, N=33

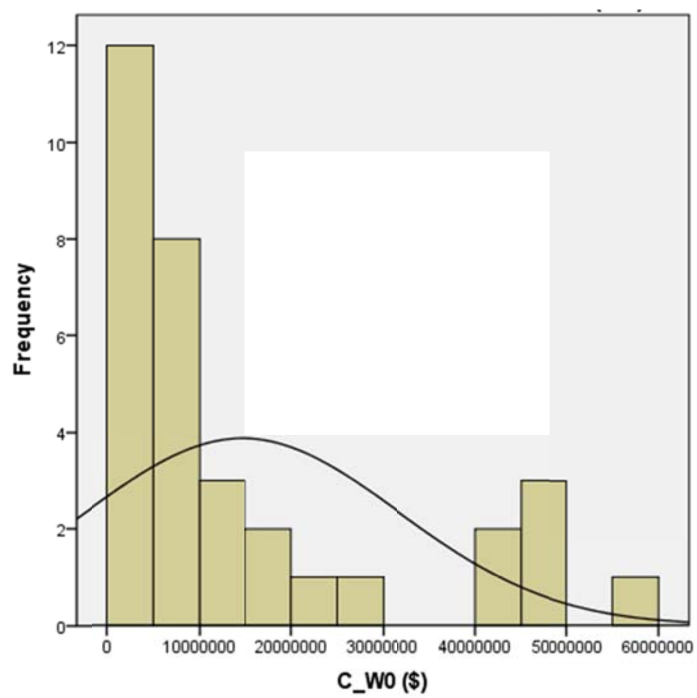


Figure 5.3: The histogram of construction estimated cost (W0), Mean=$14.70M, StDev=$16.98M, N=33

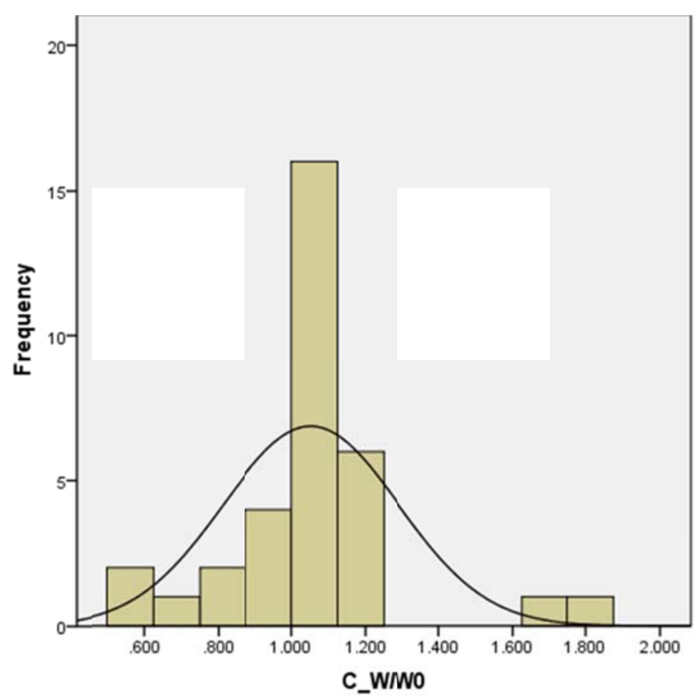


Figure 5.4: The histogram of ration of construction actual cost (W) to construction estimated cost (W0), Mean=1.05, StDev=0.24, N=33

Figure 5: The histogram of some properties of the project construction activity

1.9. Organization of the Dissertation

A review of the literature and the state of art of the related concepts are summarized in chapter 2. Chapter 3 describes the project model development, calibration and validation. Chapter 4 is dedicated to the BIM-ICM. The analysis of the results is presented in chapter 5. The model sensitivity analysis is addressed in Chapter 6. Finally, chapter 7 highlights the conclusions and discusses the avenues for future research.

Chapter 2. Literature Review

Different aspects of the problem statement, research objective and the research methodology were reviewed in the literature. More than 800 papers were gathered in several contexts including impacts of BIM on construction industry (CI), IT impacts on CI, SD applications in project management, rework loops, and change orders in construction projects. About 70 papers were selected for further review and investigation. The following sub-chapters summarize the literature review findings.

2.1. BIM Features

The following features of BIM software applications were identified during the literature review. As it was found that the Revit software family (Autodesk's version of BIM) is the application with which most of the experts have experience, the author spent 2 months training himself to use the Revit Architecture software trial version to better understand the research problem.

3D Interface

Visualization plays a crucial role at every stage of the design process. 3D virtual environment helps architects, designers, and engineers to visualize designs to explore complex ergonometric forms and develop concept variations, test designs under real-world conditions and explore complete products before they are built. A virtual 3D also helps in construction. It helps professionals not only understand the 3D geometry of the facility easier and faster but also spot errors and inconsistencies in the design easier if there is any.

Automated 2D drawing engine

This feature helps drafters create 2D drawings out of the 3D model readily by defining sections and views in the 3D model. This feature combined with the parametric modeling facilitates updates to the 2D drawings upon any changes in the 3D model automatically with minimum burden.

Geometry change management engine

Change management engine is a feature in BIM-enhanced CAD software applications that uses an underlying technology called parametric modeling. The parametric modeling engine uses parameters, also called constraints, to determine the coordination of elements. The parameters determine the behavior of a graphical entity and define relationships between the model components. For example, "the diameter of this hole is 1 inch" or "the center of this hole is midway between these edges.” This means that the design criteria or intent could be captured during the modeling process. Editing the model becomes much easier and the original design intent is preserved. It helps designers to coordinate the changes and maintain design consistency automatically, so they can focus much more on the design versus the change management.

The analogy of a spreadsheet is often used to describe parametric building modeling. A spreadsheet creates a network of element relationships. Then, it uses this network to distribute the changes throughout the required elements. A change made anywhere in a spreadsheet is expected to update everywhere automatically. The same is true for a parametric building modeler. The approach is scalable to building applications because it never starts with the entire building model; it always starts with a few elements explicitly touched by the user and continues with selective propagation of changes.

Clash detection engine

The Clash Detective tool enables effective identification, inspection, and reporting of interference clash in the 3D model between various 3D solid objects. The clash detection allows users to selectively check for clashes between any specified systems such as mechanical, plumbing, electrical, and structural systems.

Automated schedule of material engine

Compiling, counting and organizing schedules of doors, windows, fixtures and equipment are the most tedious and unrewarding tasks in the construction document preparation process. The BIM-enhanced application using a central database of the building information can create an accurate custom schedule in a matter of minutes. A change to a schedule view is automatically reflected in every other view and vice versa. Parametric modeling feature also provides tabular views of the components and maintains their association with other views of the model. If a component is edited graphically, the list is updated; if a component is edited on the list, the graphic views are updated as well.

Automated material take-off engine

Material takeoff schedules list the materials of the components in the BIM model. Material takeoff schedules have all the functionality and characteristics of the schedule view, but they allow showing more details about the assembly of a component. They are appropriate for sustainable design and checking material quantities in cost estimates. Material Takeoff simplifies tracking of material quantities. The parametric change engine ensures that material takeoffs are always accurate.

IFC compatibility

Industry Foundation Class (IFC) is a data model developed by the IAI (International Alliance for Interoperability) to facilitate interoperability across the applications that are used to design, construct, and operate buildings by capturing information about all aspects of a building throughout its lifecycle. The main idea is simply to automate data exchange among design, construction and operation software applications. BIM-enhanced software applications compatible with IFC facilitate inter-disciplinary data exchange and model reusability.

4D simulation

The BIM-enhanced software provides the project team with the capability of mapping the schedule dates from the project plan in a project scheduling software such as MS project or Primavera to the model components. The application can display building components based on their construction phase timeline. The construction process can be simulated and analyzed for construction management purposes to manage better time and space on the job site. The 4D model contains the detailed scheduling and resource information from the project planning software and it can be updated automatically on a regular basis.

4D model enables the project team to easily visualize time constraints and opportunities of improvement in the project schedule. During construction phase, potential spatial conflicts may arise between building components. These conflicts are not easy to identify when the coordination is performed using 2D or 3D layouts. The use of 4D model can easily enhance this coordination process. It can also help detect possible problems in the schedule. Moreover, 4D models can help address the safety issues during the construction.

2.2. Specific Software Impact on Construction Project

There are relatively few studies on the impact of the specific IT applications on project performance. Griffis et al. (1995), Koo and Fischer (2000), Fischer et al. (2003), and Back and Bell (1995) are the example of those studies.

Griffis et al. (1995) 3D CAD study

Griffis et al. (1995) investigated the use and impact of 3D CAD in construction. For this purpose, Griffis et al. (1995) used a survey to collect data from 55 Construction Industry Institute (CII) member companies. The survey shows that the most common uses of 3D CAD on site are:

- Checking clearances and access.
- Visualizing details from non-standard viewpoints.
- Using them as reference during project meetings.
- Performing constructability reviews.

The same survey shows that the most significant perceived benefits of the 3D computer models in construction are:

- Reducing interference problems
- Assisting in visualization
- Reducing rework.
- Improving engineering accuracy.
- Improving job site communication

Griffis et al. (1995) also studied the impact of using 3D CAD on project performance in terms of cost (actual cost/estimated cost), schedule (actual schedule/estimated schedule), and rework (additional labor expenditure due to rework/total labor expenditure of the project). With a sample of the 93 projects, they concluded that projects using 3D model experience:

- 5% reduction in cost growth
- 4% reduction in schedule slip
- 65% reduction in rework

Furthermore, Griffis et al. (1995) conducted a case study to validate the cost savings part of the survey results. They selected a project that utilized 3D CAD during construction. The project staff was asked to point incidents of potential problems that were avoided as a result of using 3D CAD along with the cost/benefit associated with each incident. Griffis et al. (1995) argued that the cost/benefits of the incidents were estimated as realistically as possible. The case study showed cost savings of 12%.

Fischer et al. (2003) and Koo and Fischer (2000) 3D and 4D case studies

Fischer and his colleagues (Fischer et al (2003) and Koo and Fischer (2000)) conducted a number of case studies on the impact of 4D CAD on project performance. Koo and Fischer (2000) investigated the feasibility of 4D CAD in commercial construction. They conducted a retrospective case study to understand the benefits of 4D models. For a completed project, the research team looked at the master CPM schedule in an effort to identify any potential problems. The research team found it difficult to conceptualize the construction process by viewing the CPM schedule alone. The research team also had difficulty associating each component in the 2D drawing with its related activity or activities.

As an alternative, they also created a 4D model. They used the PlantSpace Schedule Simulator to import Primavera's P3 schedule and CAD data and link the activities with their related components. The resulting 4D model displayed the construction sequence by showing consecutive 3D CAD drawings as time progressed. Koo and Fischer (2000) argued that their case study proved the usefulness of 4D models in visualizing and interpreting construction sequence, conveying special constraints of a project, formalizing design and construction information, anticipating safety hazard situations, allocating resources and equipment relative to site work place, and running constructability reviews. They helped managers visualize and interpret construction sequences; they conveyed any special constraints of a project; they made it easier to formalize design and construction information; they helped management anticipate safety hazard situations; they allowed for better allocation of resources and equipment relative to site work place; and they aided constructability reviews. In summary, they concluded that 4D visualization allows project stakeholders to better understand the construction schedule quickly and comprehensively than do traditional construction management tools.

According to Fischer et al. (2003), general contractors used 4D models for conducting overall and detailed planning, communicating scope and schedule information to project parties, and testing the constructability of the design and the feasibility of the execution of the schedule. Fischer et al. (2003) argued that project managers using 4D models were more likely to allocate resources (i.e., design time, client review time, management attention, construction crews) more effectively than those who did not use 4D models. 4D model helped construction teams to coordinate the flow of work and the use of space on site. Fischer et al. (2003) stressed that general contractors and subcontractors benefit from smooth, safe, and productive site operations since that contributes to the shortest and the most economical construction period.

Fischer et al. (2003) indicated that the use of 4D models facilitated the production of phasing drawings. These drawings were usually produced in 2D and for a few snapshots only, increasing the likelihood of interferences between the different trades. Combining 3D models with schedules automatically produced 3D phasing drawings at the daily, weekly, or monthly level. This enabled contractors to see who is working where on what and how the work proceeded over time and through the site.

Fischer et al. (2003 , p. 4) reported the benefits of 3D and 4D models to owners, designers, general contractors, and subcontractors as expressed by participating firms in a workshop hosted by Walt Disney Imagineering (WDI) and Center of Integrated Facility Engineering (CIFE) at Stanford University in 1999. The following is the list of benefits realized by general contractors:

1. Increase and improve information available for early decision making.
2. Reduce project management costs.
3. Improve evaluation of schedule.
4. Reduce number of change orders.
5. Increase concurrency of design and construction.
6. Reduce interest costs.
7. Maximize value to owner.
8. Increase productivity of crews.
9. Reduce wasted materials during construction.
10. Reduce rework.
11. Improve (verify, check) constructability.
12. Verify consideration of site constraints in design and schedule (sight lines, access, etc.)
13. Avoid (minimize, eliminate) interferences on site.
14. Maximize off-site work (prefabrication).
15. Increase schedule reliability.
16. Verify feasibility of execution of GC and sub schedules.
17. Shorten construction period.
18. Speed up evaluation of schedule.
19. Increase site safety.
20. Minimize in-process time in supply chain.
21. Shorten site layout/surveying time.
22. Improve site layout accuracy.
23. Reduce RFIs.
24. Improve portability of design.
25. Shorten design and construction period.
26. Improve learning and feedback from project to project.
27. Improve effectiveness of communication.
28. Bring new team members up to speed quickly.
29. Coordinate owner, GC and sub schedules.

Back and Bell (1995) electronic data management (EDM) study

Back and Bell (1995) explained that EDM technologies are information management tools designed to foster cooperative relationships and enable the integration of information across organizational interfaces. These interfaces were internal between several functional departments and external between contractors and their suppliers. The goal was to improve communications and data exchange among participants. Communication interfaces have the potential of misinterpretation, incompleteness, error, and delay. EDM, according to Back and Bell (1995), addressed these problems by creating a mechanism to create, manage, and protect project related data. This made the data accessible to a wide range of end users. Back and Bell (1995) argued that EDM fosters improved information quality that includes timeliness, accuracy, multi-locational availability, and format flexibility. Back and Bell (1995, p. 416) examined the impact of EDM on materials management.

Back and Bell (1995) conducted their examination by simulating four materials management process models. The first model was nonintegrated and intended to represent the baseline condition prior to the implementation of electronic information technologies. The second process model assumed an internal integration of information in the form of a well-developed integrated database system. The third process model included EDI and bar coding technology. The fourth process model utilized the concept of reengineering. They explained that reengineering represented a redesign of the traditional business processes to achieve dramatic improvements in performance by more carefully exploiting the EDM technologies.

Back and Bell (1995) collected data from industry practitioners. The data included durations and personnel (cost) requirements for the tasks that compromised the materials management process. Based on their simulation, Back and Bell (1995) reported significant time and cost savings when moving from one process model to the next. For example, the reengineered process model exhibited 85% time savings and 75% cost savings compared to the nonintegrated model. The results are shown in Table 2.

Table 2: Time and cost benefits of EDM Back and Bell (1995 , p. 420)

Process type	Time savings	Cost savings
Non-integrated	--	--
Internal integration	38.46%	36.04%
External integration	68.01%	51.82%
Reengineered	85.2%	75.07%

This literature review reveals that few research studies have been focused on the impact of specific IT applications on project performance. The statistical analyses such as Regression Analysis and Analysis of Variance (NOVA) are the mainstream of these studies.

2.3. System Dynamics Applications in Project Management

System dynamics has been used in engineering to analyze the mechanical, electronics and the electro-mechanical system for a long time. System dynamics is the approach to describe the behavior of the entities related together, called system, in terms of differential equations. In 1950s, system dynamics was introduced by J. Forrester as a method to model and analyze the behavior of complex organizational and socio-economic systems.

System dynamics models have been applied to project management topics in the past. There is a rich literature in system dynamics that covers project modeling in general and construction projects in particular (Lyneis and Ford 2007). This literature captures the change in projects through the rework cycle formulation (Sterman 2000). The different feedback mechanisms, then, affect change productivity and quality of work by project staff, which regulate the rate of changes made through the project life cycle. The works of Cooper (1980), Abdel-Hamid and Madnick (1991), and Ford and Sterman (1997) are examples of the studies in this area. System dynamics first was used practically in software development projects. Rodrigues and Bowers (1996) gathered an extensive list of articles mostly associated with the R&D and software development projects. More recently, Love et al. (2000) employed the causal loop diagrams to gain insight into the cause and effect relations between scope changes and construction project outcomes. Ogunlana et al. (2003) created a systems dynamics model for a construction company focusing on company management, not on projects. Park, Nepal and Dulaimi (2004) used system dynamics to model the construction company adoption issues for a new technology.

Almost all of these studies focus on managerial aspects of project management. In these models, project operation is considered as a single activity and is demonstrated with a single rework molecule attached to a cloud of causal loops which try to describe different mechanisms of project behaviors such as burnout, experience dilution, errors build errors, etc. (see Figure 6: A typical system dynamics model used in project management).

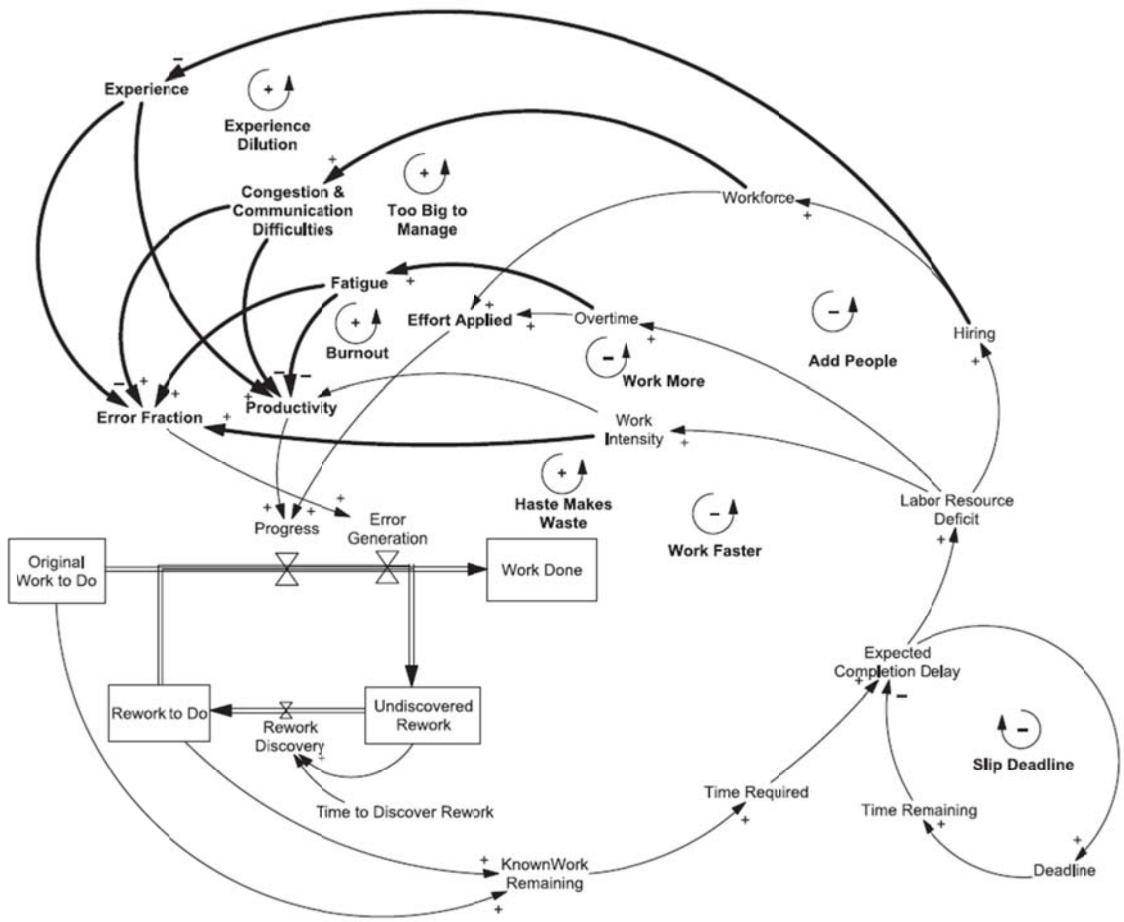


Figure 6: A typical system dynamics model used in project management (Lyneis, Ford 2007)

In reality, a project consists of many tasks and activities. Simplifying the project with a single rework molecule overlooks the dynamic interactions among activities. Pena-Mora and Park (2001) studied the inter-dependency of the project activities by proposing a system dynamics model for construction work package (CWP) to capture the dynamic behaviors between design and construction.

If we consider the two key phases of design and construction common to most projects, the impact of the design errors on the changes in construction is one of the important issues related to factors that derive project changes. Love, Mandal and Li

(1999) identified the major factors that influence rework in projects and established effective strategies for rework prevention to improve project performance using system dynamics. Sommerville (2007) studied how to minimize the occurrence and the impact of design defects and reworks on the future developments by eliminating or mitigating the underlying characteristics of the defects and reworks. In a recent study, Lopez et al. (2010) examined and classified the nature of errors and design error causation in engineering and construction. Several researchers have hypothesized that undiscovered changes in the design phase increases the latent changes in the construction phase; Hauck (1983), Martin and Macleod (2004); Ransom (2008) and Sun and Meng (2009). This hypothesis is in line with previous modeling work in the system dynamics literature (Ford and Sterman 1997) but has received limited empirical tests due to the complexity of measuring undiscovered changes in design.Rework means unnecessary effort of redoing a process or activity that is incorrectly implemented (i.e. defective). The rework itself can be defective too. Then it requires further efforts to correct the job in an iterative cycle. It can result in increasing project duration and work load far beyond what was planned or expected. In the absence of a rework cycle, the project duration is the amount of initial work divided by the available resources and their productivity. Considering defects by employing the quality of work concept will allow the rework cycle to generate extra work and prolong the project duration.

The rework loop concept was built in the ground breaking consulting project by Pugh Roberts Associates in the 70s (Cooper 1980; Rahmandad, Hu and Ratnarajah (2008)). 3 different structures were found for the rework concept in the literature: 1) Richardson and Pugh (1981), 2) Vensim modeling guide (2007), and 3) Lyneis and Ford

(2007). The model built in this research, shown in Figure 7, is based on the basic rework cycle formulation of Richardson and Pugh (1981).

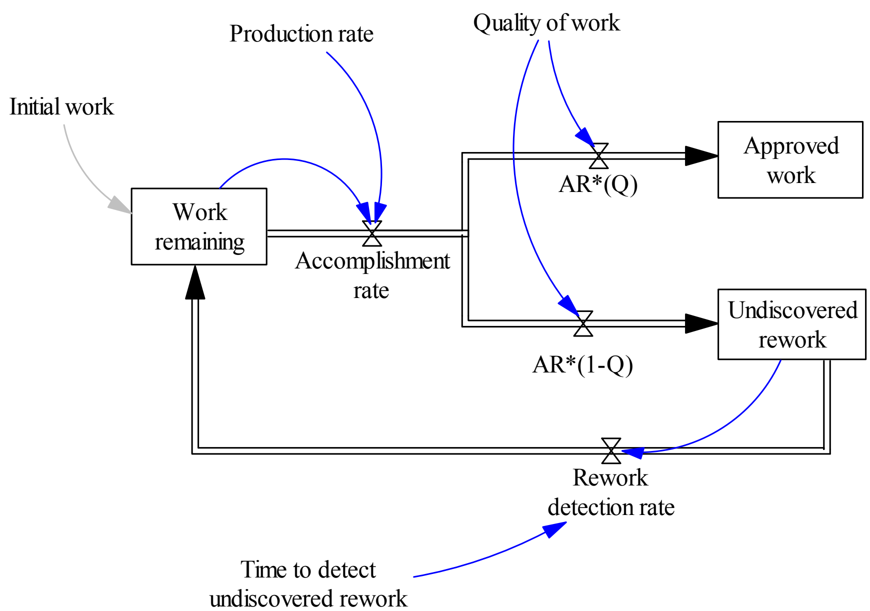


Figure 7: The rework loop adopted from Richardson and Pugh (1981)

Definition of the variables:

- W: Work remaining
- W_0: Initial work
- A: Approved work
- UR: Undiscovered rework
- P: Production rate
- Q: Quality of work
- D: Time to detect UR
- r_1: Accomplishment rate
- r_2: Rework detection rate
- t: Time
- T: Finish time

Equation 1 to Equation 3 enforce the conservation of the work flow at the work remaining, approved work and undiscovered rework stocks. Equation 3 requires that the work remaining be always non-negative. Equation 4 defines the rework detection rate as the function of the undiscovered rework (UR) divided by the time to detect undiscovered rework (D).

$$\frac{dW}{dt} = -r_1 + r_2 \qquad (1)$$

$$\frac{dA}{dt} = Q\, r_1 \qquad (2)$$

$$\frac{dUR}{dt} = (1 - Q)r_1 - r_2 \qquad (3)$$

$$r_1 = \begin{cases} 0 & if\ W = 0 \\ P & W > 0 \end{cases} \qquad (4)$$

$$r_2 = \frac{UR}{D} \qquad (5)$$

Where:

(1) P, D > 0 and $0 \leq Q \leq 1$

(2) A= 0, W=W0 and UR=0 when t = 0

(3) A=W0, W=0 and UR=0 when t = T

The "work remaining" (W) starts with the "initial work" (W_0) and begins to decrease by the production rate (P). The work flow is split up by quality of work (Q) into the two streams. Q is a parameter between 0 and 1. It means that Q portion of the work flow is fed into the "approved work" (A) and the rest, 1-Q, flows into the "undiscovered rework" (UR). A is the portion of W_0 which is accomplished. The other portion is stocked in the UR until it is discovered. UR is detected by the rate of D and it flows back into W at the beginning of the cycle. W is a positive variable. It implies that the production rate stops when W reaches zero.

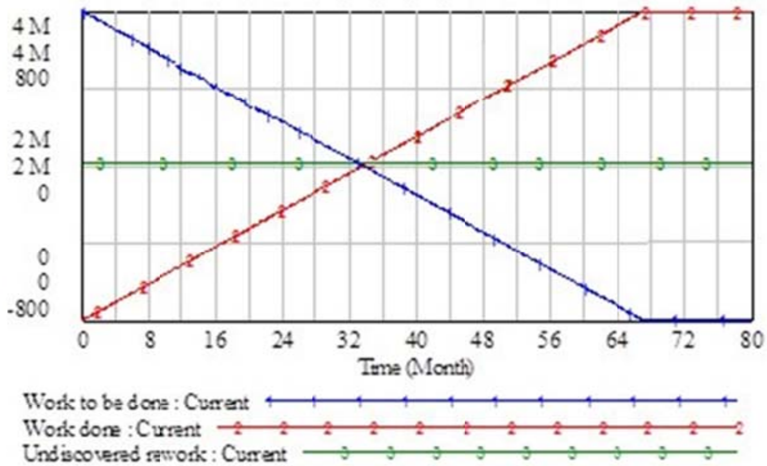
Figure 8 is an example to show the rework loop behaviors in three modes with a different set of parameters. The initial work (W_0) and the quality of work (Q) are assumed to be $4,000,000 and 0.85 respectively. Mode (1) represents the situation where the error detection rate (D) is greater than the production rate (P). In this case, as soon as any amount of undiscovered error is created, it is detected and it is sent back to the beginning of the cycle, work remaining (W). UR is zero throughout the project. Mode (2) demonstrates the equilibrium situation. Mode (2) is a specific situation of the mode (1). 6 representes the rework loop equilibrium equation.

$$(1-Q)P = D \tag{6}$$

Mode (1)

P = 70,000

D = 11,215



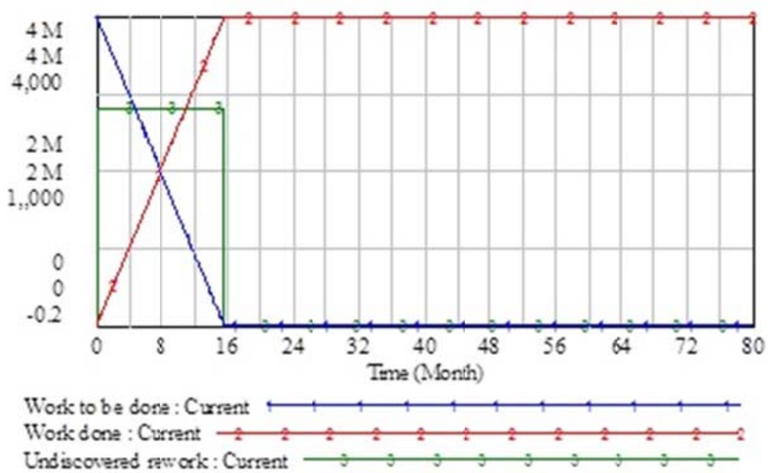
Mode (2)

P = 300,000

D= 45,000

equilibrium:

300000*(1-0.85) = 45000



Mode (3)

P =300,000

D = 11,215

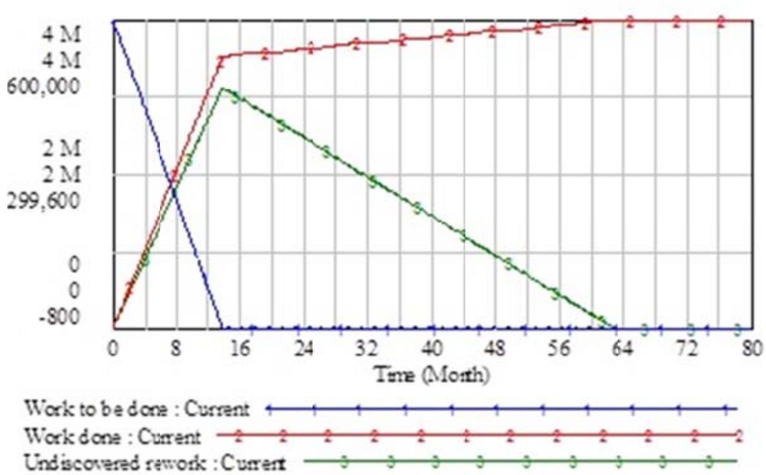


Figure 8: The rework loop three modes

Mode (3) depicts the situation where the error detection rate (D) is less than the production rate (P). In this case, the undiscovered error (UR) is overstocked until the work remaining (W) is finished. At this point in time, the green and red lines are deflected. From this point forward, the production rate does not control the work process. Instead, the magnitude of the detection rate determines how the work process goes.

2.4. Changes in Construction Projects

Changes are the main source of uncertainty in construction project planning. Changes are inevitable in most construction projects. Change is any variation to the plan. Change has been defined by many researchers as any event that results in a modification of the original scope, execution time, cost, and/or quality of work (Ibbs and Allen, 1995; Hanna et al., 2001; and Revay 2003). Change can be positive or negative. Positive change benefits the project to save cost, time, or even improve the quality or scope of work. However, negative change deteriorates the project outcomes.

Many researchers have studied the cause and effect of changes in construction projects. (Arain et al. 2004, Clough and Sears 1994; O'Brien 1998; Ibbs and Allen 1995; Chappell and Willis 1996; Sanvido et al. 1997; Gray and Hughes 2001; Wang 2000;Fisk 1997;Dell'Isola 1982; Geok 2002; Thomas and Napolitan 1995; Arain 2002; Chan et al. 1997; Hsieh et al. 2004; Wu et al. 2004; Arain et al. 2005; Hanna (2001); Bower 2002). Many hypotheses have been proposed and tested to identify the factors and measure their impacts on the project plan deviation. Hinze et al. (1992) stated that the cost overruns tend to increase with the project size. Thurgood et al. (1990) found that rehabilitation and reconstruction projects are more likely to increase the cost overruns in comparison with the maintenance projects. Riley et al. (2005) examined the effects of the delivery methods on the frequency and magnitude of change orders in mechanical construction. Gkritza and Labi (2008) showed that the project duration increases the chance of the cost overrun. Kaming et al. (1997) found the design change is one of the most important causes of time overruns in 31 high-rise projects studied in Indonesia. Moselhi et al. (2005) studied the impact of change orders on the labor productivity by using 117 construction projects in Canada and US. Acharya et al. (2006) identified the change orders as the third factor in construction conflicts in Korea. Assaf and Al-Hejji (2006) studied 76 projects in Saudi Arabia and they found the change order as the most common cause of delay identified by all parties: owner, consultant and contractor.

Changes in construction projects are documented in the form of change orders. Change orders are the official documents attached to the original contract as modifications. They are issued to correct or modify the original contract. Change orders can be categorized by different features such: reason, responsibility, legal aspects, etc. (Sun et al. (2009); Keane et al. (2010)). Change orders are carried out for 4 major reasons: Design error, design omission, different site condition and scope change. Design error and omission refer to the professional A/E mistakes or negligence. The professional negligence is defined as the failure to perform in accordance with the skill and care that the professional community is expected a reasonably prudent member to act. Different site condition usually refers to the site subsurface condition or other latent physical conditions that differ from those presented in the contract or those ordinarily encountered. Different geotechnical conditions in new projects or different conditions of the existing facilities in renovation projects are the popular examples of the different site conditions. Scope change refers to the changes in the scope of work. It can be directed by owner or A/E designer. Market change or any other unforeseen changes that influence the owner's requirement of the project are the reasons of scope change directed by owner. A/E designer can also direct the scope change to improve the design specifications.

Overall, these 4 categories can be summarized in 2 major categories: 1) constructive change, and 2) unforeseen condition. Constructive change is the change to improve the design or construction specifications which can be detected by the design error or lack of information/technology at the design or construction stage. Unforeseen change is defined as the change which is caused by any unforeseen condition in the physical and the socio-economy environment of the project. The changes caused by the unforeseen conditions are directed by the owner and usually influence the scope of the work. In contrast, the constructive changes are formed by the A/E designer and the constructor as the project evolves.

2.5. Summary

Few research studies were found that investigate the impact of specific software applications on project outcomes in the construction industry. Statistical methods are the mainstay of these studies. System dynamics methodology was found to be a promising tool to fulfill statistical method shortcomings which are essentials to serve the main goal of this research, which is considering the dynamic nature of projects. Most applications of system dynamics focus on the managerial aspects of the project management. Breaking down projects into activities and studying the activity interactions do not have many traces in the system dynamics literature. The rework loop concept was recognized as the basis to consider the dynamic nature of projects. Since this research deals with rework and change together, the concept of change were also studied a little further in construction projects. It was discovered that the rework loop formulation is not able to model the project cost curve because of the nature of change which can be not only positive but also negative. This research fills out these gaps of the existing body of knowledge in this area of research.

Chapter 3. Project Model

3.1. Project Supply Chain Concept

Construction projects are considered as the ad hoc product development projects as opposed to the manufacturing product development. The construction projects have mainly 2 particular features in contrast with the manufacturing process. The construction projects are unique in terms of the final product, the parties who are involved, and the environment. Environment means not only the physical nature that the project is located in but also the socio-economic situation with which the project is surrounded. The construction projects are complex in terms of the number of the activities and parties that are involved in the project and also the complex inter-relations among those activities and parties. As a result, changes are inevitable in such a dynamic context and uncontrolled environment.

The Design and Construction are the two main components of the construction project supply chain. Design starts with the project program report which contains essential requirements of the owner business plan. Design is a very crucial phase. In this phase, the owner requirements are identified, quantified and interpreted into a clear documentation which is communicable with contractor and sub-contractors. The construction starts when the design documentation is finished or partially finished. It depends on the type of contract, construction delivery method or the project bounds and force majors. The construction activities are planned and scheduled based on the engineering and procurement inputs. The sequence and schedule of construction activities are initially planned to reflect the most logical and cost effective approach to meet the due dates. Figure 9 shows the construction project flow and processes.

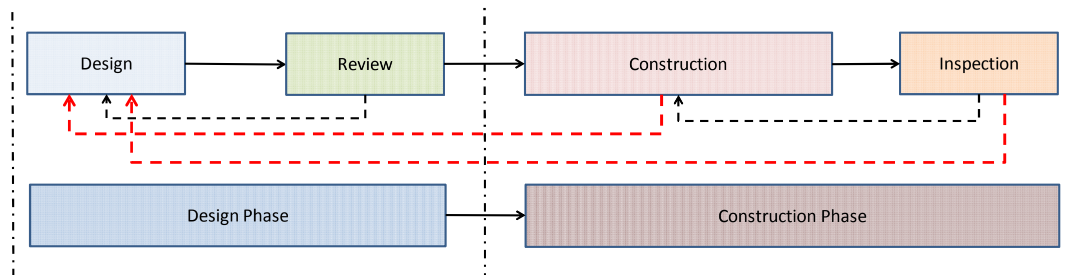


Figure 9: Construction project supply chain overview

When a change occurs in either the design or the construction process further actions may be required not only in that process but sometimes in the other process as well. These actions are known as feedbacks. Feedbacks are shown with dashed arrows in Figure 9: Construction project supply chain overview. The change feedback loops, if not controlled, can easily waste project resources and make the project a nightmare for the project stakeholders. The change feedback loops are divided in two categories: short loops (black dashed arrows) and long loops (red dashed arrows). The short loops are more frequent in projects. The short loops in design are a part of the project development and improvement process. The long loops are rare in projects; however, they are more dangerous and may have a significant impact on the project outcomes. They slow down the project progress pace, deteriorate the labor productivity, increase conflicts, increase reworks and delay the project due date.

Breaking down the construction project supply chain, shown in Figure 10 , will provide more insights into how information and work flow throughout the project.

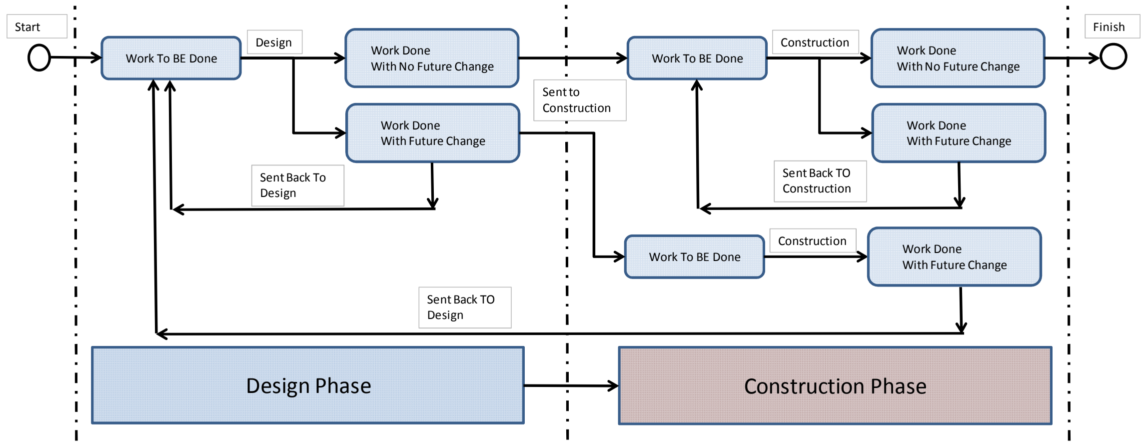


Figure 10: The construction project supply chain in the design and construction activity level

The project starts with the design's "Work to be done" stock. When the job gets designed, it passes to the "Work done". The "Work done" falls into two categories: "Work Done With No Future Change" and "Work Done With Future Change". The "Work Done With No Future Change" will pass to the next step, construction. However, "Work Done With Future Change" may experience two scenarios. Some of them may be detected and brought back to the design to be re-designed. But some of them may be ignored and sent to the construction. The same mechanism applies in construction as well. At the end, the "Work Done With No Future Change" in construction runs out to the project finish. On the other hand, the "Work Done With Future Change" needs to be fixed. They are recognized and dispatched to be fixed. Some of them are fixed in the construction process. However, some are needed to be sent far back to the design at the starting point.

All these scenarios fall into the four paths shown in Figure 11 through 14. Path (1) (Figure 11), is an open path, starts from the project beginning and ends with the project finish. It is the main stream of the work flow in the project. Any work should pass this path to get accomplished. The other 3 paths are loop paths and they do not end at the project finish. Design rework loop, Path (2), starts with “work to be done” in design (Figure 12). In this scenario, the work done will be turned into a change some time later when it is discovered. The discovered change is sent back to get re-designed. Construction is a successor activity of design. It uses the design outputs as inputs. Changes in construction may be caused by faults in the construction or even undiscovered faults in the design. Construction rework loop, Path (3), shows the rework cycle caused by the former (Figure 13). The latter cause which is more deteriorating occurs when a fault in design is not detected and it dispatches to be constructed with no precaution. The change is caught in construction and it is sent back to be redesigned and reconstructed again. The scenario is indicated in Figure 14.

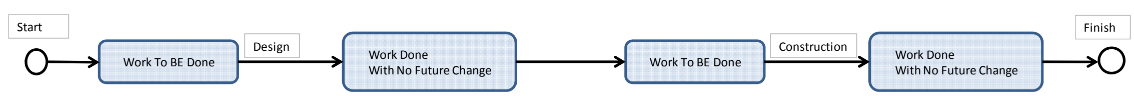


Figure 11: Path (1), Project mainstream path

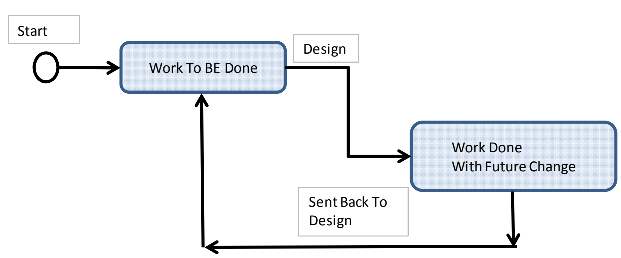


Figure 12: Path (2), Design rework loop

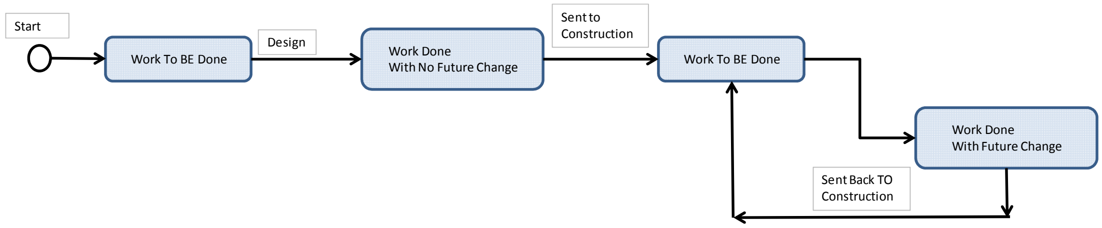


Figure 13: Path (3), Construction rework loop

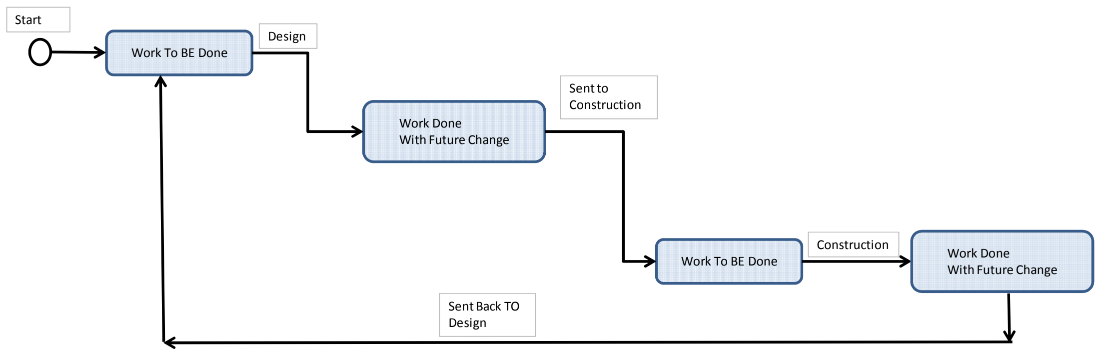


Figure 14: Path (4), Design-construction rework loop

3.2. <u>Project Supply Chain Model</u>

The project model is a system dynamics model that represents the project supply chain process in terms of cost over time during the design and construction phases. As it is shown in Figure 10, the design and the construction modules resemble the rework loop concept. The design and construction stages are replaced with two rework loops. However, this replacement entails two issues. First, the design and construction loops are completely separate and they do not have any interactions. Many hypotheses have been proposed to describe the mechanism of design and construction interactions. But none of them has been tested with empirical data yet. The impact of design errors on construction changes is the one which has grasped a little more attention in literature. Several researchers have hypothesized that undiscovered changes in design increases the latent changes in construction stage (Breytenbach et al., 2008; Burt, 2004; Chapman, 1998; Hauck, 1983, Martin and Macleod, 2004; Ransom, 2008; Sun and Meng, 2009). In this research, we propose that the extent of undiscovered design change decreases the quality of construction work in decaying exponential order.

Second, the rework loop concept is not able to model the changes in the project supply chain. The unit of work which is the data entity that flows through the rework loop is a positive real value in the rework loop concept. The quality of work is always less or equal to one ($0 \leq Q \leq 1$). As a result, the generated rework is always positive. But the data entity which flows into the change loop is cost which can be positive or negative. It means the parameter which is known as quality of work (Q) can exceed the values greater than one to produce the undiscovered change with the negative cost. The rework loop formulation slightly was changed to adopt the new change concept into the work loop model. The new loop is called "Change Loop" and the ratio that produces the changes is called the coefficient of change (Kc) corresponding to the quality of work (Q).

The model is implemented in the Vensim software application version 5.8. Figure 15 demonstrates the model structure and variables in the form of system dynamics graphic convention. The texts represent variables. Variable's names start with the stage name and then follows with the name which is equivalent to the rework loop definitions (Chapter 2.3). The boxes represent stock variables. Flow variables are shown by valve symbols. Stock variables are the integral part of flow variables. The arrows explain the relationship of variables. The arrow shows the variable at the arrow head is a function of the variable at the other end of the arrow.

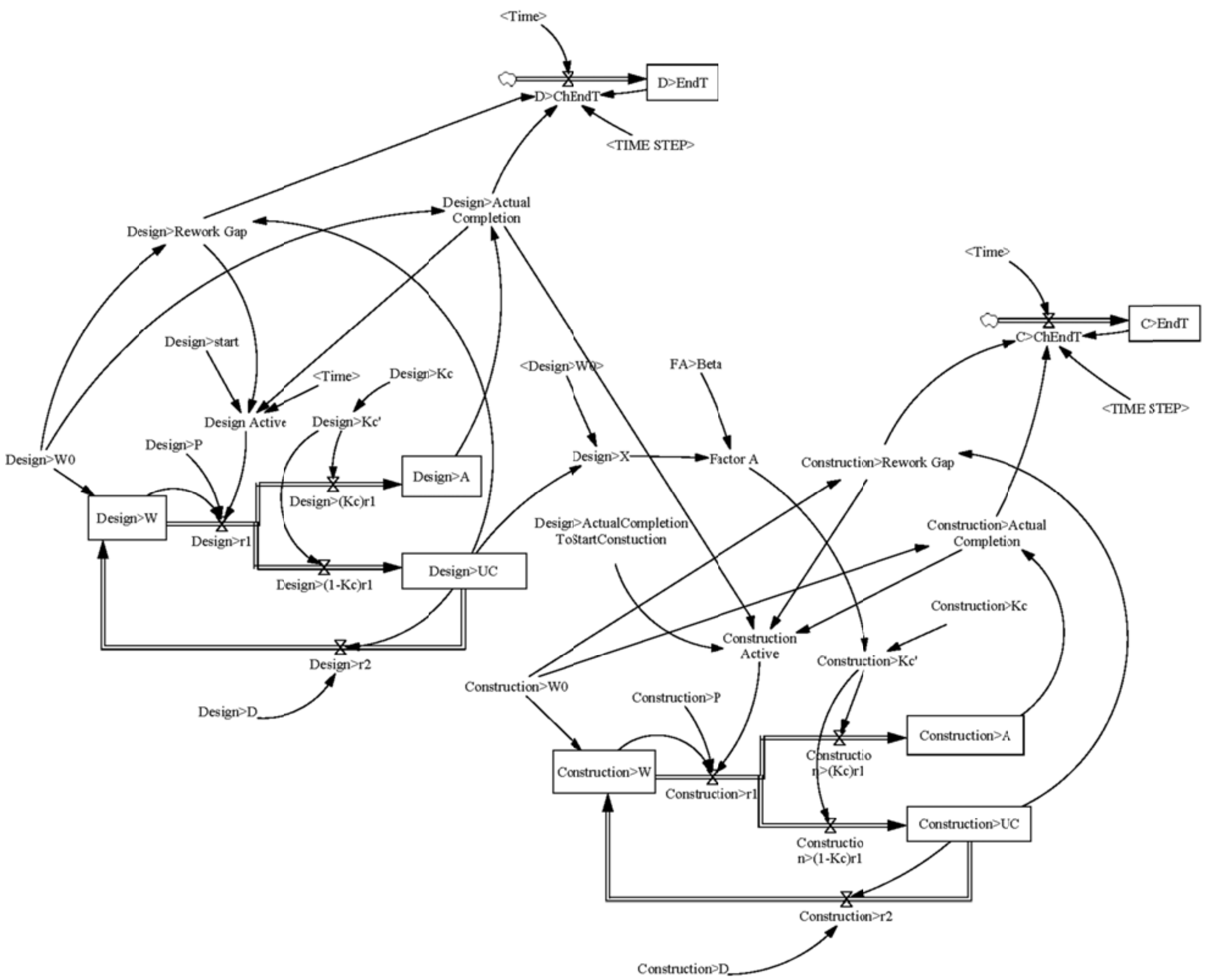


Figure 15: The system dynamics model of Design and Construction interactions

For each stage, production rate (P) indicates the rate of work accomplishment. The quality of work (Kc) which is constant specifies the fraction of work which is done correctly. This fraction is restored in work accomplished stock (A). The other fraction, (1-Kc), is restored in undiscovered change stock (UC) until it is discovered with a delay. The rate of detecting undiscovered errors (D) is defined by the amount of undiscovered change divided by time to detect errors (D). The amount of undiscovered change is the value of Stock UC, which varies over time. Time to detect errors (D) is the amount of time, on average, that is required to detect undiscovered errors. Each loop is controlled by three variables of “Active”, “Rework Gap” and “Actual Completion”. “Active” is an off-and-on key which controls the flow of work in the loop. “Active” is derived from “Rework Gap” and “Actual Completion”. “Active” switches off when the work accomplished is not complete or there still exists some undiscovered errors in Stock UC. Otherwise “Active” is on. “Actual Completion” gauges the percentage of the accomplished work. It is defined as the fraction of work accomplished (A) to the initial work (W0). The work accomplished is complete when “Actual Completion” reaches 99% threshold. “Rework Gap” measures the volume of the undiscovered error in the fraction of UC divided by initial work (W0).

“Factor A” is defined to capture the design-construction inter-relation. “Factor A” is the single causal relation that influences the construction quality of work with a function of the design undiscovered change. We use Equation 7 to formulate “Factor A”:

$$\text{“FactorA”} = (1+\text{”Undiscovered design change”}/\text{”Design initial work”})^{-\beta} \quad (7)$$

Beta (β) is the impact factor which shows the magnitude of undiscovered design change impact on construction quality of work. Construction quality of work is defined in Equation 8.

*"Construction quality of work" = "Construction normal quality of work" * "Factor A"* (8)

In Figure 15, *"Design>X"* is defined as *"Undiscovered design change"* divided by *"Design initial work"*. *"Design>Actual Completion"* measures the completion percentage of design by dividing *"Design>A"* by *"Design>W0"*. *"Design>Rework Gap"* calculates the proportion of the undiscovered design error, *"Design>UC"*, to the total design initial work, *"Design>W0"*. *"Design>Rework Gap"* along with *"Design>Actual Completion"* and *"Design>start"* are used to define *"Design Active"* which performs as a control variable to switch the design process off and on. Design finish time is set based on the 99 percent threshold for *"Design>Actual Completion"*. When design finish time occurs, it is restored into the *"D>EndT"* variable. The same set of variables is defined for the construction module as well. Besides, *"Construction Active"* is set on when *"Design>Actual Completion"* exceeds the *"Design>ActualCompletionToStartConstruiton"*.

The model output consists of four cost curves, two for each stage of design or construction. 1) Work accomplished cost curve is the value of work accomplished over time. 2) Overrun cost curve is the cumulative extent of discovered error over time. It is computed by integrating error detection rate (D) over time. The sum of Work accomplished and overrun cost curves produces the cost curve for each stage. The project cost curve is the total of design and construction cost curves. The model includes all formulations. For more details see appendices C and D. The next sections describe the model mathematics in more details.

3.3. Project Model Assumptions

A model is an intentionally abstract perspective of a reality. The abstraction is made by making assumptions. The assumptions define the boundaries within which the model is valid. The following is the list of the SD project model assumptions:

1. The production rate is constant for the project from the beginning to the end. The production rate is defined as the product of the productivity multiplied by the labor force in the SD text books. Usually in reality, the intensity of the labor force is bell-shaped. Each activity starts with few people in the beginning. More people get involved later. Then at the end, people leave the job and just a few people are left through the activity close out. As the information of the labor force intensity is not available, production rate is assumed to be constant. Moreover, sometimes the A/E designer is awarded a post-design contract to provide construction support services. The production rate is definitely less than the design contract during this service. Assuming the design production rate is constant across the project may be the source of some errors and unexplained variations in the model.

2. The coefficient of change (Kc) is constant. The design or construction activities are not single tasks. They are composed of many sub activities and tasks. Each task has its own Kc which is not possible to define due to the insufficient level of the detail in the available information.

3. The time to detect the undiscovered changes (D) is assumed constant.

4. It is assumed that "Factor A" can be summarized into a single causal relation that represents "*design undiscovered change (UC) reduces the construction coefficient of change (Kc)*". Equation 9 is the mathematical representation of Equation 9.

$$f_A(UC) = \frac{1}{\left(1 + |\frac{UC}{W_0}|\right)^{\beta}} \tag{9}$$

3.3.1. <u>Mathematical Model</u>

The project supply chain model can also be looked at as a function shown in equation 8, where ($\underline{Y}$) is the model output vector, ($\underline{X}$) is the model input vector and ($\underline{\alpha}$) is the model parameter vector.

$$\underline{Y} = f(\underline{X}\,;\,\underline{\alpha}) \tag{10}$$

3.3.2. Model Inputs

The model input vector, defined in Equation 11, comprises the design estimated duration (T_{0D}), design estimated cost (W_{0D}), construction estimated duration (T_{0C}) and the construction estimated cost (W_{0C}).

$$\underline{X} = [W_{0D}, T_{0D}, W_{0C}, T_{0C}] \tag{11}$$

3.3.3. Parameters

The model parameter vector includes two sets of parameters: 1) project parameters, 2) industry parameter (Equation 12). Subscripts D and C denote the design and construction, respectively. Parameters such as production rate (P), coefficient of change (Kc) and time to detect undiscovered changes (D) are called project parameters. Industry parameter is (β) which is the parameter of the "Factor A". The project parameters are specific for each project whereas the industry parameter is common across different projects. The project parameters are normalized to convert them to the same scales. Production rate is divided by the estimated production rate and time to detect undiscovered changes is divided by the estimated duration. . $DC_{\%}$ is the design actual completion percentage at which point construction gets started.

$$\underline{\alpha} = [P_D, K_D, D_D, P_C, K_C, D_C, DC_{\%}, \beta] \tag{12}$$

3.3.4. Auxiliary variables and equations

The auxiliary variables and equations are the elements which do not play any role in the model structure and outcomes. However, they are useful to provide more insights into the model behavior and results. The model includes formulations to compute changes, cumulative changes, total work done, and actual completion percentage in each phase. The finish time of the design and construction is computed based on the 99 percent threshold for work completion. See Appendix C for more details.

3.3.5. Outputs

The model output comprises the finish time and the cost-overrun of both design and construction stages. The model output vector is defined in Equation 13. T is the finish time and $CO(t)$ is the cost overrun curve. Subscripts D and C denote the design and construction stages, respectively.

$$\underline{Y} = [T_D, CO_D(t), T_C, CO_C(t)] \tag{13}$$

3.4. Calibration

Calibration is the process that estimates the best value of the model parameters based on a set of the observed data. Mathematically, the calibration process is an optimization to minimize the distance between the model outcome and the actual data by searching for the best model parameters (decision variables) in the model parameter space. In this problem, the actual data upon which we calibrate the model contain actual finish time, actual final cost overrun and actual cost overrun curve. Each project consists of two stages: design and construction. The calibration is performed on finish time, final cost overrun and cost overrun curve simultaneously for both design and construction. The parameters of project are calibrated to fit the model outcome with actual data. Each project is calibrated upon two cost overrun curves and 4 data points. 18 projects are randomly selected (out of 33 projects) for calibration purpose.

Since each project is independent from the other projects, the model would be calibrated for each project individually. The result would contain the parameters of 18 isolated projects. The parameters explain the characteristics of the project performed. However, the result would not convey any meaning to explain the shared characteristics of the industry sampled by the 18 projects. As we are interested in providing more insights into the project's behavior in the targeted industry, we need to measure the average impact factor β over all projects. As such, we propose that Parameter β which regulates the impact of undiscovered design error on the construction quality of work is an industry wide characteristic and it is common among all projects. In this respect, the model parameters can be classified into two categories: 1) project-specific parameters, and 2) industry parameters which are common across different projects. The project-specific parameters consist of design and construction production rate (P), quality (Q) and time to detect undiscovered changes (D). Parameter β is considered as the only industry parameter. To implement this proposition a compound model is built including 18 layers, each devoted to a project. Each layer is independent form others except

Parameter β that is shared among all layers. Figure 16 shows the schematic diagram of the model. The calibration is performed by simultaneously estimating the project-specific parameters and the common parameter (β) across all 18 calibration projects.

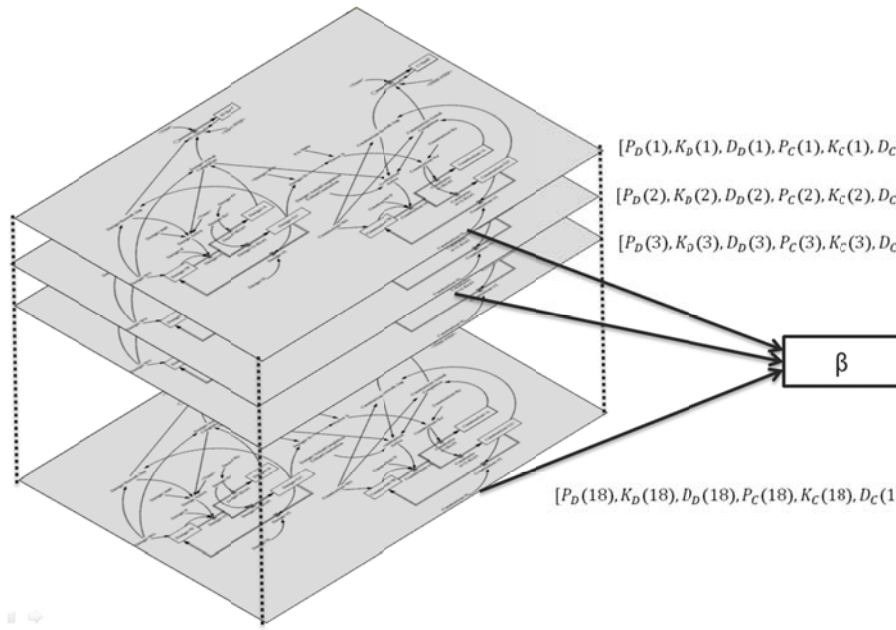


Figure 16: The compound calibration model (18 layers)

Calibration can be summarized in an optimization problem framework. The following chart organizes the calibration concept in a brief optimization problem structure. C is the set of the randomly selected 18 projects (out of 33 projects) to perform calibration.

Objective function:	Minimize {*Payoff*()}	
Decision variables:	$\underline{\alpha_i}$	$\forall i \in C$
Constraints(1):	$\underline{Y_i} = f(\underline{X_i}\ ;\ \underline{\alpha_i})$	
Constraints(2):	$\underline{\alpha_i} > \underline{0}$	$\forall i \in C$

($\underline{\alpha}_i$) is the decision variable vector shown in Equation 14. For more details about Constraints(1) please see Equation 10 in section 3.2.2, Mathematical Model.

$$\underline{\alpha}_i = [P_D(i), K_D(i), D_D(i), P_C(i), K_C(i), D_C(i), DC_{\%}(i), \beta] \tag{14}$$

The objective function also called Payoff function is used to define the distance between the model outcome and the actual data. It is usually defined as the sum of the squared errors (SSE). It is the concept of the least square method. The error is the subtraction of the model outcome from the actual data. Since the parameter space is multidimensional in this problem, the error is normalized to the form of the error percentage (EP) to cancel out the dimension magnitudes of the different decision variables in the payoff function.

Vensim 5.8 is used to calibrate the model with a set of 18 project selected randomly for this purpose. Vensim has an embedded optimization module to perform calibration. The payoff function and decision variables need to be defined for the module. The rest is taken care of by Vensim. The results are restored on a file at the end of the process. The next sections explain the construction of the payoff function in details.

3.4.1. Objective function

The objective function (payoff function) is the weighted sum of three error terms (Equation 15): (1) sum of the squared error percentage of the project final time (SSEP[T]), (2) sum of the squared error percentage of the project final cost overrun (SSEP[CO1]), and (3) sum of the squared error percentage of the project cost overrun behavior (SSEP[CO2]). Figure 17 shows those terms.

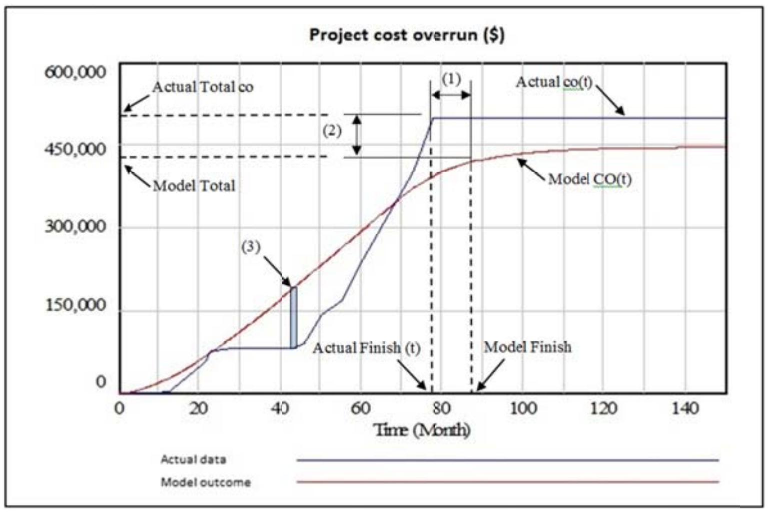


Figure 17: Calibration payoff function terms

$$Payoff() = \sum_i \sum_j W_i^t \left(\frac{T_{ij} - t_{ij}}{t_{ij}}\right)^2 + \sum_i \sum_j W_i^{co1} \left(\frac{CO_{ij} - co_{ij}}{co_{ij}}\right)^2 + \sum_i \sum_j W_i^{co2} \frac{1}{T'_{ij}} \int_0^{T'_{ij}} \left(\frac{CO_{ij}(t) - co_{ij}(t)}{coMax_{ij}(t)}\right)^2 dt \tag{15}$$

The first term is the sum of the squared error percentage of the project final time (SSEP[T]) defined in Equation 16 , where "T" is the model finish time, "t" is the actual finish time, i = 1 (design), 2 (construction) and j = 1, …, 18 (calibration sample projects).

$$SSEP[T] = \sum_i \sum_j \left(\frac{T_{ij} - t_{ij}}{t_{ij}}\right)^2 \tag{16}$$

The second term is the sum of the squared error percentage of the project final cost overrun (SSEP[CO1]) defined in Equation 17, where "CO" is the model total cost overrun and "co" is the actual model cost overrun, i = 1 (design), 2 (construction) and j = 1, …, 18 (calibration sample projects).

$$SSEP[CO1] = \sum_{i}\sum_{j}\left(\frac{CO_{ij} - co_{ij}}{co_{ij}}\right)^2 \tag{17}$$

The final term is the sum of the square error percentage of the project cost overrun behavior (SSEP[CO2]) defined in Equation 18, where “CO(t)” is the model cost overrun behavior, “co” is the actual cost overrun behavior, i = 1 (design), 2 (construction) and j = 1, …, 18 (calibration sample projects). ${T_{ij}}'$ is the maximum of the actual and the model finish time.

$$SSEP[CO2] = \sum_{i}\sum_{j}\frac{1}{{T'}_{ij}}\int_{0}^{{T'}_{ij}}\left(\frac{CO_{ij}(t) - co_{ij}(t)}{coMax_{ij}(t)}\right)^2 dt \tag{18}$$

Where:

- ${T_{ij}}' = Max(T_{ij}, t_{ij})$
- $coMax_{ij}(t) = Max\big(CO_{ij}(t)\,, co_{ij}(t)\,, coMax_{ij}(r)\big)$ and $0 \leq r < t$

In this research, 18 projects are selected randomly out of the 33 gathered projects for the calibration purpose. Table 3 and Figure 18 to Figure 25 show some statistics for the calibration sample projects.

Table 3: The calibration sample statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
D_T0	18	1.9	26.3	9.787	7.5422	56.884
D_W0	18	69000	4416480	1300324.78	1512035.104	2.286E12
D_T_2_T0	18	.943	2.072	1.25496	.332642	.111
D_W_2_W0	18	.351	2.188	1.21411	.366656	.134
C_T0	18	2.5	24.8	12.635	7.6868	59.087
C_W0	18	348316	55056526	16350075.50	19401450.70	3.764E14
C_T_2_T0	18	.778	1.409	.98381	.155481	.024
C_W_2_W0	18	.525	1.827	1.04183	.319184	.102
Valid N (listwise)	18					

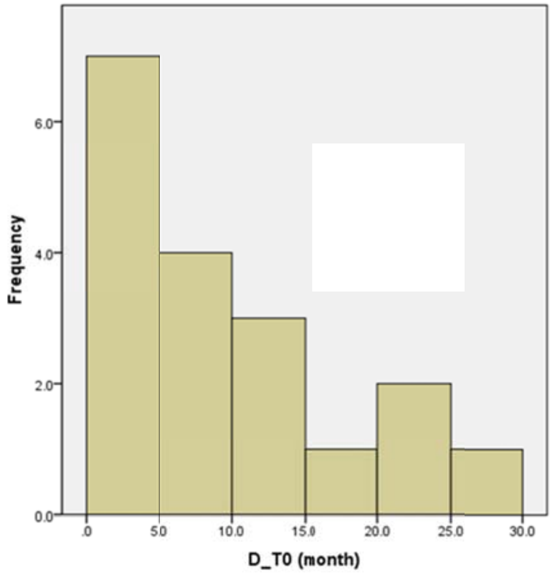


Figure 18: Design estimated duration, Mean=9.79, StDev=7.54, N=18

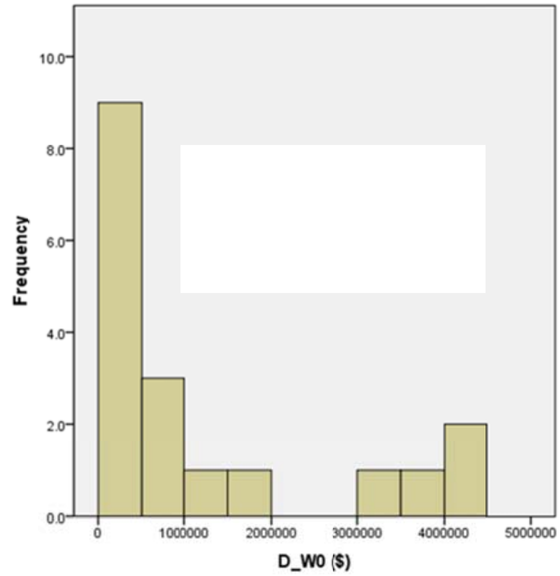


Figure 19: Design estimated cost, Mean=$1.3M, StDev=$1.5M, N=18

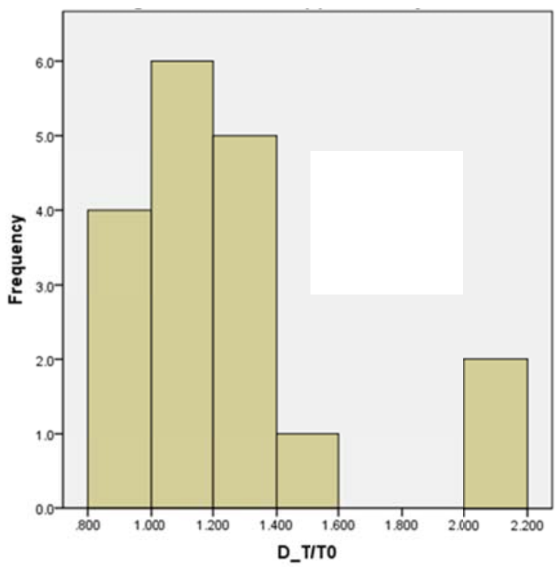


Figure 20: Design actual to estimated duration ratio, Mean=1.25, StDev=0.33, N=18

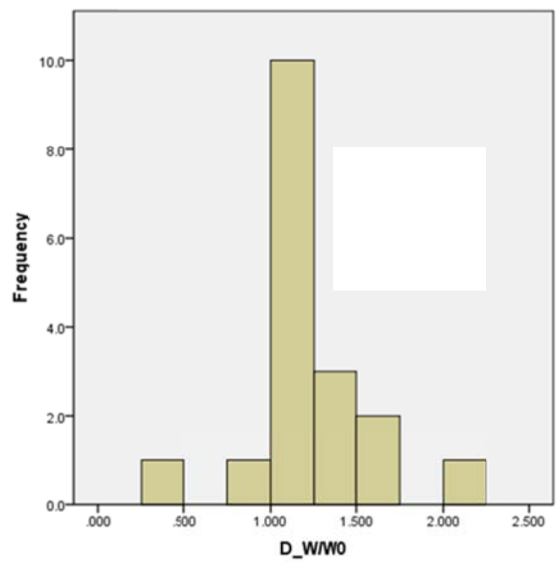


Figure 21: Design actual to estimated cost ratio, Mean=1.21, StDev=0.37, N=18

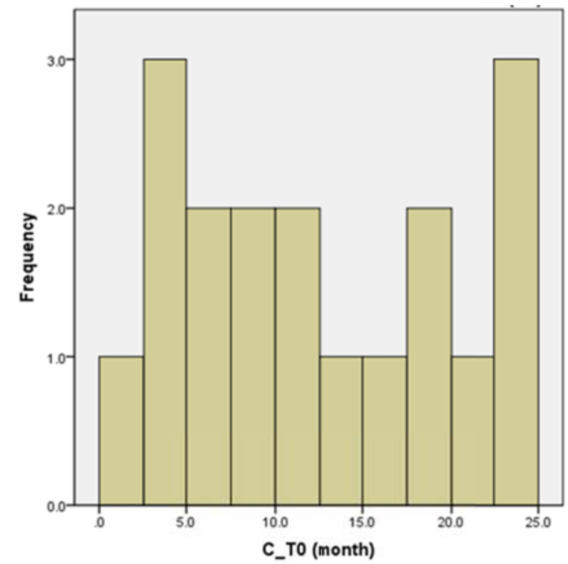


Figure 22: Construction estimated duration, Mean=12.63, StDev=7.69, N=18

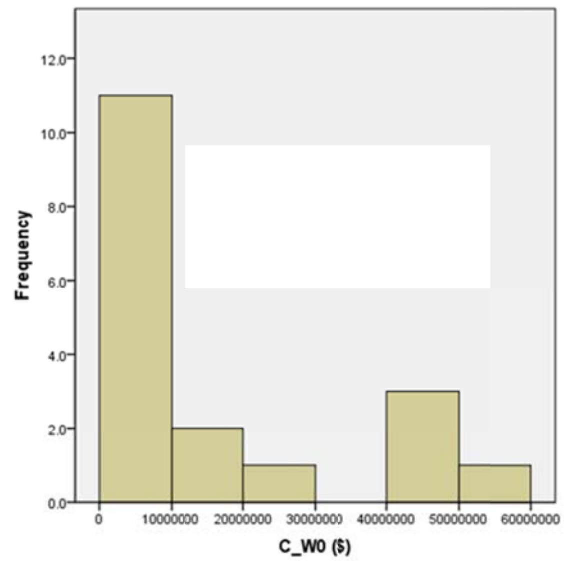


Figure 23: Construction estimated cost, Mean=$16.4M, StDev=$19.4M, N=18

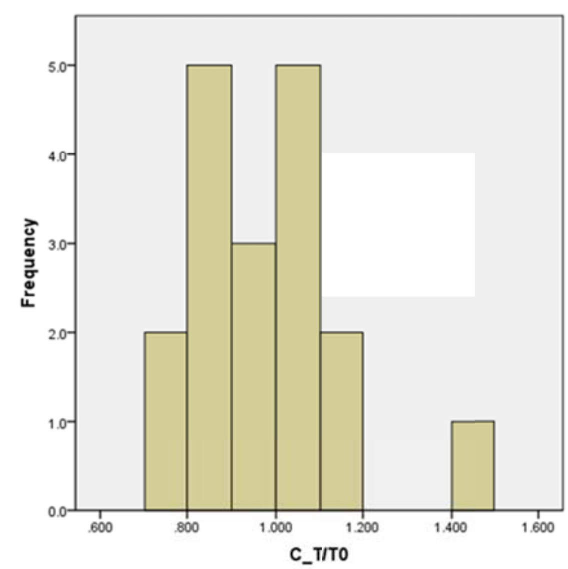


Figure 24: Construction actual to estimated duration ratio, Mean=0.98, StDev=0.15, N=18

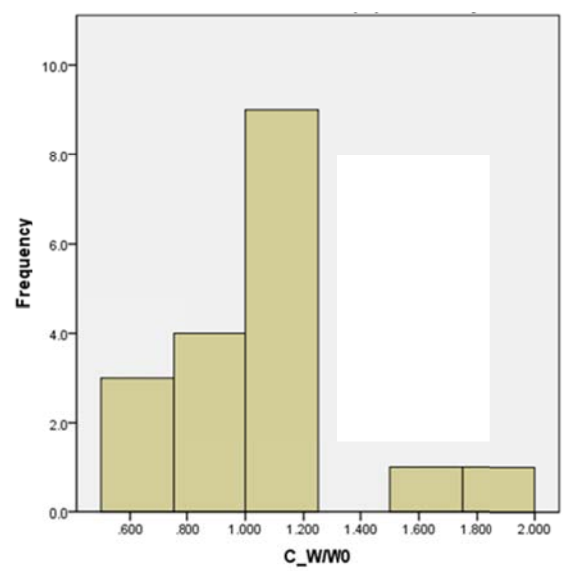


Figure 25: Construction actual to estimated cost ratio, Mean=1.04, StDev=0.32, N=18

The project data consists of the design and construction estimated durations (T_0) and costs (W_0), actual durations (T) and costs (W), and the list of change orders including the dates and amounts. The cost overrun data basically is a time series which presents the cumulative cost change of the project compared to the initial cost estimate. Figure 26 shows the design and construction cost overruns for an example project

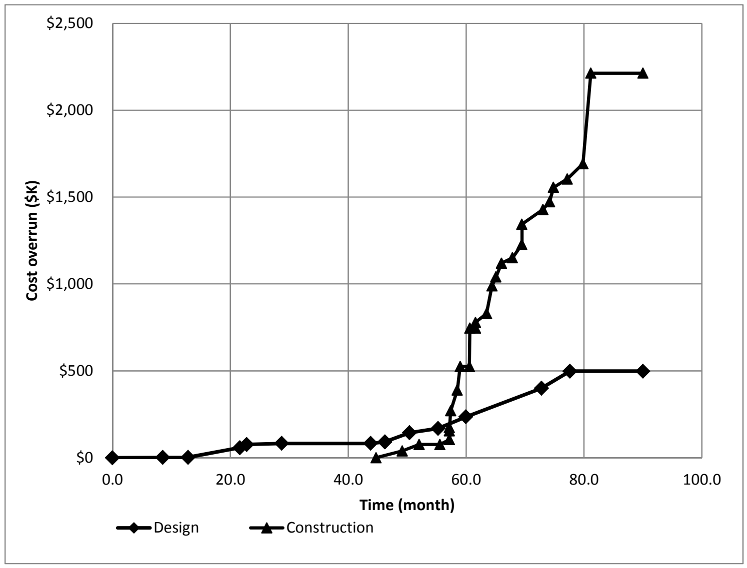


Figure 26: The cost overrun curve of the design and construction of an example project

3.4.2. <u>Size of the problem</u>

The size of the calibration problem in this project is medium to large in the context of the system dynamics problems. The 669 project data points including the project initial values and outcomes are used in the calibration process. The Number of the calibration sample data points shown in table 5 shows the details. There are 127 decision variables including 7 variables for each of 18 projects plus one common parameter across all projects. On average, there are almost 5 (669/5=5.27) empirical data points per each decision variable.

The optimization run time is almost 24 to 27 hours. But the entire calibration process took about 2-3 days to reach the general optimum point. The optimization process gets trapped in local optimal very frequently. Finding new initial points and updating the parameters was very cumbersome. Also when the best solution was found, it was tested by a dozen different random initial values to make sure that all result in the same optimum solution. Overall, the calibration process took about a week.

Table 4: Number of the calibration sample data points

Project ID	Design input	Design CO time series	Construction input	Construction CO time series	Total data points per project
[P008]	5	15	5	29	54
[P010]	5	29	5	40	79
[P011]	5	20	5	28	58
[P016]	5	27	5	23	60
[P017]	5	9	5	27	46
[P019]	5	15	5	14	39
[P021]	5	11	5	16	37
[P023]	5	8	5	8	26
[P027]	5	9	5	9	28
[P040]	5	13	5	13	36
[P054]	5	6	5	11	27
[P055]	5	9	5	11	30
[P058]	5	4	5	7	21
[P061]	5	7	5	13	30
[P062]	5	6	5	9	25
[P065]	5	5	5	9	24
[P066]	5	7	5	8	25
[P067]	5	6	5	8	24
Total					669

3.4.3. Error Weights

The error percentage is the value of the model outcome normalized by the actual data. The normalization balances out the magnitude of the outcomes and makes them comparable on the same scale. To be fair, the weight of the error percentages used in the payoff function should be the same. However, sometimes researchers would like to force the calibration process to pay more attention to some of the outcomes by assigning unequal error weights in the calibration payoff function. The error weight emphasizes the importance of one term upon the others, which is subjective to the purpose of research. As the term (1), time error percentage, is competing against the two other cost overrun terms (2) and (3) in the payoff function, the author proposes the weight of the finish time term twice as the other terms to balance out the significance of the time against the cost in the model.

3.4.4. Results

Figure 27 shows the cost overrun curves for the four calibrated projects; P008, P011, P017 and P054, against their actual cost overrun curves.

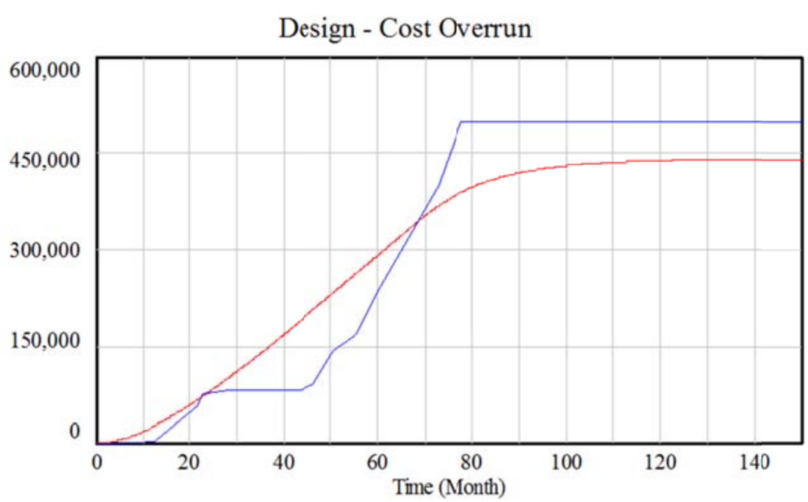


Figure 27.1: Design cost overrun, Project [P008], Actual data blue line, Simulation red line.

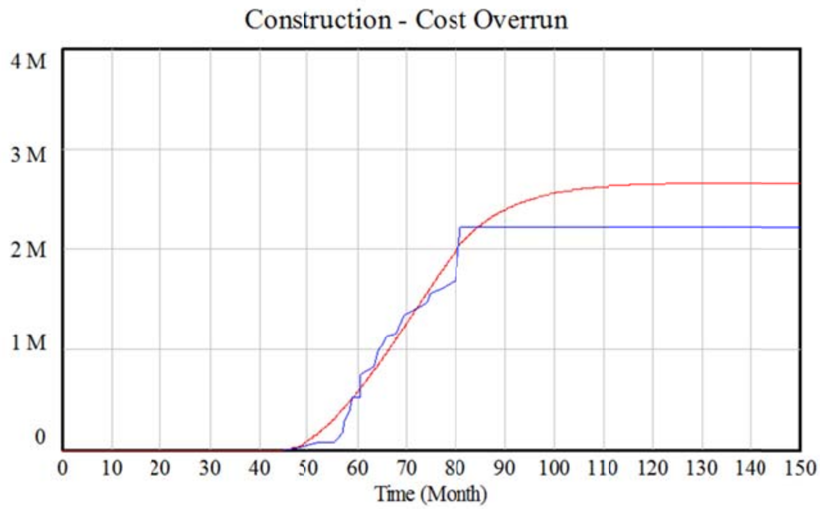


Figure 27.2: Construction cost overrun, Project [P008], Actual data blue line, Simulation red line.

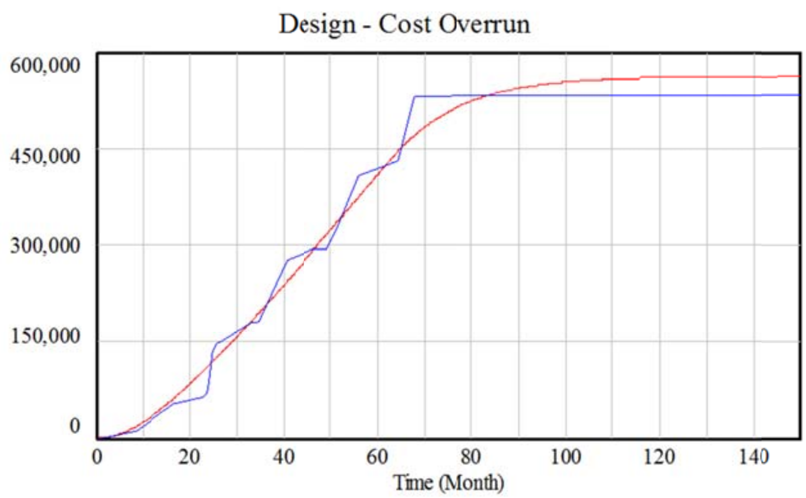


Figure 27.3: Design cost overrun, Project [P011], Actual data blue line, Simulation red line

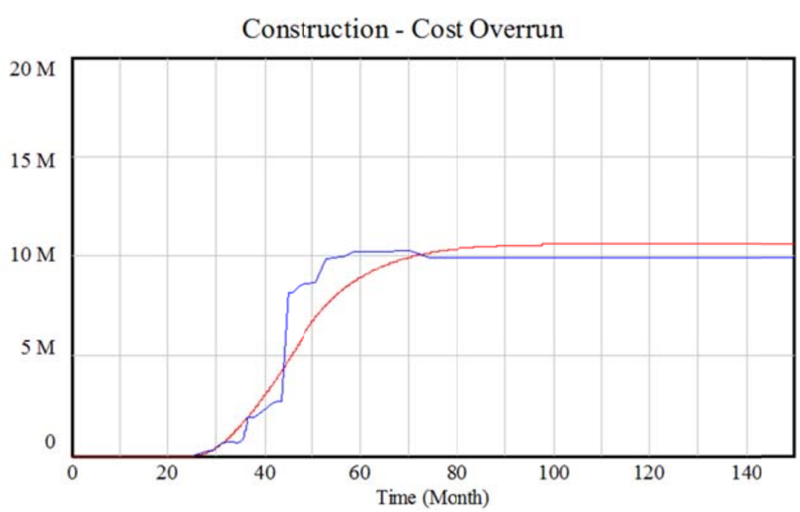


Figure 27.4: Construction cost overrun, Project [P011], Actual data blue line, Simulation red line.

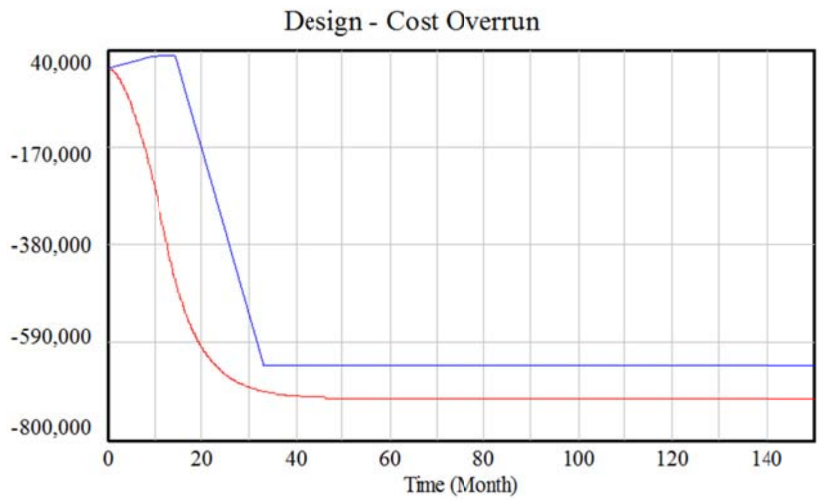


Figure 27.5: Design cost overrun, Project [P017], Actual data blue line, Simulation red line

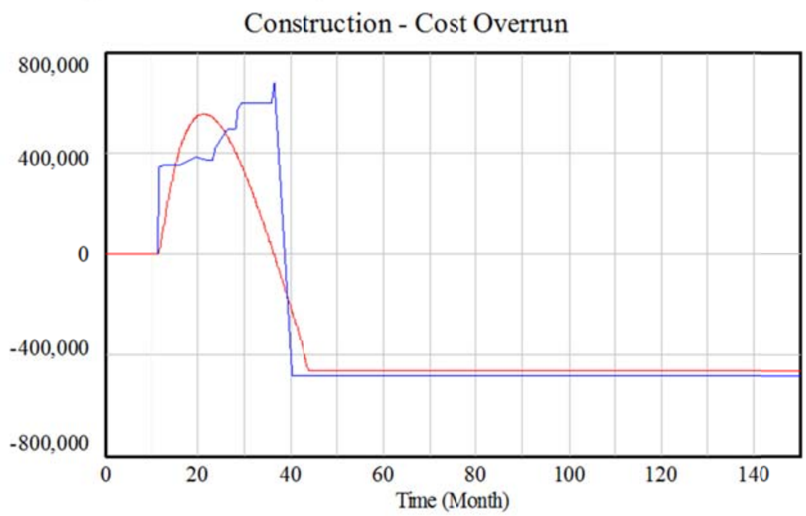


Figure 27.6: Construction cost overrun, Project [P017], Actual data blue line, Simulation red line.

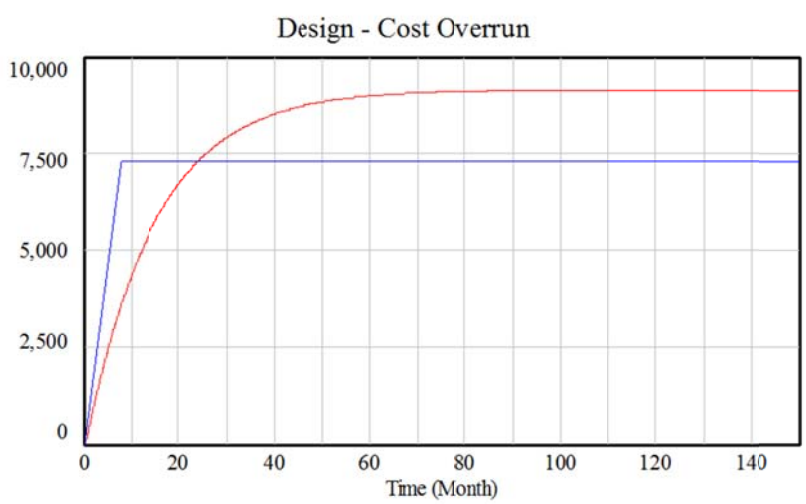


Figure 27.7: Design cost overrun, Project [P054], Actual data blue line, Simulation red line

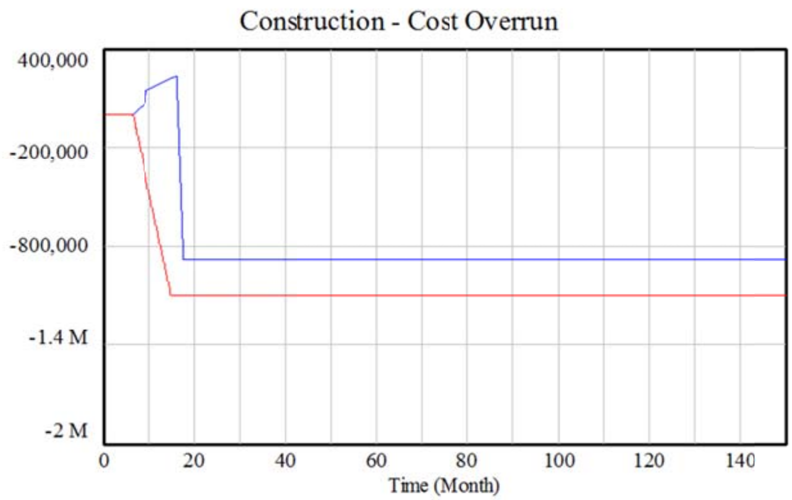


Figure 27.8: Construction cost overrun, Project [P054], Actual data blue line, Simulation red line.

The calibrated industry parameter that is obtained is $\beta = 1.239$. Figure 28 and Figure 29 show the calibrated parameters of the design and construction stages, respectively.

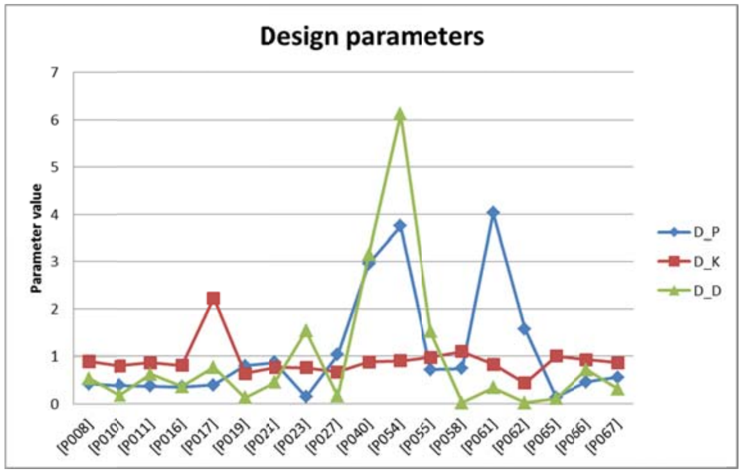


Figure 28: Calibrated design parameters of the 18 sample projects

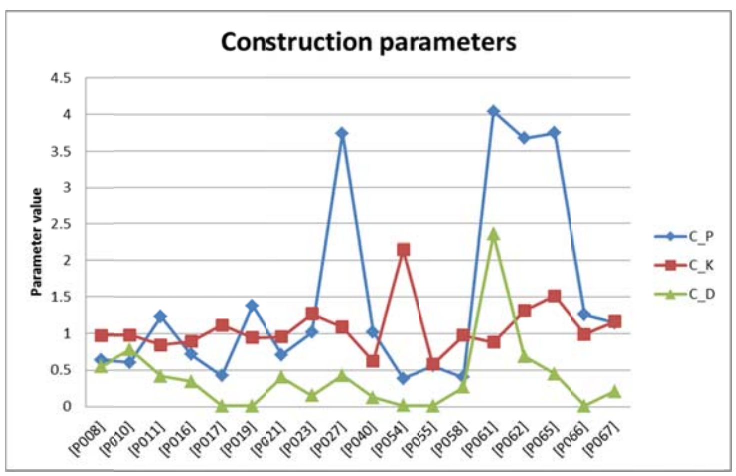


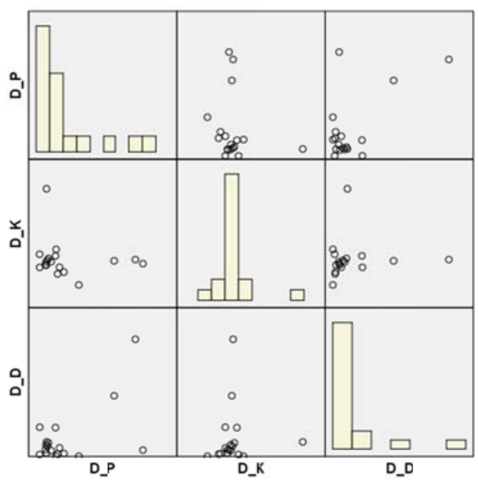
Figure 29: Calibrated construction parameters of the 18 sample projects

Table 5 shows some statistics for the calibrated project parameters.

Table 5: Statistics of the calibrated parameters

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
D_P	18	3.893	.128	4.021	1.08824	1.208873	1.461
D_K	18	1.799	.426	2.224	.90252	.362167	.131
D_D	18	6.111	.010	6.121	.94171	1.503708	2.261
C_P	18	3.660	.383	4.044	1.48185	1.312440	1.722
C_K	18	1.567	.577	2.144	1.06914	.350114	.123
C_D	18	2.344	.010	2.354	.40064	.543848	.296

Figure 30 shows the matrix of scattered diagrams of the calibrated parameters to identify if there is any obvious linear or non-linear correlation.



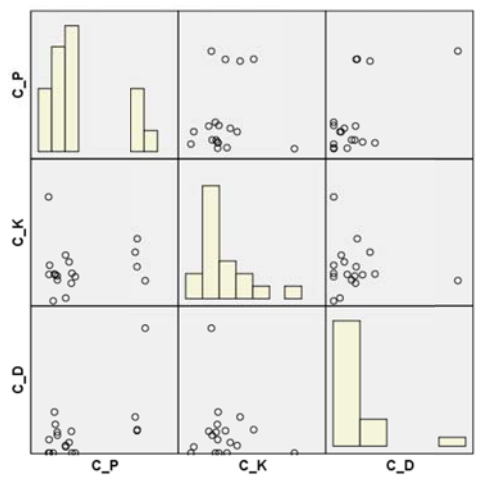


Figure 30: Matrix scattered diagram of the calibrated parameters

The error percentage of duration and cost is shown in Figure 31 to Figure 34 to present the calibration performance.

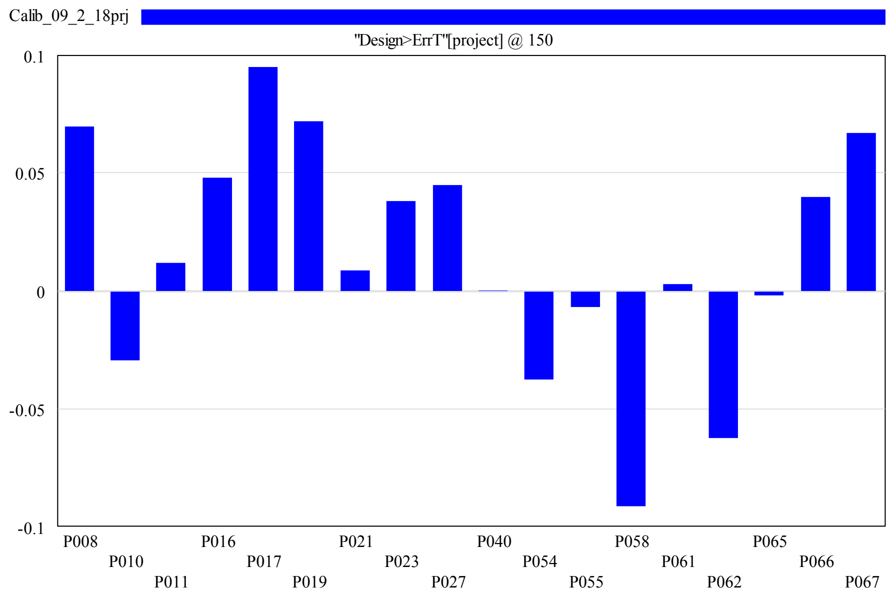


Figure 31: The error percentage of design duration

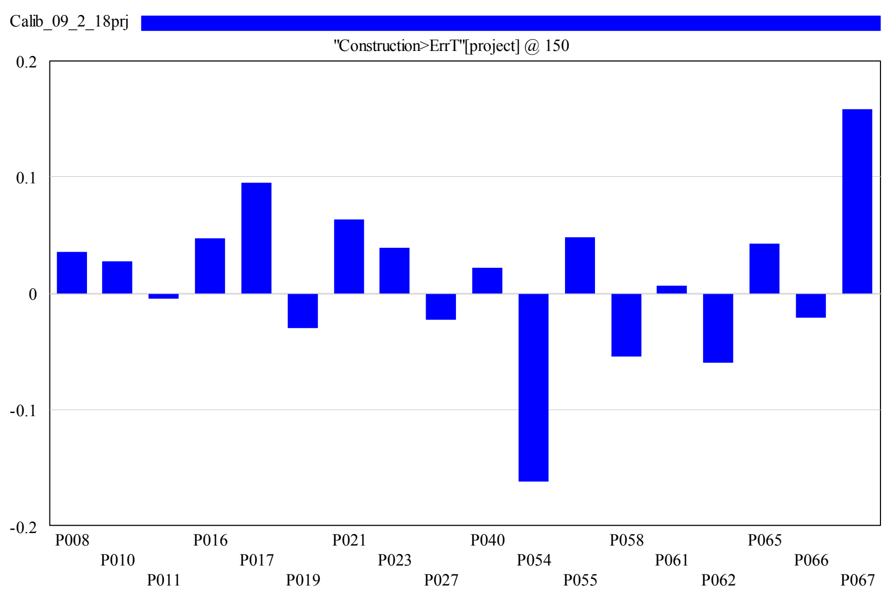


Figure 32: The error percentage of construction duration

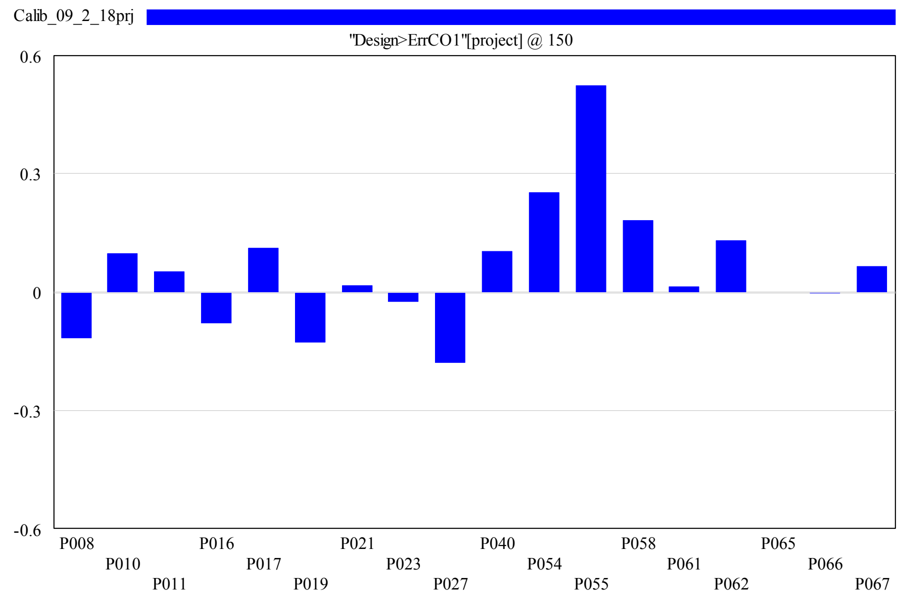


Figure 33: The error percentage of design cost

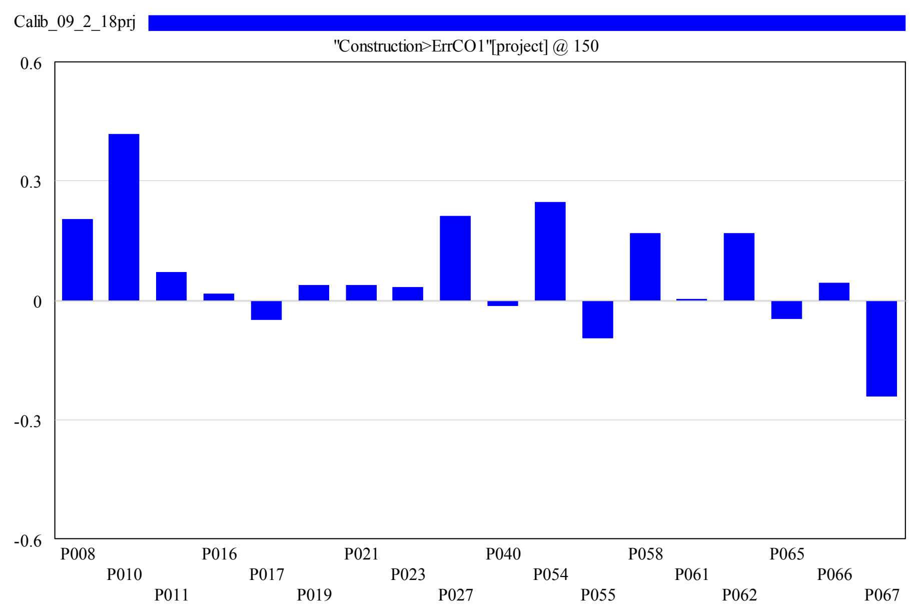


Figure 34: The error percentage of construction cost

Finally, Figure 35 to Figure 38 summarizes the calibration error percentage in the histogram format to demonstrate the calibration error percentage distributions.

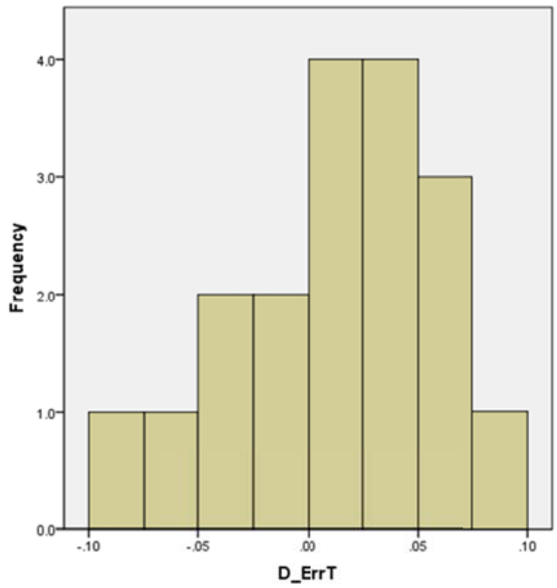


Figure 35: Distribution of design duration error percentage, Mean=0.01, StDev=0.05, N=18

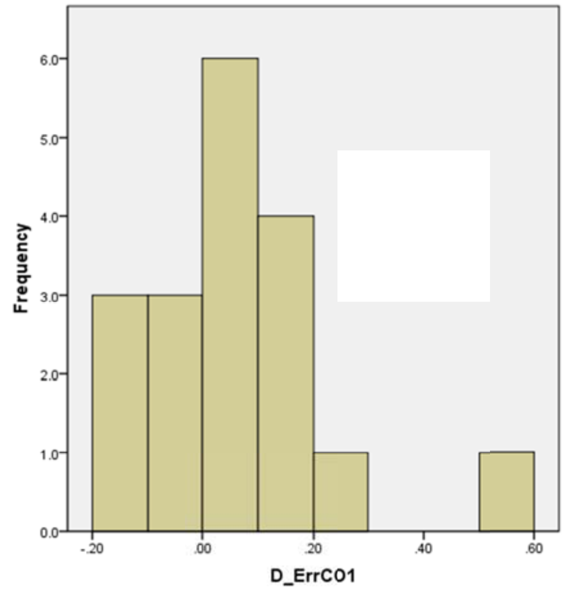


Figure 36: Distribution of design cost overrun error percentage, Mean=0.06, StDev=0.16, N=18

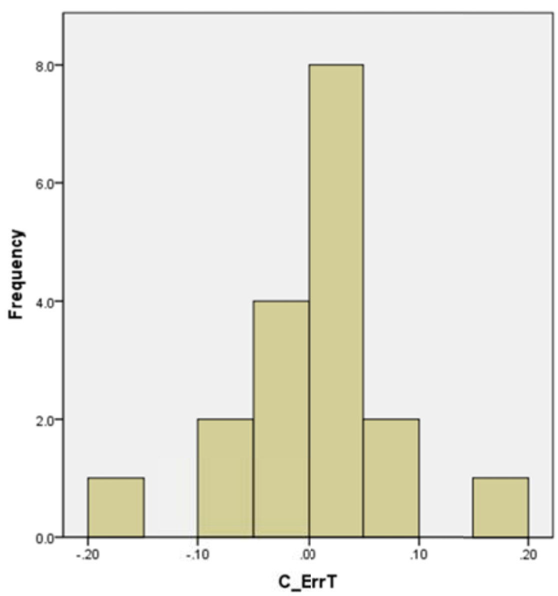


Figure 37: Distribution of construction duration error percentage, Mean=0.01, StDev=0.07, N=18

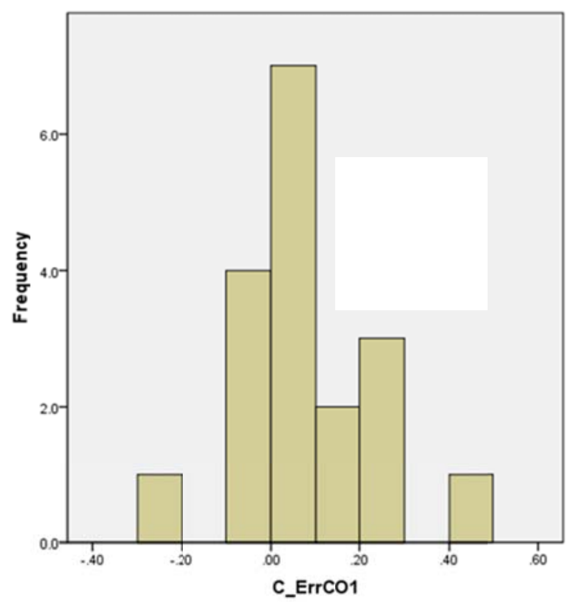


Figure 38: Distribution of construction cost overrun error percentage, Mean=0.07, StDev=0.15, N=18

3.5. Validation

Validation is the process to quantify the degree of the credibility of the model which is the purpose-specific representative of the reality under the study. The validation process is performed based on two perspectives: 1) system dynamics qualitative validation, and 2) quantitative validation.

3.5.1. System dynamics qualitative validation

The qualitative test of system dynamics models falls into two major categories: 1) test of the logic of the model structure including structural test, structure-oriented behavior test, dimension check, and 2) test of the model behavior including the behavior pattern test. In this research, the structure of the model is adopted from the well-known supply chain concept in the construction industry. However, the inter-relation of the design and construction is a controversial subject. There are many hypotheses to address this issue. The author found that the impact of the undiscovered design error on construction is one of those hypotheses that have been studied further by the researchers such as Martin and Macleod (2004); Ransom (2008) and Sun and Meng (2009). Evaluating the best fitted inter-relation between the design and construction process is out of the scope of this research. For further discussion please see chapter 9. Despite that, the model structure was reviewed, discussed and approved by four experts who had enough managerial background and experience (For more information about experts' experience and background see **Error! Reference source not found.** in section 4.3). The behavior test of the model is performed qualitatively by comparing the cost overrun curve of calibrated projects with the cost overrun curve of actual projects, Figure 27. To see all 18 cost overrun curves see appendix E.

3.5.2. Quantitative validation

The quantitative validation evaluates the model accuracy by comparing the model outcome with the actual dataset. As discussed, the model parameters fall into two categories: 1) the project parameters including the design and construction production rate (P), coefficient of change (K) and time to detect undiscovered changes (D), and 2) the industry parameter (β). The industry parameter is constant for all projects. However, the project parameters are different from project to project. In a simple approach, the average of the calibrated project parameter set can be used as an estimate to perform the validation in the project model. This approach is easy and efficient to address the model average error. However, it does not reveal how the model error varies for each validation sample projects and it does not address the model uncertainty. The simple average method covers up the details of the information which is captured in the project parameter distributions by aggregating the data with its average. The alternative approach employs random variables with the best fitted distribution to the set of the calibrated project parameters as opposed to the average as a simple point estimate. Monte-Carlo simulation is being utilized to simulate the model outcomes. The model outcomes are presented in form of distributions. This research uses the alternative approach to better address the model accuracy and uncertainty. The model provides the distributions for the final time (T) and cost (C) outcome and also an envelope of cost curves for the cost behavior (CB) outcomes. Moreover, the final time (T) and cost (C) are data points in contrast with the cost curve. To validate the final time and cost, the actual data should be compared with the model final time (t) and cost (c) outcome distribution. This concept is a very well-known concept in the statistics. The comparison is performed in terms of evaluating two criteria:

1) if the actual data point fits in the range that includes α% of the model outcomes. α is the degree of the level of confidence. In this research, α is assumed as 90% to be consistent with the BIM-ICM validation, section 4.5, since it did not pass the 95% level of confidence test. Figure 39 shows the concept of the data point-to-distribution comparison concept.

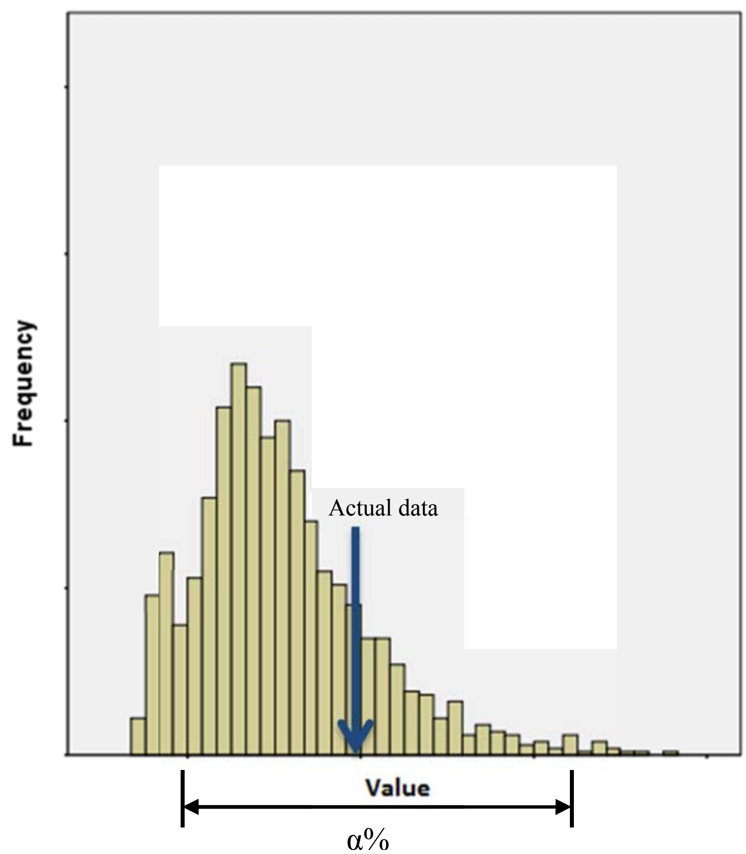


Figure 39: Data point and the distribution comparison concept

2) If the model outcome variation is tight enough to produce a reasonable estimate. This criterion is assessed as if the coefficient of variation (CV) of the distribution is less than ɣ%. The CV is the ratio of the standard deviation to the mean (Equation 19). CV is a useful metric, for the positive values, to compare the degree of variation of different distributions. The value of (ɣ) is subjective to the area of the research. ɣ is usually between 10% to 20%. However, in this research, CV is compared with 30% as the variation of the validation results is high.

$$CV = \frac{\sigma}{\mu} \tag{19}$$

Moreover, the final time and cost are not the only outcomes of the model. The other outcome of the model is the cost curve. The design and construction cost curves also need to be validated with the actual data. To validate the model cost curve, there are two perspectives. The first approach is the generalized method of comparing a single data point with a distribution as described above. In this approach the project timeline is divided to many time steps. In each time step, the actual value of the cost curve is compared with the distribution of the simulated cost curves at that time step in terms of 1) fitting in the 90% confidence interval, and 2) measuring the coefficient of variation to ensure that it is reasonably small enough. At the end, the entire results get summarized into the average statistics as a metric to rank the validation result. Equation 20 computes the ratio of fitting the actual cost into the 90% of the cost simulations. Equation 21 averages CV of the cost curve over time, where; $c(t)$ is the actual cost at time t, $C_i(t)$ is the cost outcome of simulation (i) at time t, and $T' = Max(T, t)$.

$$Fit[CB] = \frac{1}{T'} \int_0^{T'} If(\, C_{5\%}(t) \leq \, c(t) \, \leq C_{95\%}(t)\, ,1\, ,0)\, dt \tag{20}$$

$$CV[CB] = \frac{1}{T'} \int_0^{T'} \frac{StdDev[C_i(t)]}{E[C_i(t)]} dt \tag{21}$$

The second approach is based on the Theil's coefficient of inequality (Bliemel, Friedhelm (1973)), Equation 22, where; $c(t)$ is the actual cost at time t, $C(t)$ is the cost outcome of simulation (i) at time t, and $T' = Max(T, t)$.

$$Theil[CB] = \frac{[\frac{1}{T'} \int_0^{T'} [C(t) - c(t)]^2 dt]^{1/2}}{[\frac{1}{T'} \int_0^{T'} [C(t)]^2 dt]^{1/2} + [\frac{1}{T'} \int_0^{T'} [c(t)]^2 dt]^{1/2}} \tag{22}$$

To evaluate the criteria discussed above, a set of the random parameters based on the 18 calibrated projects in the calibration is generated. The best fits for the calibrated parameter histograms are examined. Since the project parameters are all positive, the author assumes the distribution of the calibrated parameters are lognormal.

Figure 40 shows the best fit lognormal to the calibrated parameter distributions.

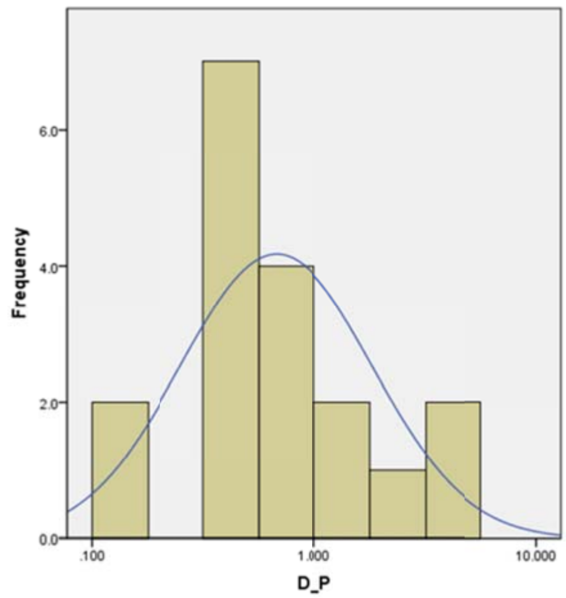


Figure 40: Distribution of D_P. Mean=1.09, StDev=1.21, N=18

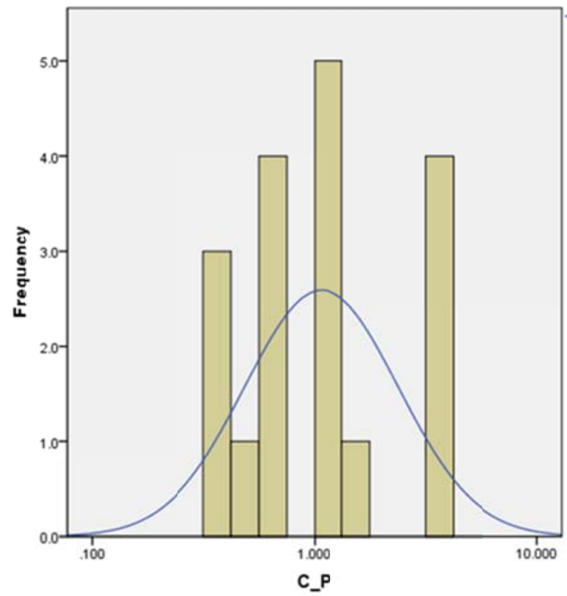


Figure 40.2: Distribution of C_P. Mean=1.48, StDev=1.31, N=18

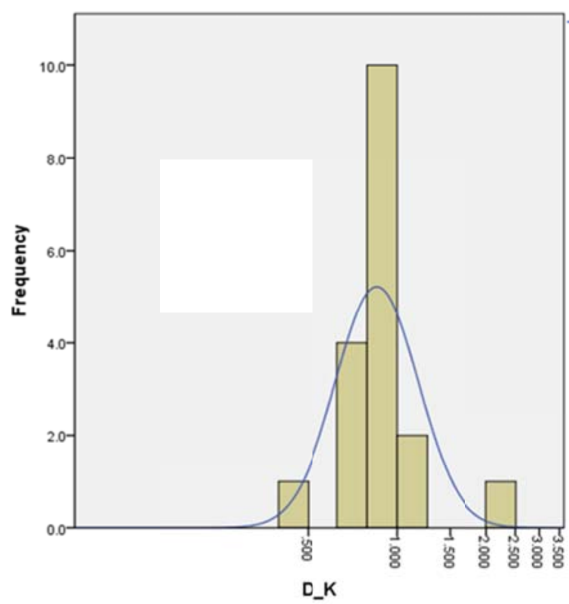


Figure 40: Distribution of D_K. Mean=0.90, StDev=0.36, N=18

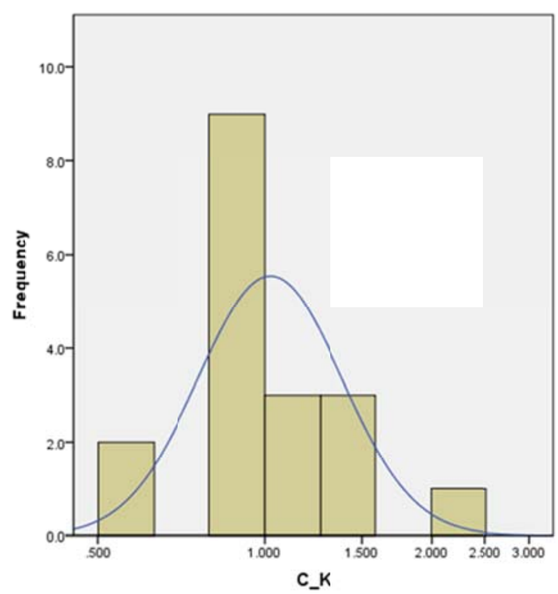


Figure 40: Distribution of C_K. Mean=1.07, StDev=0.35, N=18

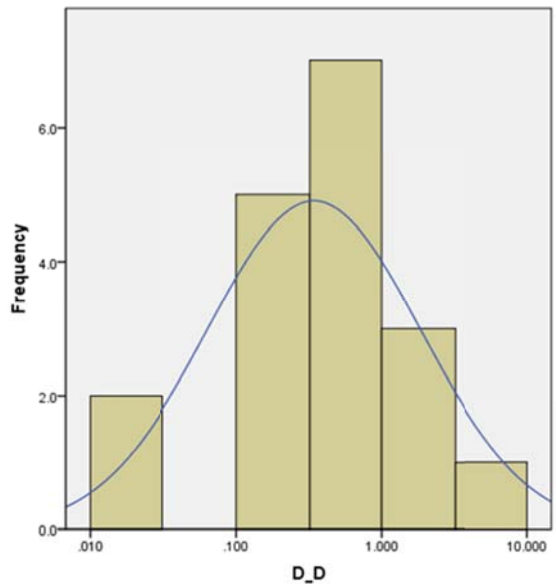


Figure 40: Distribution of D_D. Mean=0.94, StDev=1.50, N=18

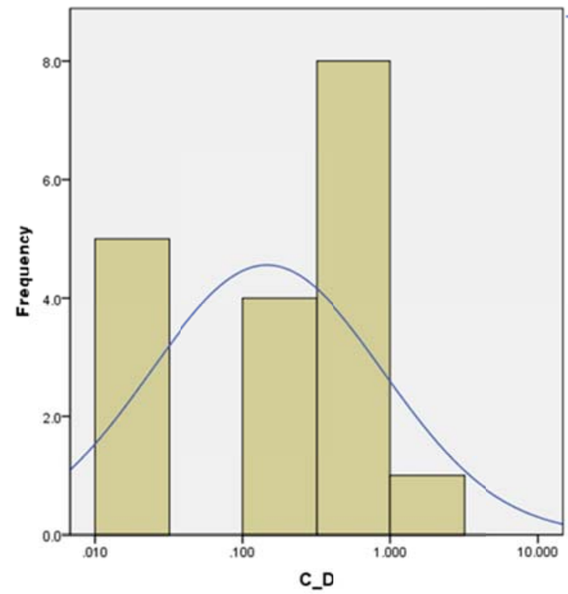


Figure 40: Distribution of C_D. Mean=0.40, StDev=0.54, N=18

Figure 40: The best lognormal fit to the calibrated project distribution

A set of 200 random parameters based on the fitted lognormal distribution is generated to run the simulation. The random numbers are assumed correlated as there is no evidence that they are independent. The variance-covariance matrix method is used to generate the correlated random parameters. Each of the 15 validation sample projects is simulated with the 200 random parameter samples. The simulated results are compared to the actual data to assess the model validation. As the simulation results of each project is in different order of magnitude, the results are scaled by the initial project values such as the estimated duration and estimated cost. As the matter of fact, the outcomes are the ratio of cost and time based on the estimated values. Table 6 evaluates the design duration (D_T), Table 7 the design cost (D_C), Table 8 the construction duration (C_T) and Table 9 the construction cost (C_C). Table 10 and Table 11 assess the project duration (P_T) and cost (P_C), respectively.

Table 6: Design duration (D_T) validation table

Proj#	Term	Mean	StDev	Median	CV	Z-5%	Z-95%	Actual	Criterion (1)	Criterion (2)
P009	D_T	2.41	0.50	2.75	21%	0.92	4.33	2.24	+	+
P012	D_T	2.32	0.50	2.72	21%	0.87	4.24	3.10	+	+
P015	D_T	1.68	0.49	2.48	29%	0.00	3.32	2.03	+	NG
P018	D_T	2.53	0.50	2.74	20%	1.02	4.42	1.85	+	+
P020	D_T	2.17	0.47	2.71	22%	0.87	4.02	2.20	+	+
P022	D_T	2.23	0.47	2.72	21%	0.87	4.06	3.33	+	+
P025	D_T	2.53	0.50	2.78	20%	1.03	4.45	1.56	+	+
P026	D_T	2.41	0.50	2.74	21%	0.91	4.32	3.44	+	+
P028	D_T	2.41	0.50	2.72	21%	0.91	4.31	1.74	+	+
P031	D_T	2.54	0.50	2.78	20%	1.03	4.45	1.07	+	+
P034	D_T	2.23	0.47	2.72	21%	0.87	4.06	2.62	+	+
P052	D_T	2.54	0.50	2.79	20%	1.03	4.45	0.97	NG	+
P057	D_T	2.53	0.50	2.75	20%	1.03	4.42	2.04	+	+
P063	D_T	2.53	0.51	2.79	20%	1.02	4.45	1.66	+	+
P064	D_T	2.53	0.50	2.78	20%	1.03	4.45	1.61	+	+

Table 7: Design final cost (D_C) validation table

Proj#	Term	Mean	StDev	Median	CV	Z-5%	Z-95%	Actual	Criterion (1)	Criterion (2)
P009	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.29	+	+
P012	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.13	+	+
P015	D_C	1.18	0.33	1.15	28%	0.70	1.83	1.11	+	+
P018	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.14	+	+
P020	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.20	+	+
P022	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.13	+	+
P025	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.08	+	+
P026	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.14	+	+
P028	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.37	+	+
P031	D_C	1.19	0.32	1.16	27%	0.72	1.84	1.00	+	+
P034	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.17	+	+
P052	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.00	+	+
P057	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.90	NG	+
P063	D_C	1.19	0.32	1.15	27%	0.72	1.83	1.16	+	+
P064	D_C	1.19	0.32	1.16	27%	0.72	1.83	1.10	+	+

Table 8: Construction duration (C_T) validation table

Proj#	Term	Mean	StDev	Median	CV	Z-5%	Z-95%	Actual	Criterion (1)	Criterion (2)
P009	C_T	2.18	0.59	1.62	27%	0.78	2.52	2.25	+	+
P012	C_T	2.02	0.36	1.61	18%	0.69	2.48	2.40	+	+
P015	C_T	2.02	0.40	1.63	20%	0.59	2.58	3.25	NG	+
P018	C_T	2.00	0.35	1.61	18%	0.72	2.42	1.40	+	+
P020	C_T	2.02	0.36	1.61	18%	0.69	2.48	0.92	+	+
P022	C_T	2.01	0.36	1.61	18%	0.72	2.47	1.37	+	+
P025	C_T	2.19	0.59	1.62	27%	0.78	2.57	3.69	NG	+
P026	C_T	2.01	0.36	1.61	18%	0.73	2.46	1.33	+	+
P028	C_T	2.17	0.59	1.61	27%	0.77	2.52	1.17	+	+
P031	C_T	2.16	0.58	1.62	27%	0.76	2.49	0.99	+	+
P034	C_T	2.02	0.36	1.61	18%	0.73	2.50	2.41	+	+
P052	C_T	2.15	0.58	1.62	27%	0.75	2.49	2.49	+	+
P057	C_T	2.17	0.58	1.62	27%	0.76	2.49	2.13	+	+
P063	C_T	2.17	0.59	1.62	27%	0.77	2.54	2.00	+	+
P064	C_T	2.18	0.59	1.62	27%	0.77	2.51	1.93	+	+

Table 9: Construction final cost (C_C) validation table

Proj#	Term	Mean	StDev	Median	CV	Z-5%	Z-95%	Actual	Criterion (1)	Criterion (2)
P009	C_C	1.05	0.19	1.01	18%	0.76	1.42	1.18	+	+
P012	C_C	1.04	0.21	1.00	20%	0.75	1.42	1.05	+	+
P015	C_C	1.05	0.23	1.02	22%	0.74	1.42	1.10	+	+
P018	C_C	1.03	0.21	1.00	20%	0.74	1.39	1.02	+	+
P020	C_C	1.04	0.21	1.00	20%	0.74	1.42	0.93	+	+
P022	C_C	1.04	0.21	1.00	20%	0.74	1.41	1.07	+	+
P025	C_C	1.06	0.19	1.02	18%	0.77	1.42	1.22	+	+
P026	C_C	1.04	0.21	1.00	20%	0.74	1.41	1.15	+	+
P028	C_C	1.04	0.21	1.01	20%	0.75	1.42	1.10	+	+
P031	C_C	1.04	0.19	1.00	19%	0.76	1.40	1.00	+	+
P034	C_C	1.04	0.21	1.00	20%	0.75	1.42	1.11	+	+
P052	C_C	1.04	0.21	1.00	20%	0.74	1.41	1.02	+	+
P057	C_C	1.04	0.19	1.00	19%	0.76	1.41	0.93	+	+
P063	C_C	1.05	0.21	1.01	20%	0.75	1.42	1.09	+	+
P064	C_C	1.05	0.19	1.01	18%	0.77	1.42	1.01	+	+

Table 10: Project duration (P_T) validation table

Proj#	Term	Mean	StDev	Median	CV	Z-5%	Z-95%	Actual	Criterion (1)	Criterion (2)
P009	P_T	1.82	0.33	1.52	18%	0.78	3.41	1.72	+	+
P012	P_T	1.75	0.23	1.53	13%	0.74	3.54	2.18	+	+
P015	P_T	1.45	0.21	1.28	14%	0.57	2.87	1.62	+	+
P018	P_T	1.82	0.25	1.63	14%	0.67	3.91	1.28	+	+
P020	P_T	1.75	0.23	1.54	13%	0.73	3.52	1.15	+	+
P022	P_T	1.78	0.24	1.58	13%	0.72	3.79	1.23	+	+
P025	P_T	1.76	0.31	1.45	17%	0.75	3.41	2.51	+	+
P026	P_T	1.79	0.24	1.60	13%	0.71	3.83	1.32	+	+
P028	P_T	1.81	0.34	1.51	19%	0.75	3.42	1.30	+	+
P031	P_T	1.91	0.40	1.63	21%	0.84	4.01	1.23	+	+
P034	P_T	1.74	0.23	1.51	13%	0.73	3.46	1.50	+	+
P052	P_T	1.90	0.39	1.62	21%	0.75	3.95	2.09	+	+
P057	P_T	1.89	0.38	1.59	20%	0.81	3.84	1.41	+	+
P063	P_T	1.78	0.32	1.47	18%	0.73	3.57	1.18	+	+
P064	P_T	1.84	0.35	1.54	19%	0.77	3.52	1.75	+	+

Table 11: Project final cost (P_C) validation table

Proj#	Term	Mean	StDev	Median	CV	Z-5%	Z-95%	Actual	Criterion (1)	Criterion (2)
P009	P_C	1.06	0.18	1.04	17%	0.79	1.39	1.19	+	+
P012	P_C	1.05	0.19	1.03	18%	0.78	1.39	1.05	+	+
P015	P_C	1.06	0.22	1.04	21%	0.76	1.40	1.10	+	+
P018	P_C	1.05	0.19	1.03	18%	0.78	1.38	1.03	+	+
P020	P_C	1.05	0.19	1.04	18%	0.77	1.39	0.96	+	+
P022	P_C	1.05	0.19	1.03	18%	0.76	1.38	1.07	+	+
P025	P_C	1.08	0.17	1.06	16%	0.81	1.36	1.20	+	+
P026	P_C	1.05	0.19	1.04	18%	0.78	1.37	1.15	+	+
P028	P_C	1.07	0.18	1.05	17%	0.79	1.36	1.14	+	+
P031	P_C	1.06	0.17	1.05	16%	0.81	1.36	1.00	+	+
P034	P_C	1.05	0.19	1.03	18%	0.78	1.39	1.11	+	+
P052	P_C	1.05	0.20	1.03	19%	0.77	1.39	1.02	+	+
P057	P_C	1.05	0.18	1.03	17%	0.78	1.39	0.99	+	+
P063	P_C	1.07	0.18	1.06	17%	0.80	1.35	1.10	+	+
P064	P_C	1.06	0.18	1.03	17%	0.78	1.39	1.02	+	+

D_T passed Criterion (1) and (2) both in 93% cases. D_C passed both Criterion (1) in 93% and Criterion (2) in 100% cases. C_T passed Criterion (1) in 87% cases and Criterion (2) in 100% cases. C_C passed both Criteria in 100% cases. Overall, the estimated completion time and total cost with 90% confidence interval pass Criterion (1) and (2) in 93% and 98% of cases, respectively. Figure 41 shows the validation results on finish time and final cost Table 6 to Table 9 in graphics.

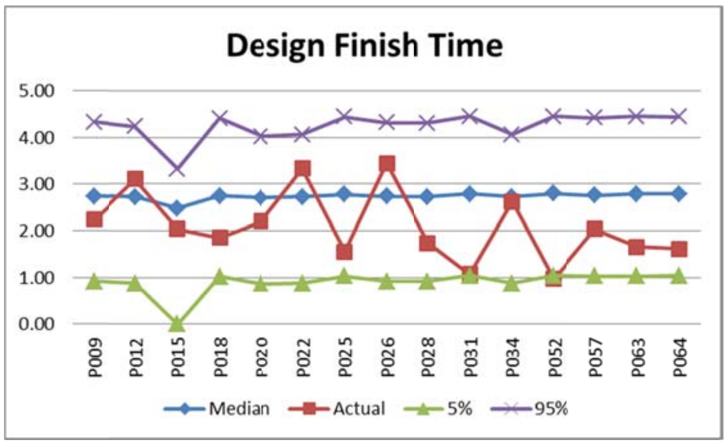


Figure 41.1: Validation results on design finish time

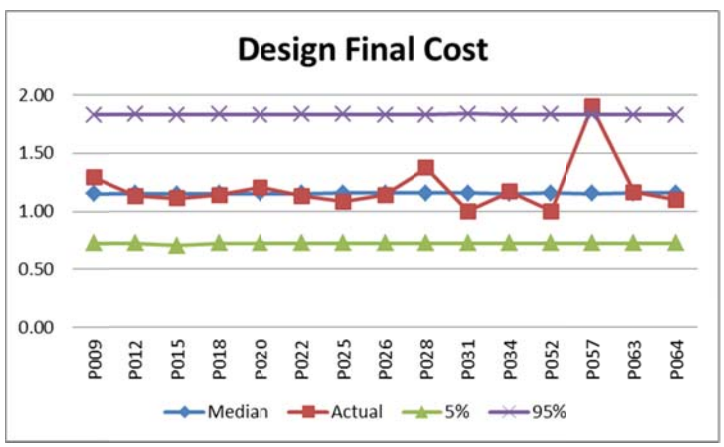


Figure 41.2: Validation results on design final cost

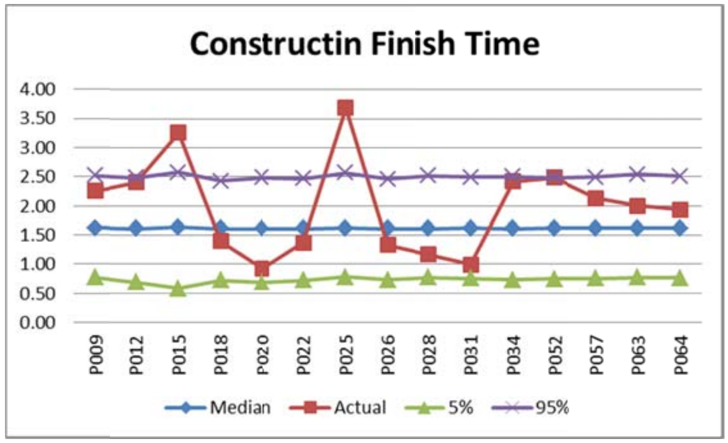


Figure 41.3: Validation results on construction finish time

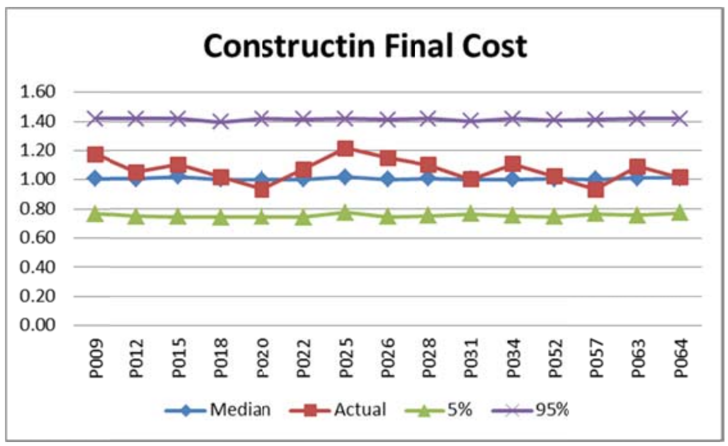
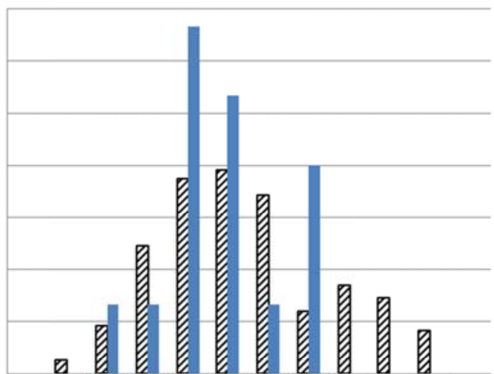


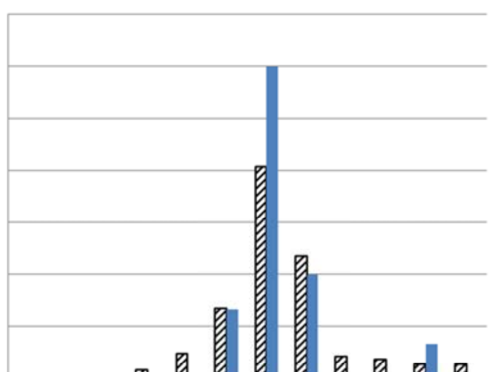
Figure 41.4: Validation results on construction final cost

From another perspective to provide a general point of view that how actual data fits in 90% level of confidence of the simulation runs, the distribution of actual data is compared with the distribution of the correspondingly simulated outcomes (Figure 42). The frequency of the distributions is scaled to one with the total number of population in each case. As a result, the red and blue bar charts show the probability distribution of the simulated outcomes and actual data, respectively.



	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	More
Design>RO DurSim	0.0	0.0	0.0	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0
Design>RO DurAct	0.0	0.0	0.1	0.1	0.3	0.3	0.1	0.2	0.0	0.0	0.0	0.0

Figure 42.1: Probability distribution of simulated design duration versus actual data



	0	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2	More
Design>RO CostSim	0.0	0.0	0.0	0.0	0.1	0.1	0.4	0.2	0.0	0.0	0.0	0.0
Design>RO CostAct	0.0	0.0	0.0	0.0	0.0	0.1	0.6	0.2	0.0	0.0	0.1	0.0

Figure 42.2: Probability distribution of simulated design cost versus actual data

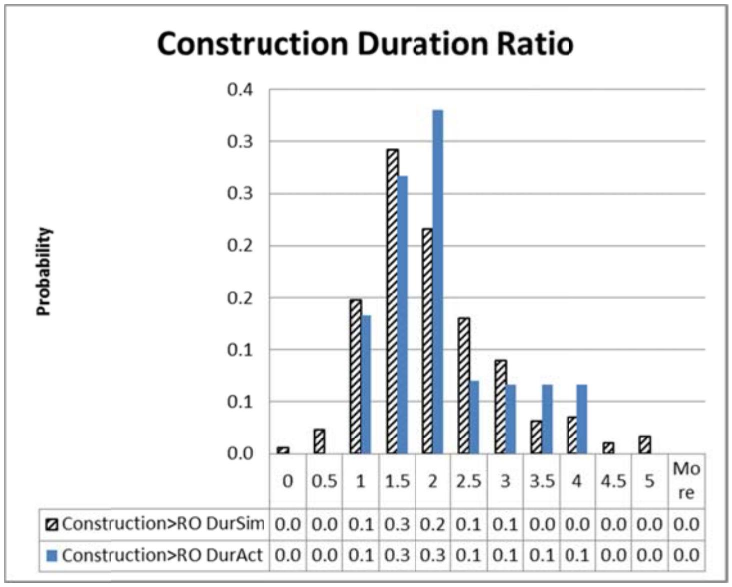


Figure 42.3: Probability distribution of simulated construction duration versus actual data

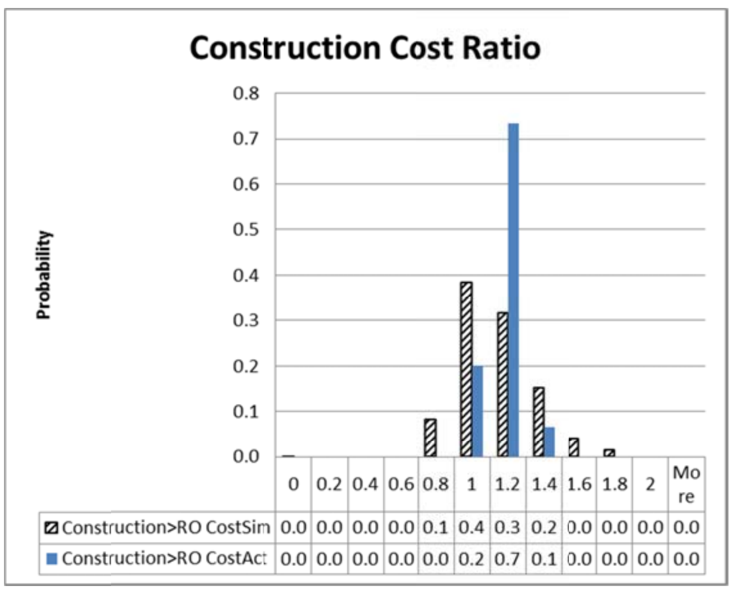


Figure 42.4: Probability distribution of simulated construction cost versus actual data

In summary, the number of cases which passed Criteria 1 and 2 are reported in table 12. Table 12 also shows the validation result in the case that Criterion (2) is compared with 20%.

Table 12: Validation Summary

Validation Metrics	Criterion (1)	Criterion (2)<30%	Criterion (2)<20%	**Average**
Design Finish Time	93%	100%	47%	97%
Design Final Cost	93%	100%	0%	97%
Construction Finish Time	87%	100%	47%	93%
Construction Final Cost	100%	100%	67%	100%
Project Finish Time	100%	100%	80%	100%
Project Final Cost	100%	100%	93%	100%
Average	96%	100%		

As shown, Criteria (1) and (2) were passed by 96% and 100% of cases respectively. The validity of Criterion (2) was not significant when it was compared with 20%. Design Finish Time, Design Final Cost, Construction Finish Time, Construction Final Cost, Project Finish Time and Project Final Cost were passed, in average, by 97%, 97%, 93%, 100%, 100% and 100% of cases, respectively.

On the other hand, P_T and P_C passed both Criteria, (1) and (2), in 100% cases. Figure 43 shows the results in graphics.

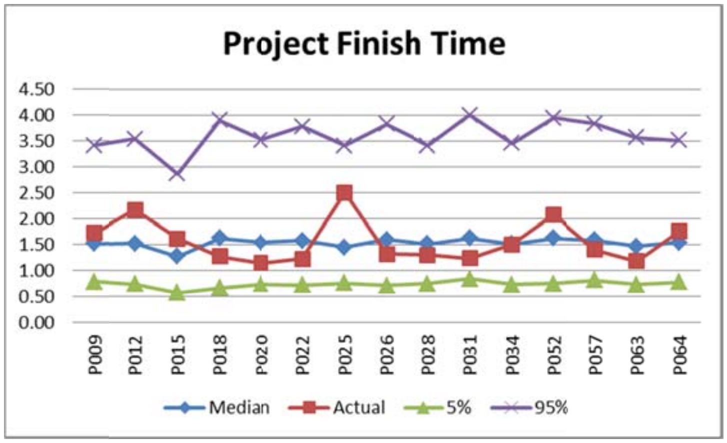


Figure 43.1: Validation results on project finish time

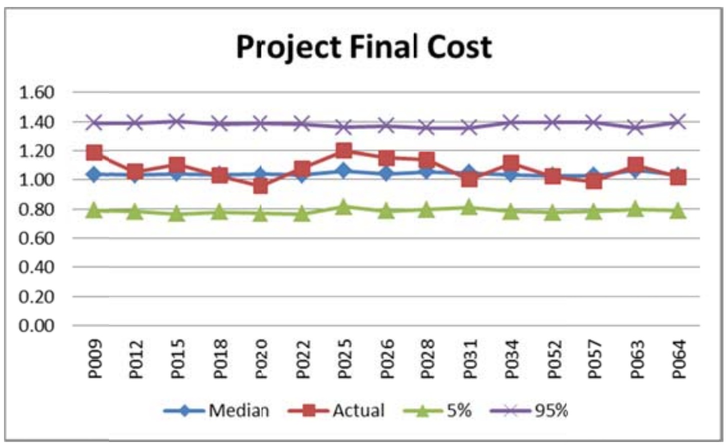


Figure 43.2: Validation results on project final cost

To validate the behavior of the model, design and construction cost curves are examined by the two discussed approaches. Approach (1) is applied and the results of Fit[CB] (Equation 20) and CV[CB] (Equation 21) are shown in Table 13 to Table 15. Criterion (1) examines whether the actual cost curve fits in the 90% confidence interval of the simulated cost curves (If Fit[CB] $\leq$ 90%). Criterion (2) examines whether CV[CB] is less than 30%. Table 13 indicates design cost curve (D_CC) validation result. D_CC passed Criteria (1) and (2) in 93% and 40% of the cases. In another attempt using Approach (2) to validate the cost curve behavior of the model, Theil's coefficient of inequality, Equation 19, is calculated. The result is presented in Table 16 and Table 17 for the design and construction cost curves, respectively. Criterion (1) examines whether the Theil's of 90% of simulated cases fits between 0 and 30%. Theil's of none of the cases passed the validation. In conclusion, the cost curve behavior of the model is not quantitatively validated. Table 14 shows construction cost curve (C_CC) validation result. C_CC passed Criteria (1) and (2) in 100% and 20% of the cases, respectively. Project cost curve (P_CC) also passed Criteria (1) and (2) in 100% and 40% of the cases, shown in Table 15.

Table 13: Design cost curve validation result, Approach (1)

ProjectID	Outcome	Fit[CB]	CV[CB]	Criterion (1)	Criterion (2)
P009	D_CC	100%	31%	+	NG
P012	D_CC	100%	33%	+	NG
P015	D_CC	100%	49%	+	NG
P018	D_CC	100%	29%	+	+
P020	D_CC	100%	37%	+	NG
P022	D_CC	100%	33%	+	NG
P025	D_CC	100%	28%	+	+
P026	D_CC	100%	32%	+	NG
P028	D_CC	100%	31%	+	NG
P031	D_CC	100%	27%	+	+
P034	D_CC	100%	35%	+	NG
P052	D_CC	100%	28%	+	+
P057	D_CC	10%	29%	NG	+
P063	D_CC	100%	30%	+	NG
P064	D_CC	100%	28%	+	+

In another attempt using Approach (2) to validate the cost curve behavior of the model, Theil's coefficient of inequality, Equation 19, is calculated. The result is presented in Table 16 and Table 17 for the design and construction cost curves, respectively. Criterion (1) examines whether the Theil's of 90% of simulated cases fits between 0 and 30%. Theil's of none of the cases passed the validation. In conclusion, the cost curve behavior of the model is not quantitatively validated.

Table 14: Construction cost curve validation result, Approach (1)

ProjectID	Outcome	Fit[CB]	CV[CB]	Criterion (1)	Criterion (2)
P009	C_CC	97%	43%	+	NG
P012	C_CC	100%	43%	+	NG
P015	C_CC	100%	132%	+	NG
P018	C_CC	100%	37%	+	NG
P020	C_CC	100%	66%	+	NG
P022	C_CC	100%	49%	+	NG
P025	C_CC	100%	26%	+	+
P026	C_CC	100%	40%	+	NG
P028	C_CC	100%	44%	+	NG
P031	C_CC	100%	24%	+	+
P034	C_CC	97%	52%	+	NG
P052	C_CC	100%	37%	+	NG
P057	C_CC	90%	37%	+	NG
P063	C_CC	100%	38%	+	NG
P064	C_CC	100%	28%	+	+

Table 15: Project cost curve validation result, Approach (1)

ProjectID	Outcome	Fit[CB]	CV[CB]	Criterion (1)	Criterion (2)
P009	P_CC	97%	34%	+	NG
P012	P_CC	100%	40%	+	NG
P015	P_CC	100%	95%	+	NG
P018	P_CC	100%	30%	+	+
P020	P_CC	100%	52%	+	NG
P022	P_CC	100%	42%	+	NG
P025	P_CC	100%	21%	+	+
P026	P_CC	100%	35%	+	NG
P028	P_CC	100%	31%	+	NG
P031	P_CC	100%	20%	+	+
P034	P_CC	100%	48%	+	NG
P052	P_CC	100%	28%	+	+
P057	P_CC	90%	30%	+	NG
P063	P_CC	100%	28%	+	+
P064	P_CC	100%	26%	+	+

Table 16: Design cost curve validation result, Approach (2)

ProjID	Outcome	Mean	StDev	Median	CV	Z-90%	Actual	Criterion (1)
P009	D_CC	0.20	0.12	0.17	60%	0.38	0.30	NG
P012	D_CC	0.25	0.17	0.19	68%	0.52	0.30	NG
P015	D_CC	0.23	0.16	0.19	70%	0.50	0.30	NG
P018	D_CC	0.19	0.13	0.18	68%	0.36	0.30	NG
P020	D_CC	0.22	0.15	0.19	68%	0.43	0.30	NG
P022	D_CC	0.25	0.17	0.21	68%	0.51	0.30	NG
P025	D_CC	0.17	0.11	0.15	65%	0.36	0.30	NG
P026	D_CC	0.28	0.19	0.25	68%	0.58	0.30	NG
P028	D_CC	0.19	0.12	0.15	63%	0.40	0.30	NG
P031	D_CC	0.17	0.10	0.15	59%	0.33	0.30	NG
P034	D_CC	0.24	0.16	0.19	67%	0.48	0.30	NG
P052	D_CC	0.17	0.10	0.16	59%	0.34	0.30	NG
P057	D_CC	0.28	0.14	0.26	50%	0.43	0.30	NG
P063	D_CC	0.19	0.12	0.17	63%	0.37	0.30	NG
P064	D_CC	0.17	0.12	0.15	71%	0.37	0.30	NG

Table 17: Construction cost curve validation result, Approach (2)

ProjID	Outcome	Mean	StDev	Median	CV	Z-90%	Actual	Criterion (1)
P009	C_CC	0.31	0.20	0.28	65%	0.65	0.30	NG
P012	C_CC	0.40	0.23	0.36	58%	0.76	0.30	NG
P015	C_CC	0.53	0.36	0.40	68%	1.00	0.30	NG
P018	C_CC	0.20	0.14	0.16	70%	0.37	0.30	NG
P020	C_CC	0.27	0.20	0.22	74%	0.66	0.30	NG
P022	C_CC	0.21	0.15	0.17	71%	0.40	0.30	NG
P025	C_CC	0.55	0.28	0.55	51%	0.89	0.30	NG
P026	C_CC	0.24	0.17	0.20	71%	0.48	0.30	NG
P028	C_CC	0.30	0.22	0.25	73%	0.75	0.30	NG
P031	C_CC	0.26	0.19	0.22	73%	0.60	0.30	NG
P034	C_CC	0.20	0.12	0.17	60%	0.39	0.30	NG
P052	C_CC	0.32	0.20	0.29	63%	0.61	0.30	NG
P057	C_CC	0.36	0.11	0.37	31%	0.34	0.30	NG
P063	C_CC	0.21	0.11	0.20	52%	0.34	0.30	NG
P064	C_CC	0.38	0.24	0.33	63%	0.79	0.30	NG

Overall, design completion time (D_T), construction completion time (C_T), design final cost (D_C) and construction final cost (C_C) passed 93%, 93%, 97% and 100% of the simulated cases, respectively. Figure 44 indicates the model accuracy overall. The blue bar, "EP_Median", shows the average of median error percentage and the red bar, CV, the average of CV of the 200 simulation runs.

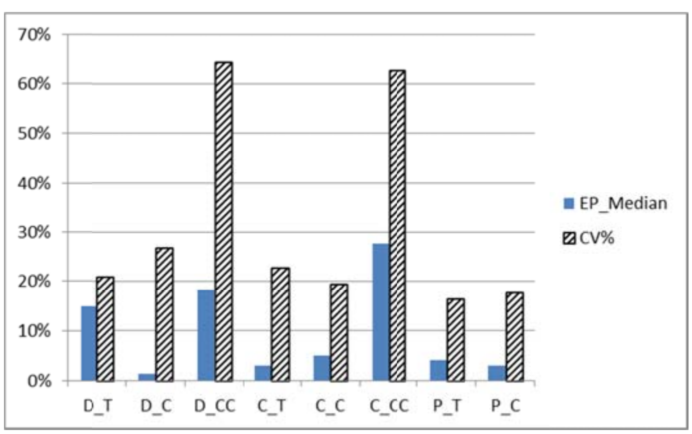


Figure 44: Validation overview

Chapter 4. BIM impact causal model

The BIM impact causal model (BIM-ICM) is a cause-and-effect model which determines the influence of the BIM on the project parameters such as the production rates (P), coefficient of change (Kc), and time to detect undiscovered change (D). As there is no hard-data to identify and quantify the effect of BIM on project parameters, this research employs the expert elicitation (EE) technique to build the BIM causal model. The following sections describe the EE concepts including expert definition and attributes, expert panel size, expert opinion aggregation methods and the EE issues.

4.1. Expert Elicitation

Decision makers are sometimes limited by insufficient data. In those cases, utilizing the expert judgments/opinions can supplement the lack of available decision-relevant data sources. Expert elicitation (EE) is the systematic process of formalizing and quantifying expert judgments about uncertain quantities. EE process may facilitate integrating empirical data with scientific judgment, and identifying the range of possible outcomes and their likelihoods. Expert judgment has been recognized as a powerful and legitimate source of data where there is a gap in existing research, or additional research is not feasible. It has been used by private sectors, academia and federal agencies such as Nuclear Regulatory Commission (NRC), Army Corps of Engineers, National Aeronautics and Space Administration (NASA), Department of Transportation / Federal Railroad Administration and US Department of Agriculture (EPA workshop summary, January 2006).

Booker and Meyer (1996) describe that the expert judgment can be helpful in two ways. First, it can utilize grasping and recognizing the problem structure. Second, expert judgment can be employed to provide quantitative estimates. The following is a brief list of the EE benefits and issues:

Benefits:

- It is relatively cheap and easy
- It is translated into the casual relationships
- The irrelevant information is filtered.

Issues:

- it is very subjective
- it is limited to the scope of the expert knowledge
- The expert opinion can be biased

Generally, using the expert judgment is appropriate when the information is not available from historical records, and the data collection is difficult or costly. However, since expert judgment is not experimental fact, it should be used with much consideration and deliberation. In some fields such as meteorology, expert judgment has been established with relatively well-calibrated performance (Murphy and Winkler, 1977). However, Chatfield et al. (1989) and Dechow and Sloan (1997) showed the opposite result in finance. They showed the experts significantly overestimate the corporate earnings growth.

Expert judgment is the human's assessment which is subject to uncertainty and mistake. The uncertainty simply means the range of possible outcomes as opposed to a single value. There are many factors that can influence the uncertainty of the expert opinion, such as expert definition, expert attributes, expert panel size, expert opinion aggregation method, human psyche and so forth. Some of those factors have been studied by researchers very well. Some of them have not.

4.1.1. <u>Expert definition</u>

Expert is an individual with the knowledge or expertise related to the subject under study. The definition of expert is different from different perspectives such as medicine, engineering and legal. Several authors have defined expert from different points of view. Table 18 shows the list of some of those definitions given by different researchers, adopted from Forrester and Mosleh (2005).

Table 18: List of expert definitions, Forrester and Mosleh (2005)

Author/Reference	Definition
Weiss et al. 2003	Individuals who carry out a specified set of tasks expertly
Camerer and Johnson (1997)	Experienced predictors in a domain and have appropriate social or professional credentials
Cox (2002) and Lesgold et al (1988)	High-speed recognizers of abnormalities, and diagnostic classifiers who use a personal, organized, perceptual library linked into case-based knowledge.
Daubert vs. Dow Pharmaceuticals by Supreme Court	Individuals with scientific, technical, skill, experience, training, or education that will assist the trier of fact to understand the evidence or to determine a fact at issue.
Dreyfus and Dreyfus (1986, 1996)	The expert has high levels of procedural knowledge and skills (knowing how) as well as declarative knowledge (knowing what), and contextual flexibility (knowing when and where)

4.1.2. <u>Expert attributes</u>

Wright and Bolger (1992) showed that the special characteristics of the experts improve the judgment performance. The qualification attributes of the expert are almost unclear in most disciplines. "Several authors have proposed their taxonomy for identification and selection, but very few intra- or interdisciplinary standards exist" stated by Forrester and Mosleh (2005). The reason may root in the unclear relation between the expert qualification attributes and the accuracy of the expert judgment. The selection of qualifying attributes is subjective. Many researchers have defined their own criteria to distinguish the experts. Appendix-C of Forrester and Mosleh (2005) includes a long list of those examples. Forrester and Mosleh (2005) used expert attributes such as peer nominations, certification or specialized training in expertise, publications expertise or field, membership in professional organizations, and organization specialization in expertise, as well as institution type, average level of formal education, event frequency, and average years of experience to measure the quality of the expert performance in the field of medicine. Sufficient knowledge or expertise in the targeted discipline is the common-sense criteria to select the experts but the details are left open to individual interpretation. Vegelin et al., (2003) states that an expert's experience significantly influences the accuracy of the expert's judgment. During the literature review, the author came up with two criteria as guidelines to define the expert qualification attributes in the AEC industry: 1) Proficiency of the expert in the expertise/technology, 2) Maturity in the domain of knowledge/industry. The proficiency measure aims to quantify the exposure of the expert to the domain of knowledge. The experience scope and duration are the two main factors to estimate the expert proficiency. The job position is a good measure to identify the scope of the expert experience. However, the maturity measures the exposure of the expert in the related industry or discipline. The expert background such as the list of past experience/job position along with the number of years, educational degrees, publications, certificates, and memberships falls into this category.

4.1.3. Expert panel size

The number of experts in the panel is another controversial topic in EE. Libby and Blashfield (1978) showed that increasing the size of the expert panel from 1 to 3 improves the accuracy of the forecasts. They recommended 5-9 experts for an expert panel. Ashton and Ashton (1985) reported that the error of estimates using 4 experts is reduced by 3.5%. Armstrong (2001) stated that combining expert opinion can reduce the error. In a comprehensive study by Shirazi and Mosleh (2009), they evaluated the impact of the expert panel size on the accuracy of the aggregated estimate in a Bayesian framework. They declared that about 50% of estimates are improved by increasing the expert panel size to two. They showed that selecting more than 2 experts can improve the estimate over 60%. However, increasing the expert panel from 3 to 10 betters the results less than 10%.

4.1.4. Expert opinion aggregation method

Combining the expert judgments falls into two broad categories: consensus methods (behavioral methods) and mathematical methods. The consensus method is performed by facilitating the discussion among the experts to reach some common agreeable point. The major issues with this method are: 1) strong-minded individuals domination of the group thought process and opinion, 2) collection of information about socially reinforced irrelevant issues, 3) group motive or bias due to the common background, and 4) difficulty of organization and costliness of gathering a relatively large group of expert all together.

The mathematical methods include axiomatic methods, Bayesian methods, fuzzy-logic-based method, evidence-theory-based method, and possibility-theory-based methods (Franciscus and Mosleh 2000). Familiar examples of the axiomatic methods are arithmetic average, geometric average, harmonic average, maximum value, and minimum value. The study of the Bayesian method in the expert judgment first was proposed by Morris (1974, 1977). Since then, many researchers have been working on this method in many different forms. The Bayesian aggregation is basically the Bayesian update method. In this method, the initial probability of the quantity (also called prior probability function) is updated by the evidence. The updating process is iterative in case of several observations. The updated probability function is called posterior probability function. The initial probability can be an assumed probability function based on the common accepted knowledge in the field under study or a uniform probability function if there is no information available. Bayes' theory is based on the conditional probability. Equation 23 shows the Bayes' theorem in the continuous form, where (b) is the continuous variable that represents different states of the event (B), and (a) is the observed evidence in discrete or continuous form.

$$P(b|a) = \frac{L(a|b).P(b)}{\int L(a|b).P(b)\ db} \tag{23}$$

In the general state, where the likelihood function is unknown, there is no closed-form formulation to estimate the posterior probability distribution of event (B). The Markov Chain Monte Carlo (MCMC) simulation is the technique to resolve this issue. However, knowing the likelihood function does not completely help either. Calculating the denominator of the Bayes' theorem in continuous form (Equation 23) yields the closed-form formulation in some special cases. It has been found that there exist pairs of the distributions which if the prior distribution and likelihood are the members of the pair, then the posterior distribution will be member of the same pair. These pairs of distributions are called conjugate distributions.

4.1.5. Human psyche

Expert decision is subject to the individual psyche and thought process. Tversky et al. (1974), and Kadane et al. (1988) studied the biasness of the expert opinion. Biasness means that the expert personal interests may lean the expert's judgment. Heuristic approach was studied by Tversky et al. (1974) and Slovic (1972). Heuristic is the approach of estimating an unknown with an initial value. In this approach, the individual selects the initial value called anchor and then tries to adjust it to obtain a nominal value. Tversky et al. (1974) conducted an experiment to show the impact of the anchoring (selecting the initial value) to the individual's opinion. In another study by Slovic (1972) the adjustment of the initial value was studied. He showed that the individuals usually adjust the anchor very little. It means the heuristic is very sensitive to anchoring. Overconfidence is the other issue of individual judgment. Overconfidence is the tendency of an individual to give overly narrow confidence intervals which reflect more certainty than is justified by their knowledge about the assessed quantities (Lichtenstein and Fischhoff (1980), Cooke (2003), Shlyakhter et al. (1994), Soll and Klayman (2004)). Utilizing the calibration techniques and encouraging individuals to actively identify the counterfeit evidences are some effective techniques to reduce the overconfidence issues (Alpert and Raiffa (1982), Morgan and Henrion (1990) and Shlyakhter et al. (1994)).

4.1.6. Elicitation process/protocol

The earliest use of expert judgment in a scientific way was introduced by the Research and Development Corporation (RAND) during World War II (Cooke, 1991). The method is called Delphi Method. They developed the second method a bit later, which is called Scenario Analysis. Delphi method is a group interview using the consensus technique. However, scenario analysis is the process of analyzing the possible outcomes by considering the potential events and scenarios. This method helps investigate all possible outcomes and their implications. It can be performed in group or in person.

In general, expert elicitation is conducted by interviews. The interview can be either in person or in focus groups. It also can be face-to-face, by phone or by web-conference. The interview can be structured, driven by a carefully worded interview script that directs the topics of the interview. It can also be highly unstructured, allowing the respondent to tell stories, give examples, and often unearth issues that the interviewer finds novel or counterintuitive. Interviews allow for further clarification of the definitions, elaboration on topics, and collection of the respondent's own words or usage in a way not supported by questionnaires or surveys. The main role of the interviewer is to guide the dialog, clearing up any confusion before the interview is over, and remaining neutral so that the respondent's remarks are not biased by the behavior of the researcher (McCracken 1988). The human psyche factors can be mitigated to reduce the expert judgment uncertainty by employing an effective interview methodology. The following shows the list of the author's suggestions and hints to moderate the interview:

(1) The unknown of interest should be projected to the most tangible value or metric in the targeted scope for each expert. This strategy will reduce the expert judgment uncertainty caused by the heuristic.

(2) The experts should be inquired about the stories and histories to support their opinion. Despite the stories may be biased; however, they reveal the logic path of the expert though process to reach their opinions.

(3) The experts should be asked with the counter-evidence hypothetical situation. It helps the experts incorporate different points of view in their judgments and may reduce the expert biasness and overconfidence. It should be borne in mind however, that overstating those questions may be taken offensive by the experts and may result in the expert overreaction.

After conducting a number of interviews, the researcher will analyze the data, looking for patterns, definitions, stories, and lessons that cut across the material elicited from all respondents. Additionally, during and after the interview the researcher looks for dynamic hypotheses, stories about how dynamic systems work, and tests these hypotheses by asking for more specific information, or presenting the developing causal story and asking the respondent to comment upon it. The Interviewing process stops when saturation is observed in the data gathered.

4.1.7. Types of uncertainty

The uncertainty simply means the range of possible outcomes as opposed to a single value. It is usually measured by the standard deviation of the probability distribution function of the model outcome. Uncertainty and error have been used interchangeably in literature very often. Error is defined as the deviation of the model outcome from the true value of interest. However, uncertainty is defined as the variation of the model outcome. Measuring uncertainty usually deals with quantifying the probability distribution of the model outcome. Uncertainty analysis is an important part of modeling. If model deviation is not addressed properly, the result may be misleading for decision makers (Roy and Oberkampf, 2011). Inadequate safety or reliability of the result may put customers, public or environment at risk. Uncertainty impacts not only the meaningfulness but also the level of confidence and the reliability of results.

Uncertainty falls into two categories: aleatoric and epistemic. The word aleatoric derives from the Latin word, alea, which means the rolling of dice. Aleatoric uncertainty is referred to as the intrinsic randomness (spatial or temporal) of reality. It is stochastic and irreducible. It exists and it cannot be suppressed by more data and accurate measurements. The word epistemic derives from the Greek word, episteme, which means knowledge (Kiureghian, and Ditlevsen, 2009). Epistemic uncertainty is an uncertainty which is due to a lack of knowledge about the quantities or processes identified with the idealized model. It is subjective and reducible. Sufficient information which is subject to cost and time may, in principle, eliminate the epistemic uncertainty.

The distinction between aleatoric and epistemic uncertainties is not always clear purely through the properties of model. Some quantity in one study may be treated as having aleatory uncertainty while in another study the uncertainty maybe treated as epistemic (Hora, 1996). Sources of uncertainty should not be mistaken with the uncertainty types. Neither epistemic nor aleatoric uncertainty is limited to the model uncertainty or real data variability. For instance, imagine the variability of a data set is known to be normal by the modeler. However the distribution of normal distribution parameters such as mean and standard deviation is not known. In this case, the uncertainty of these two parameters is epistemic and defined by intervals (uniform random distribution). The variability of data which seems aleatoric in the first sight constitutes of epistemic uncertainty.

In summary, reducibility is the essence to identify the type of uncertainty. The uncertainty of a quantity may be addressed as aleatoric in one model; however, in another model it may be considered as epistemic. So the characterization of uncertainty becomes subjective dependent on the purpose of the model. Uncertainty is characterized epistemic, if the modeler sees a possibility to reduce it by gathering more data or by refining models. Uncertainty is categorized as aleatoric if the modeler does not foresee the possibility of reducing it by adding any more information (Kiureghian, and Ditlevsen, 2009).

In our causal model, BIM-ICM, two sources of uncertainty are recognized: model structure uncertainty and model parameter uncertainty. The model structure uncertainty is considered epistemic. It means more expert interview may improve the model structure to produce more accurate result (Mosleh et al., 1993). The parameter uncertainty usually contains both epistemic and aleatoric forms of uncertainty. One part of uncertainty of estimated parameters by experts comes from the variability which is embedded in the nature of reality, e.g. the variability of the impact of BIM on different projects. In this research, variability of project data comes from non-homogeneity of the sample set. There is a flurry of factors such as: project, type, size complexity, delivery method, facility type, location and economic situation that many believe affect the project behavior. Since these factors were not considered in the first part of this research, project supply chain model, there is no use considering them in this part. As the matter of fact, we accepted this variability as aleatoric uncertainty and no effort was inserted to reduce it

The next part of uncertainty of estimated parameters is the uncertainty of aggregated opinion of experts. It has roots in randomly selecting experts and expert opinion aggregation method. This uncertainty is epistemic. More experts and better aggregation technique may reduce this uncertainty.

The other part of uncertainty of estimated parameters stems from the elicitation uncertainty factors which were discussed earlier in this chapter. This uncertainty seems to be epistemic in the first place. However, since a comprehensive study by Shirazi and Mosleh (2009) has addressed it in more details, it is considered aleatoric. We use the outcome of this research later to estimate the expert elicitation uncertainty. For more details please see chapter 4.2.2.

4.2. Expert judgment aggregation methodology

As discussed, it is a common belief that the expert attributes impact the expert judgment performance. In the absence of a standard to select qualifying attributes of experts and to aggregate the expert judgments, the author proposes a three-step method shown in Figure 45. In the first step, the degree of expertise is defined, based on the expert qualification attributes. Second, the expert judgment uncertainty is addressed as a function of the degree of expertise. Finally Bayesian technique is used to aggregate the expert opinions.

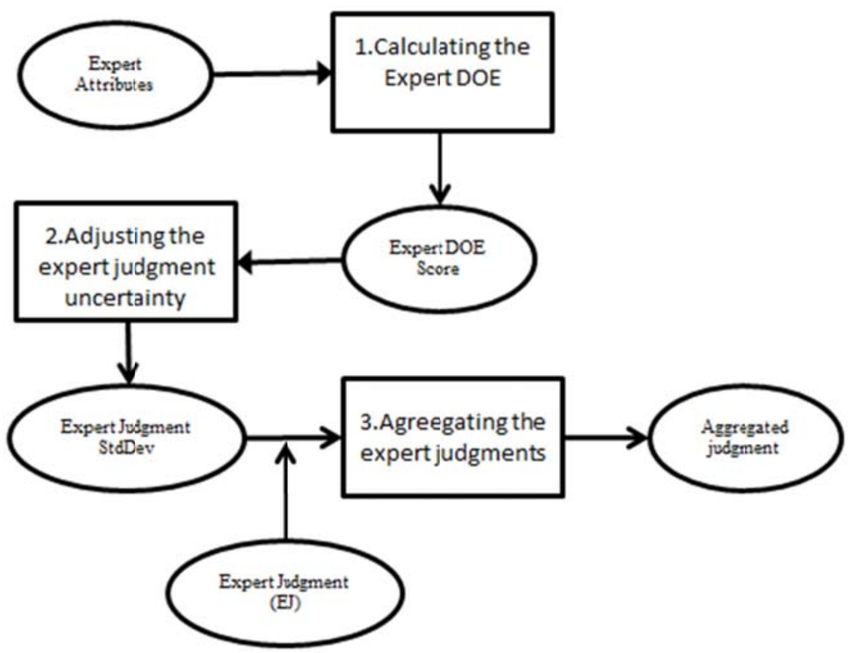


Figure 45: Three-step expert judgment aggregation methodology

4.2.1. Step 1: Defining the degree of expertise

DeGroot (1988) believes that there is no expert whose judgment simply can be adopted without any modification. In this research, we developed a scoring system which is consistent with the literature and also rational to the domain of knowledge under study. We define the degree of expertise (DOE) which is a scoring system to weigh the expert judgment. The DOE is employed to estimate the degree of uncertainty in the expert judgment. This is discussed in more details in the next step. The degree of expertise is a scoring system between 0 and 10 to quantify the expert's expertise in the targeted scope under study. The degree of expertise is defined as a function of the expert's qualification attributes. The expert qualification attributes are categorized in three groups for this purpose: 1) the attributes to estimate the scope of the expert's expertise, 2) the attributes to measure the exposure of the expert to the expertise, also called proficiency, and 3) the attributes to measure the maturity of the expert.

The scope of expert's expertise is the area that the individual is qualified to provide opinion as an expert. An individual may be recognized as an expert in more than one field with different levels of judgment credibility. For instance, a design professional with 5 years of experience as a design manager and also another 5 years as a mechanical engineer can be recognized as the expert in two scopes: engineering design and the mechanical design but with different DOEs.

The other aspect of the DOE is proficiency. Proficiency is defined with respect to the concept of length and discontinuity of the experience. Ericsson, Krampe, and Tesch-Römer (1993) noticed this concept too. They state that the expert knowledge is only achieved through continuing involvement in the subject matter. It means not only the length of experience but also the continuity of experience does matter to develop the expert's expertise. In another research also, Simon et al. (1973) suggested a minimum of ten years of experience to gain expertise for most domains.

In conclusion, we formulate proficiency as the number of years of experience in the targeted scope, maximum to 10, minus the length of the time that the experience was discontinued up to present. The definition of proficiency is presented in Equation 24, where (X) is "length of experience in scope", and (d) is "length of discontinuity of the experience in the scope up to the present".

$$Proficiency = \text{Max}\,(\text{Min}(X, 10) - d\,, 0) \tag{24}$$

The maturity is defined as the number of the years of experience in the related industry up to the 10 years. The definition of maturity is presented in Equation 25, where Y is "length of experience in related industry".

$$Maturity = \text{Min}(Y, 10) \tag{25}$$

These two measures are combined to calculate the degree of expertise (DOE) score as below in Equation 26. DOE is defined as the convex combination of the proficiency and maturity. The linear combination should be convex in order that DOE would not exceed 10. In addition, maturity is dominant when the expert has discontinuty in his/her experience or he/she has irrelevant experience. To make distinction between the indivituals with irrelevant/discontinued experience and the not-experienced the maturity linear combination factor should be greater than 0. The coefficient is selected as 0.25 to make irrelevant/discontinued score consistant with the standard novice score (2) in the next section.

$$DOE\ score = 0.75\ Proficiency + \ 0.25\ Maturity \tag{26}$$

Figure 46 is an example to demonstrate the behavior of the DOE score based on (d), length of discontinuity of experience. The graph shows four scenarios. Each scenario includes an expert with a different length of experience in the targeted scope (X). The total length of experience in the related industry (Y) is 10 years and it is the same for all scenarios..

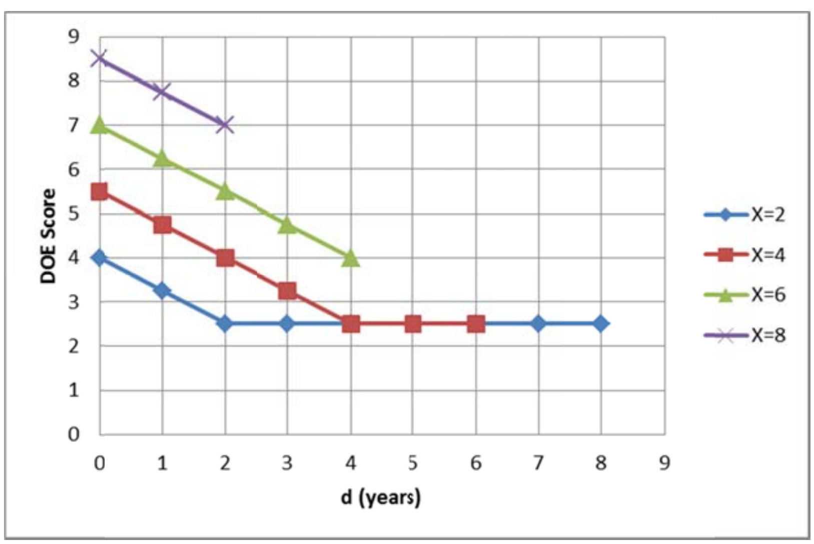
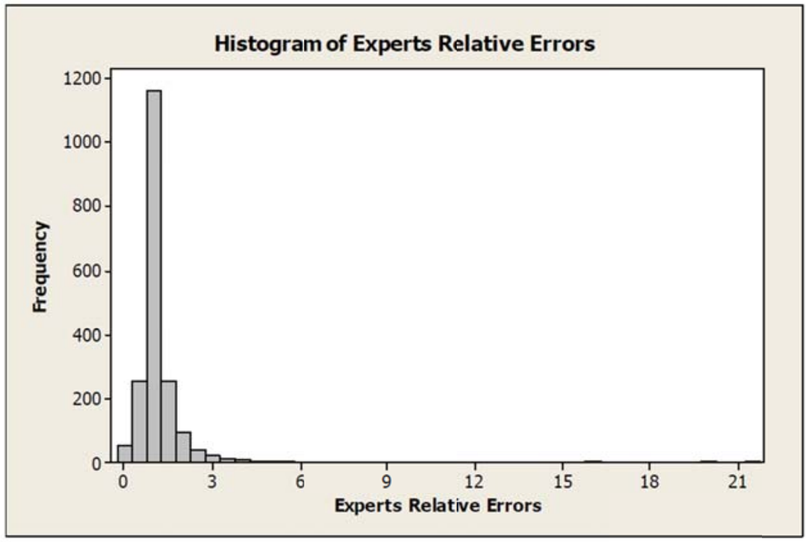


Figure 46: The impact of discontinuity on DOE score

Figure 46 shows the importance of the discontinuity of the expert's experience in the scope. The expert with 2 recent years of experience in the scope has the same score as the expert with 4 years of experience and 2 years discontinuity, as well as the expert with 6 years of experience, but 4 years discontinuity. If discontinuity exceeds the expert's experience in the scope, maturity becomes the dominant factor in the DOE score. Discontinuity emphasizes that if an expert was away from the current practice of the scope expertise, his/her knowledge is not up-to-date and should be considered with the extra caution and care.

4.2.2. Step 2: Adjusting the expert judgment uncertainty

Measuring the confidence level of the expert judgments is the basis of the expert judgment uncertainty analysis. In some research, the experts are asked about the confidence level of their judgment. However, this study follows a different methodology. Shirazi and Mosleh (2009) studied the uncertainty of the expert judgment aggregation over 1922 data points in a Bayesian framework. It was the continuation of two early studies by Mosleh and Apostolakis (1984), and (1986). Shirazi and Mosleh (2009) stated that the best fit to the relative error of the expert opinion is a lognormal distribution with mean of $\boldsymbol{Ln(1.27)}$ and standard deviation of 0.46. Figure 47 and Figure 48 are borrowed form that study.



Descriptive Statistics: Relative Error (Minitab®)

Variable	N	Mean	StDev	Median	Min	Max
Relative Error	1922	1.2	1.5	1.0	0.0003	21.3

Figure 47: Histogram of all relative errors, Shirazi and Mosleh (2009) page 60

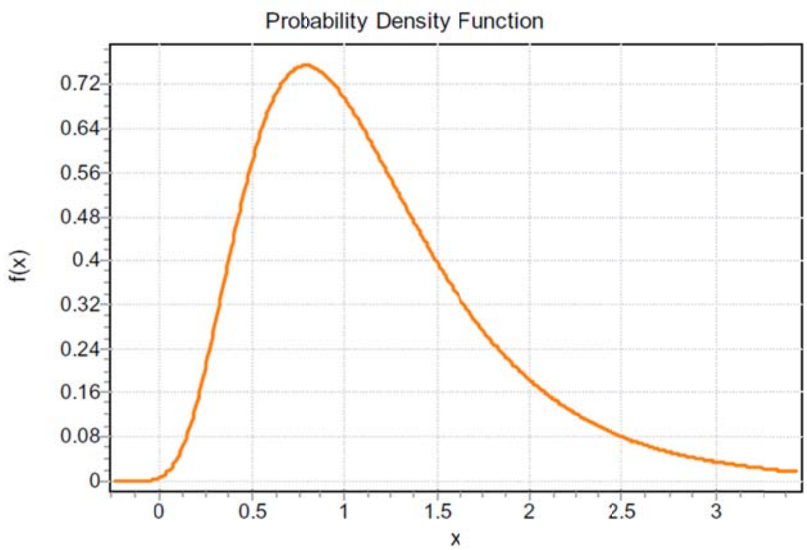


Figure 48: Fitted lognormal distribution for all relative errors, Shirazi and Mosleh (2009) page 61

On the other hand, some researchers have compared the expert judgment performance to the novice. Reischman et al. (2002) showed that in the field of cardiovascular care experts significantly judge better compared to novices. They reported that 72% of the experts are providing good judgment in comparison to the 23% of novice. This basically means that a panel of novice with a size 3 times larger than the expert panel population can produce the same expert opinion result with the same mean and standard deviation. Assuming that σ_e and σ_n are the standard deviation of the expert and novice opinion population respectively, the standard deviation of sampling from the expert and novice population should result in the same sampling standard deviation.

$$\frac{\sigma_e}{\sqrt{n}} = \frac{\sigma_n}{\sqrt{3n}} \tag{27}$$

Restating the Equation 27 results in Equation 28.

$$\sigma_n = \sigma_e\sqrt{3} \tag{28}$$

Equation 28 describes the association of the standard deviation of the expert judgment to the novice judgment. It would be a good rule of thumb to compare the uncertainty of the expert and non-expert (novice) judgments. Combining these two outcomes, we propose a linear function based on the expert DOE score to adjust the expert judgment uncertainty. The standard deviation of the expert judgment relative error is defined as a line function between two points called standard expert and standard novice (see Figure 49). The standard expert is the individual with the DOE score of 10 in the targeted scope. The standard novice is the individual with DOE score of 2. It is assumed that the likelihood function of the standard expert judgment is equivalent to the best fitted lognormal distribution to the relative errors of the experts studied by Shirazi and Mosleh (2009) shown in Figure 48. As a result, the standard deviation of the standard expert judgment lognormal distribution is 0.46. Consequently, the standard deviation of the standard novice judgment is √3 x 0.46.

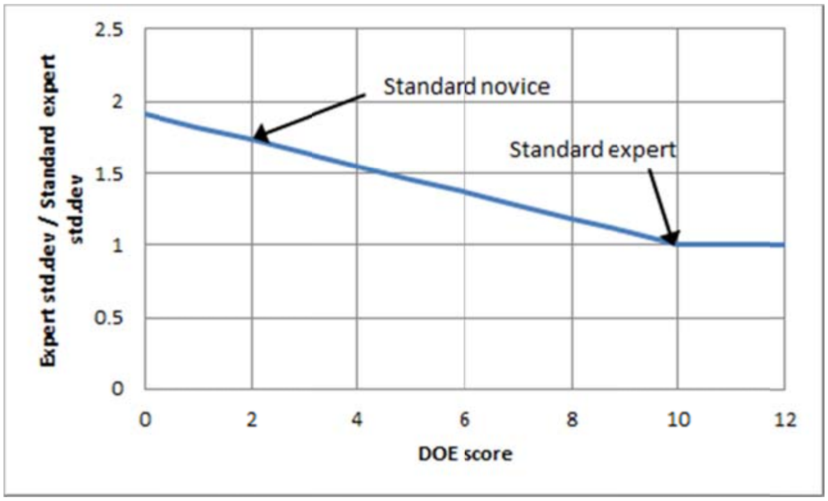


Figure 49: Expert judgment uncertainty function

There is an argument about the proposition that assumes the expert performance in the domain of expertise studied by Shirazi and Mosleh (2009) is the same as that being studied in this research. However, this assumption basically means that the experts behave in the same way in terms of the judgment uncertainty and error regardless of the domain of knowledge. Moreover, as Figure 48 shows the expert judgment relative error has the median of 1.27. This means that the experts in general tend to overestimate. As a result, the expert opinions are adjusted to balance off the overestimation in judgments in the later analysis.

4.2.3. Step 3: Aggregating the expert opinions using Bayesian method

In the context of the expert elicitation, if the unknown value of interest is (u) and the expert opinion as an observable evidence is (u'), the Bayes' theorem can be translated herein Equation 29.

$$P(u|u') = \frac{L(u'|u).P(u)}{\int L(u'|u).P(u)\ du} \tag{29}$$

In Equation 29, the likelihood function $L(u'|u)$ is basically the conditional probability of the expert opinion, E, given that the true value of the unknown in which we are interested is x. This concept basically is in accordance with the probability of the expert misjudgment. In this research, the probability distribution of the relative error of expert opinion is assumed to follow a lognormal distribution equivalent to the Shirazi and Mosleh (2009) studies, Equation 30.

$$f(E) = \frac{1}{\sqrt{2\pi}\sigma_E E}\ EXP(-\frac{1}{2}\left(\frac{\ln(E) - \ln(E_{50})}{\sigma_E}\right)^2) \tag{30}$$

Where E is the relative error ($\frac{u\prime}{u}$), E_{50} is the median (1.27), and σ_E is the standard deviation of the error distribution (0.46). To construct the likelihood function $L(u'|u)$, the following steps need to be taken. Equation 33 shows the likelihood of the unknown value of interest based on the expert judgment.

$$E = \frac{u'}{u} \rightarrow \; dE = \frac{1}{u} du' \tag{31}$$

$$f(u')du' = f(E)dE \; \rightarrow \; f(u') = \frac{1}{u} f(E) \tag{32}$$

$$L(u'|u) = f(u') \tag{33}$$

$$= \frac{1}{\sqrt{2\pi}\sigma_E u'} \, EXP(-\frac{1}{2}\left(\frac{\ln\left({u'}/{u}\right) - \ln(E_{50})}{\sigma_E}\right)^2)$$

As the conjugate family of the lognormal is also the lognormal, we assume the prior probability distribution of the unknown of interest is also lognormal for the sake of convenience. Equation 34 and Equation 35 show the parameters of the posterior lognormal probability of the unknown of the interest, LogNorm(μ' , σ') , when the expert opinion as an evidence is available. In this formulation, the prior lognormal distribution is LogNorm(μ_0 , σ_0) and the expert opinion is X which is an observation of a lognormal distribution, LogNorm(μ , σ), with known σ and an unknown μ.

$$Ln(\mu') = \frac{\frac{Ln(\mu_0)}{{\sigma_0}^2} + \frac{Ln(X)}{\sigma^2}}{\frac{1}{{\sigma_0}^2} + \frac{1}{\sigma^2}} \tag{34}$$

$$\sigma' = \frac{1}{\sqrt{\frac{1}{{\sigma_0}^2} + \frac{1}{\sigma^2}}} \tag{35}$$

4.3. Building the BIM impact causal model

A group of ten experts including architects, structural engineers, mechanical engineers, project managers and sub-contractors were interviewed. **Error! Reference source not found.** shows the experts' position and experience. The interviews were performed in a semi-structured format. We created a very brief presentation about his research and the goals of the interview and recorded the interviews. The audio files were used to produce transcripts of the interviews. Any information deemed sensitive was removed from the transcripts. Finally, the interview transcripts were sent back to the experts for approval. The expert DOE scores are calculated based on the expert background and experience. We investigated two approaches to design the interview questions. In the first approach the expert was asked to estimate the overall effect of BIM utilization on the design and construction parameters of the project supply chain model. The author noticed two major issues after the first interview. First, it was found that asking the high level and general question such as "evaluating the overall impact of BIM on the design and construction" is not tangible for the expert. It was also found that the expert feels more comfortable and confident to state his/her opinion by breaking down the design and construction activities to sub-activities. This was the second approach that we devised and implemented.

Table 19: Experts experience and background

Expert	Experience	Total work experience (years)	Scope
1	Structural engineer	10	Structural design
2	Architect, Project manager	20	Design, Architectural, MEP
3	Architect, Project manager	15	Design, Architectural, MEP
4	Architect	10	Architectural
5	Subcontractor	30	Construction, Shop drawing
6	Mechanical engineer	10	MEP
7	Subcontractor	30	Construction, Shop drawing
8	Project manager	20	Construction, Shop drawing
9	Architect	5	Architectural
10	Project manager	15	Construction, Shop drawing

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Table 20 shows the expert DOE scores and the expert judgment standard deviation in corresponding scopes.

Table 20: Expert DOE scores and standard deviations

Expert	Scope	Experience in scope (X) (year)	Total experience (Y) (year)	Discontinuity (d) (year)	Maturity	Proficiency	DOE Score	Standard Deviation
1	Structural	6	15	0	10	6	7.0	0.59
2	Design	10	20	0	10	10	10.0	0.46
2	Architectural	10	20	0	10	10	10.0	0.46
2	MEP	10	20	0	10	10	10.0	0.46
3	Design	5	15	0	10	5	8.5	0.52
3	Architectural	10	15	0	10	10	10.0	0.46
3	MEP	10	15	0	10	10	10.0	0.46
4	Architectural	5	10	5	10	0	2.5	0.78
5	Shop drawing	10	40	0	10	10	10.0	0.46
6	MEP	5	10	0	10	5	6.3	0.62
7	Shop drawing	10	30	0	10	10	10.0	0.46
8	Construction	10	20	0	10	10	10.0	0.46
8	Shop drawing	8	20	0	10	8	8.5	0.52
9	Architectural	3	5	0	5	3	3.5	0.73
10	Construction	5	15	0	10	5	8.5	0.52
10	Shop drawing	3	15	0	10	3	4.8	0.68

In the second approach the design and construction are broken down into 9 major sub-activities and disciplines. Two tentative causal models based on the common acceptable knowledge in the AEC industry were built for the design and construction processes (Figure 50 and Figure 51).

Design:

- Architectural design
- Structural
- Mechanical/Electrical/Plumbing (MEP)
- Drafting
- Estimating

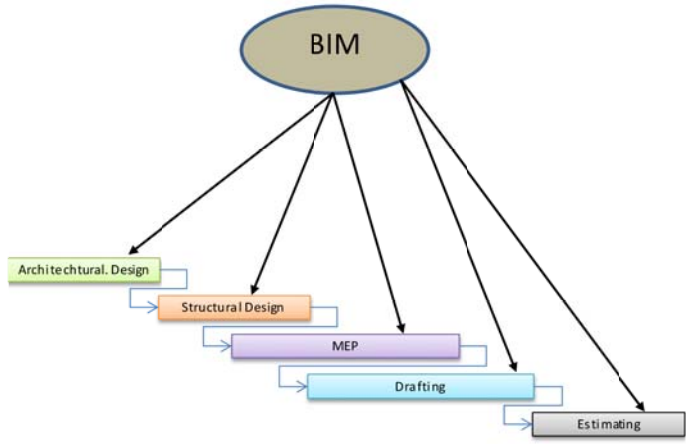

Figure 50: The tentative causal model of the BIM impact on design

Construction:

- Shop drawing
- Estimating
- Planning
- Execution

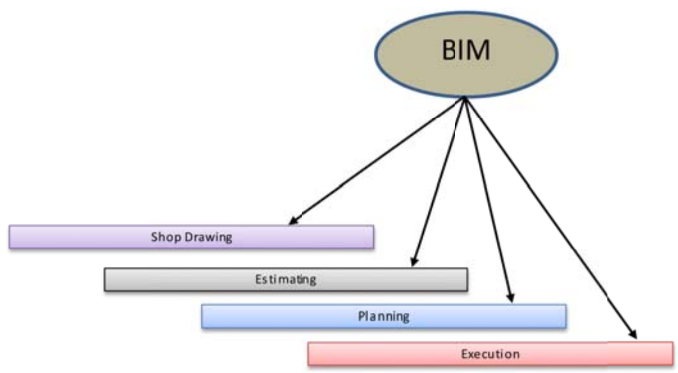

Figure 51: The tentative causal model of the BIM impact on construction

The experts were asked to estimate the impact of the BIM utilization on each sub-activity. The only issue of concern in this approach is how to combine the sub-activity impacts into the dominant activity parameters namely design and construction. The theoretical concept developed in chapter 3 provides a very good foundation to use system dynamics to combine the sub-activity impacts into a single activity. The inter-relation links among the sub-activities are crucial elements that make this approach work. As there is no data to justify those links, we decided to ask experts to justify the parameters of those links. However, just after the first interview, it was found that since the inter-relation activity link concept is a very new concept, asking experts questions to quantify the link parameters (such as the industry parameter (β) defined in chapter 3) was unrealistic because the concept was very intangible for the experts. However, during the expert interviews, it was found that measuring the sub-activity significance level to quantify the level of contribution of the sub-activity to its parent activity is more meaningful to the experts. Furthermore, we broke down the BIM factor into the BIM features such as the clash detection, automated 2D drawing and so forth.

The two tentative causal models described in Figure 50 and Figure 51 were discussed with the experts. The structures of the two models were adjusted during the interviews in an iterative process until a unanimous consensus was reached. Here is the list of model adjustments:

1) The architectural and MEP in the design and shop drawing in construction are the sub-activities most influenced by BIM

2) Although BIM may facilitate structural design and construction planning processes, it is not practiced often in the industry.

3) Each sub-activity in design has a drafting process of its own and it is hard to separate the drafting process from each sub-activity.

4) Estimating in design basically means estimating the design progress to bill the client. Cost estimate in a very meticulous manner, such as the way it is practiced in construction, is not performed in the design process. Architects and mechanical engineers use BIM in a very limited way. They use BIM sometimes just to come up with an initial estimate of the material take-offs. Most of the times, they use their own heuristics and datasheet to do the project cost estimate.

5) Cost estimate in construction is very different. Cost estimate is performed in more details in construction. Although BIM has some potential to facilitate cost estimate in construction, not even a single case was found in which BIM was used to estimate cost in the construction process.

6) Mechanical subcontractors were the main user of BIM. In some cases, they had developed a semi-automated production line integrated with BIM.

7) The idea of using BIM in construction execution was found vague by experts. They had different hypotheses of how BIM may be integrated in the construction execution and improve the execution automation.

8) The “3D interface”, “3D to 2D” and “Change Management” features of BIM were identified as the factors that save time to perform the sub-activity.

9) “Clash detection” was identified as the only feature that improves the “Time to detect undiscovered changes” in the sub-activity.

10) Since the “3D interface” feature is not a new feature introduced by BIM, “3D interface” feature was found to have neutral impact.

The experts were asked two questions about each of the BIM features in the scope of his/her expertise: 1) how much does the feature save time in the scope? and 2) what percentage of the errors in the scope is associated with the feature? For example, the architects were asked to quantify 1) how much does the clash detection feature save time in the architectural design, and 2) what percentage of the errors in the architectural design are related to clashes. The expert responses are tabulated in Appendix-A: Expert responses. The responses of the experts are aggregated in Table 21.

Table 21: Aggregated expert opinion

Scope	Cause/BIM feature	Effect	Expert judgment	Std.Dev
Architectural	3D to 2D	Time saving % on P	0.129	0.533
Architectural	Change Management	Time saving % on P	0.069	0.533
Architectural	Clashes	Time saving % on D	0.235	0.533
MEP	3D to 2D	Time saving % on P	0.116	0.369
MEP	Change Management	Time saving % on P	0.076	0.369
MEP	Clashes	Time saving % on D	0.131	0.369
MEP	IFC	Time saving % on P	0.209	0.369
Shop drawing	3D to 2D	Time saving % on P	0.172	0.415
Shop drawing	Clashes	Time saving % on D	0.244	0.415
Shop drawing	Change Management	Time saving % on P	0.100	0.415
Shop drawing	IFC	Time saving % on P	0.180	0.415
Architectural	3D to 2D	Error reduction%	0.099	0.533
Architectural	Change Management	Error reduction%	0.090	0.533
Architectural	Clashes	Error reduction%	0.450	0.533
MEP	3D to 2D	Error reduction%	0.076	0.369
MEP	Change Management	Error reduction%	0.172	0.369
MEP	Clashes	Error reduction%	0.200	0.369
MEP	IFC	Error reduction%	0.256	0.369
Shop drawing	3D to 2D	Error reduction%	0.225	0.415
Shop drawing	Clashes	Error reduction%	0.264	0.415
Shop drawing	Change Management	Error reduction%	0.134	0.415
Shop drawing	IFC	Error reduction%	0.213	0.415
Arch-Inf	Architectural	Design	0.447	0.325
MEP-Inf	MEP	Design	0.173	0.325
Shop-Inf	Shop drawing	Construction	0.126	0.345

The causal model structures were adjusted accordingly. The results are shown in Figure 52 and Figure 53. The causal models comprise 3 layers. The expert opinions about the impact of each BIM feature are aggregated in layer (1). The impact of the features on the sub-activities parameters, i.e. production rate, quality of work and time to detect errors is computed in layer (2) This impact is measured by the time saving percentage, “time saving%”, on production rate and time to detect error, and the error reduction percentage, “error reduction%”, on quality of work. Layer (3) aggregates the sub-activity effects into the design and construction stage. Finally, the impacts are interpreted into the percentage change of the design and construction parameters which are used directly on the project supply chain model in chapter 4.4.

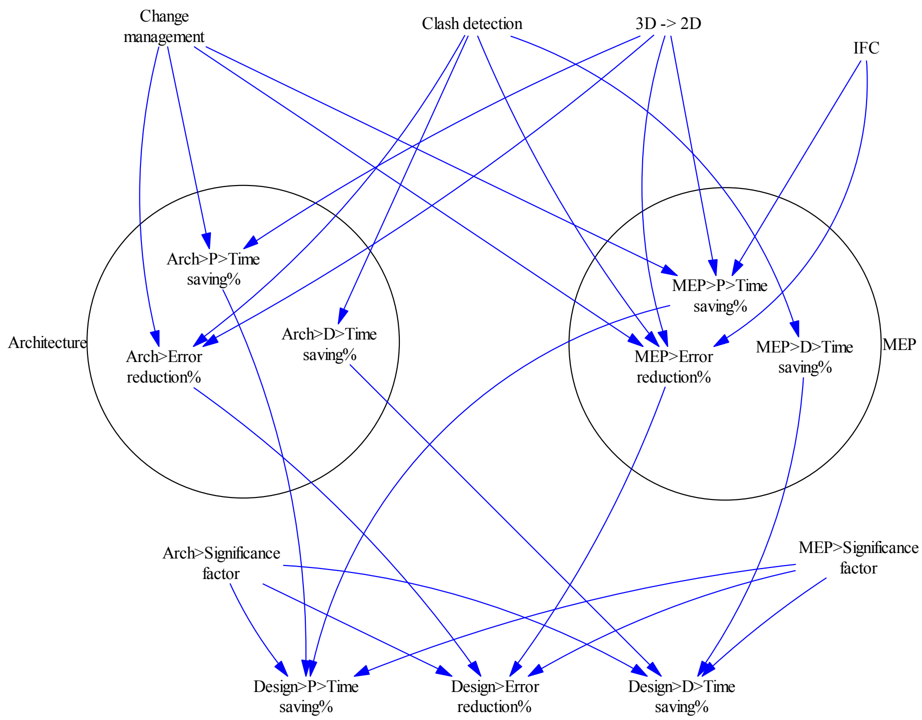

Figure 52: The causal model of the BIM impact on design

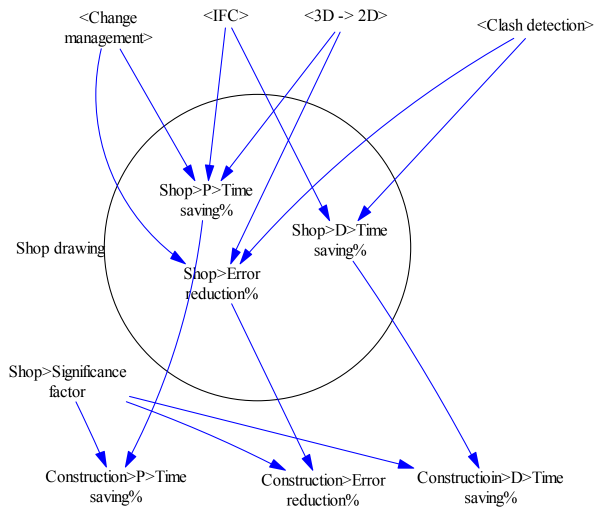

Figure 53: The causal model of the BIM impact on construction

Equation 36, Equation 37 and Equation 38 show the formula to compute the layer (2) variables.

$$\left(\frac{\Delta t_P}{t_P}\right)_{subctivity(i)} = \sum_j \left(\frac{\Delta t_P}{t_P}\right)_{feature(j)} \tag{36}$$

$$(\Delta Err)_{subactivity(i)} = \sum_j (\Delta Err)_{feature(j)} \tag{37}$$

$$\left(\frac{\Delta t_D}{t_D}\right)_{subctivity(i)} = \sum_j \left(\frac{\Delta t_D}{t_D}\right)_{feature(j)} \tag{38}$$

The "time saving%" and "error reduction%" of the design and construction activities impacted by the BIM utilization are calculated in layer (3) using; Equation 39, activity production time saving percentage $\left(\frac{\Delta t_P}{t_P}\right)$, “P_dt%”;Equation 40, activity error reduction percentage (ΔErr), “K_dErr%”; Equation 41, and activity error detection time saving percentage $\left(\frac{\Delta t_D}{t_D}\right)$, “D_dt%”.

$$\left(\frac{\Delta t_P}{t_P}\right)_{Activity} = \sum_i (Significance\ Factor)_{subactivity(i)} \cdot \left(\frac{\Delta t_P}{t_P}\right)_{subactivity(i)} \tag{39}$$

$$(\Delta Err)_{Activity} = \sum_i (Significance\ Factor)_{subactivity(i)} \cdot (\Delta Err)_{subactivity(i)} \tag{40}$$

$$\left(\frac{\Delta t_D}{t_D}\right)_{Activity} = \sum_i (Significance\ Factor)_{subactivity(i)} \cdot \left(\frac{\Delta t_D}{t_D}\right)_{subactivity(i)} \tag{41}$$

As discussed, expert opinions which are the inputs in layer (1) are random variable. To calculate the causal model outcome in layer (3), design and construction

"P_dt%", "K_dErr%" and "D_dt%", a Monte-Carlo simulation with 200 samples is. Figure 54 shows the results.

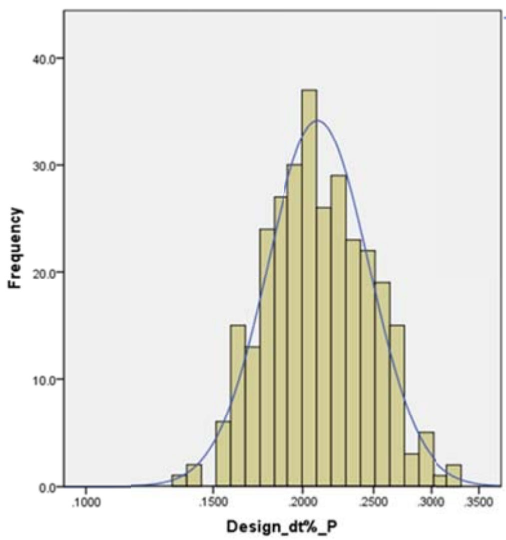

Figure 54.1: Distribution of Design dt%_P; Mean=0.21, StDev=0.03, N=200

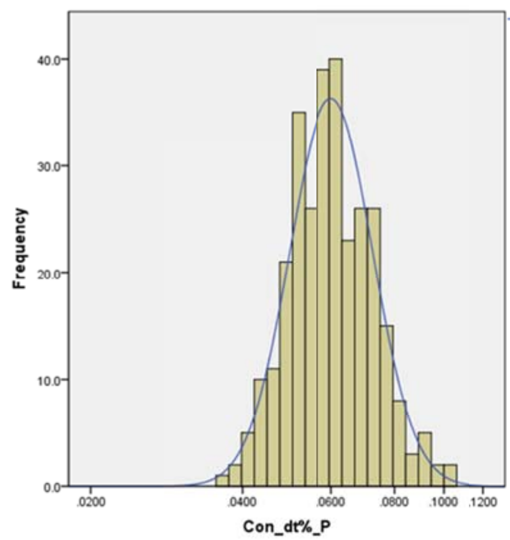

Figure 54.2: Distribution of Construction dt%_P; Mean=0.06, StDev=0.01, N=200

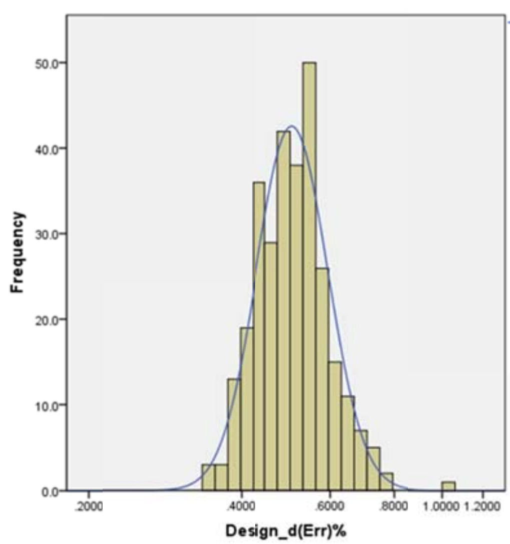

Figure 54.3: Distribution of Design d(Err)%; Mean=0.51, StDev=0.09, N=200

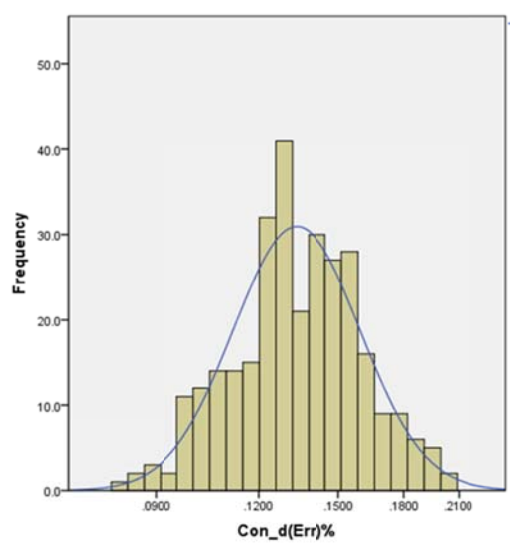

Figure 54: Distribution of Construction d(Err)%; Mean=0.13, StDev=0.02, N=200

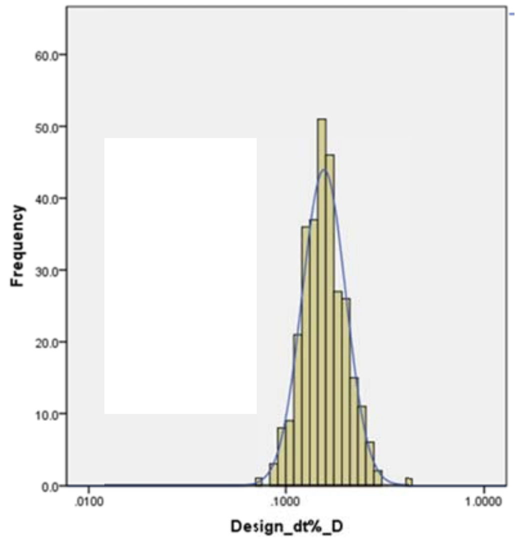

Figure 54.5: Distribution of Design dt%_D; Mean=0.16, StDev=0.04, N=200

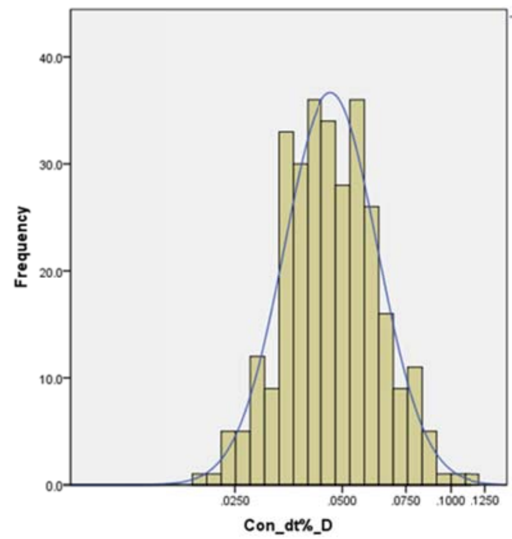

Figure 54.6: Distribution of Construction dt%_D; Mean=0.05, StDev=0.02, N=200

Figure 54: Distribution of the design and construction "P_dt%", "K_dErr%" and "D_dt%", using Monte-Carlo simulation with 200 samples

4.4. Project parameters adjusted for BIM-utilized projects

The outcome of the causal model, design and construction "P_dt%", "K_dErr%" and "D_dt%", should be transformed into the project parameters, i.e. production rate (P), coefficient of change (Kc), and time to detect undiscovered change (D), which are the direct input to the project model. The following describes the concepts and the computation procedure.

Assuming the BIM-feature-related errors are mutually exclusive, each error can correspond to a BIM feature in each sub-activity. For instance, "3D geometry misunderstanding error" corresponds to "3D interface" feature, "clash error" corresponds to the "clash detection" feature and the "error regarding undistributed change updates" corresponds to the "change management" feature. The assumption of the mutually exclusive errors also means that the impact of using features on each sub-activity error can follow the superposition rule. Assuming that the utilization of the feature removes the all feature-related errors, the impact of the BIM feature utilization on the quality of work is calculated as shown in Figure 55.

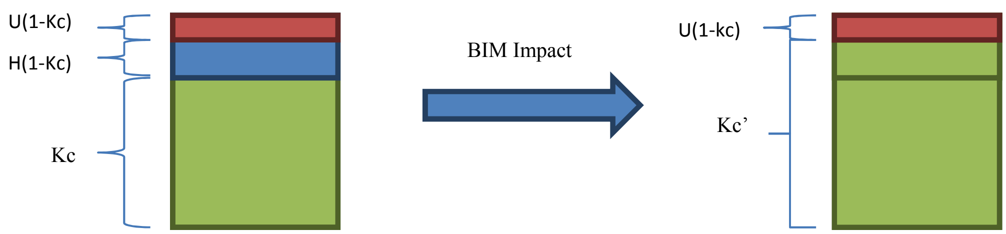

Figure 55: Association of the feature-related errors with the coefficient of change (Kc)

The green box represents the flawless portion of the sub-activity work done. The red and blue parts are the defected portion of the work done, caused by unutilized BIM feature. There are two types of the defected portions: 1) the portion that can be handled by BIM features (Blue box, H), and 2) the portion that cannot be handled by BIM features (U, red box). By concept the sum of H and U equals 1 (H+U=1). Utilizing the BIM feature changes the sub-activity ratio of the defected job (Kc) as below. The error percentage of sub-activities before utilizing the BIM feature is calculated in Equation 42. Equation 43 shows the error percentage of sub-activity after utilizing BIM. Transforming these equations constructs Equation 46 which computes the percentage change of the coefficient of change $\left(\frac{\Delta Kc}{Kc}\right)$ caused by utilizing BIM.

$$Err\%_1 = 1 - Kc_1 \tag{42}$$

$$Err\%_2 = 1 - Kc_2 = U(1 - Kc_1) \tag{43}$$

$$\Delta Kc = Kc_2 - Kc_1 \tag{44}$$

$$\Delta Kc = (1 - U)(1 - Kc_1) \tag{45}$$

$$\left(\frac{\Delta Kc}{Kc}\right)_{activity} = H_{activity} \frac{(1 - Kc_1)}{Kc_1} \tag{46}$$

The following steps are taken to calculate the percentage change of production rate.

$$P_1 = \frac{W}{t_1} \tag{47}$$

$$P_2 = \frac{W}{t_2} \tag{48}$$

$$\Delta P = \frac{W}{t_2} - \frac{W}{t_1} = \frac{W}{t_1 + \Delta t} - \frac{W}{t_1} = \frac{-\Delta t . W}{t_1(t_1 + \Delta t)} \tag{49}$$

$$\frac{\Delta P}{P_1} = \frac{-\,{}^{\Delta t}/_{t_1}}{(1 + {}^{\Delta t}/_{t_1})} \tag{50}$$

$$\left(\frac{\Delta P}{P}\right)_{activity} = \frac{-\left({}^{\Delta t_P}/_{t_P}\right)_{activity}}{(1 + \left({}^{\Delta t_P}/_{t_P}\right)_{activity})} \tag{51}$$

Equation 47 calculates the production rate before utilizing BIM. Production rate after utilizing BIM is computed in Equation 48. Equation 51 shows the percentage change of production rate $\left(\frac{\Delta P}{P}\right)$ caused by utilizing BIM.

The change percentage of time to detect undiscovered changes $\left(\frac{\Delta D}{D}\right)$ is calculated in Equation 52.

$$\left(\frac{\Delta D}{D}\right)_{activity} = \left(\Delta t_D / t_D\right)_{activity} \tag{52}$$

In summary, the BIM-utilized project parameters are calculated by Equation 53, Equation 54 and Equation 55 . Table 22 shows the result.

$$P_{activity,BIM} = P_{activity,Non}\left(1 + \left(\frac{\Delta P}{P}\right)_{activity}\right) \tag{53}$$

$$K_{activity,BIM} = K_{activity,Non}\left(1 + \left(\frac{\Delta Q}{Q}\right)_{activity}\right) \tag{54}$$

$$D_{activity,BIM} = D_{activity,Non}\left(1 + \left(\frac{\Delta D}{D}\right)_{activity}\right) \tag{55}$$

Table 22: The statistics of the BIM-utilized parameter distribution

Parameter	Mean	Std.Dev	CV	0.05	0.95	Range	Range/ Std.Dev	Range CV
D_P	0.64	0.30	0.46	0.28	1.22	0.94	3.16	1.47
D_K	0.91	0.03	0.03	0.86	0.95	0.09	3.29	0.09
D_D	0.18	0.26	1.48	0.01	0.64	0.63	2.38	3.52
C_P	0.73	0.32	0.44	0.35	1.29	0.94	2.93	1.29
C_K	0.95	0.02	0.03	0.91	0.99	0.08	3.29	0.09
C_D	0.18	0.24	1.29	0.01	0.76	0.74	3.15	4.06

4.5. BIM impact causal model (BIM-ICM) validation

5 BIM-utilized projects were found, two with complete cost overrun details and 3 without. For the projects with missing cost overrun data, it is assumed that cost overrun occurs in a linear fashion between the project start and finish to complete the missing information for the validation process. Moreover, all those projects are not implemented fully in the design and construction with BIM capabilities and features. The project model was calibrated with those 5 BIM-utilized projects. The calibration procedure is the same as the procedure described in chapter 3.3. However the industry parameter (β) is assumed constant with the same value as that of the Non-BIM project model ($\beta = 1.239$). The reason is the few numbers of BIM-utilized projects. As the number of the projects used to calibrate the model is few, the model may tend to make a harsh change to the industry parameter to minimize the payoff function. Besides, the industry parameter is conceptually the parameter that is inherited from the nature of the project work flow and adopting BIM does not alter the project supply chain work flow at least at this level of aggregation, design and construction activity level. Table 23 includes the calibrated parameters of the 5 BIM-utilized projects.

Table 23: The calibration result of the project model with the 5 BIM-utilized projects

Project	BIM utilization	D_P	D_K	D_D	C_P	C_K	C_D
1	Design & Construction	0.76	0.89	0.02	0.62	0.93	0.01
2	Design	0.60	0.88	0.01	5.63	0.93	0.97
3	Design & Construction	0.98	0.97	0.01	1.24	0.94	0.01
4	Construction	0.67	0.94	0.01	0.55	0.97	0.24
5	Construction	0.43	0.87	0.09	0.39	0.94	0.01

The calibrated parameters as the actual data points are compared with the BIM-utilized parameter distributions produced by the BIM-ICM shown in Table 22. Table 24 shows the validation result.

Table 24: BIM-ICM validation result table

Project	Parameter	Actual data	Distribution Mean	Distribution Std.Dev	CV	Percentile 5%	Percentile 95%	Passed
1	D_P	0.76	0.64	0.30	0.46	0.28	1.22	+
2	D_P	0.60	0.64	0.30	0.46	0.28	1.22	+
3	D_P	0.98	0.64	0.30	0.46	0.28	1.22	+
1	D_K	0.88	0.91	0.03	0.03	0.86	0.95	+
2	D_K	0.88	0.91	0.03	0.03	0.86	0.95	+
3	D_K	0.97	0.91	0.03	0.03	0.86	0.95	-
1	D_D	0.02	0.18	0.26	1.48	0.01	0.64	+
2	D_D	0.01	0.18	0.26	1.48	0.01	0.64	+
3	D_D	0.01	0.18	0.26	1.48	0.01	0.64	+
1	C_P	0.62	0.73	0.32	0.44	0.35	1.29	+
3	C_P	1.24	0.73	0.32	0.44	0.35	1.29	+
4	C_P	0.55	0.73	0.32	0.44	0.35	1.29	+
5	C_P	0.39	0.73	0.32	0.44	0.35	1.29	+
1	C_K	0.93	0.95	0.02	0.03	0.91	0.99	+
3	C_K	0.94	0.95	0.02	0.03	0.91	0.99	+
4	C_K	0.97	0.95	0.02	0.03	0.91	0.99	+
5	C_K	0.94	0.95	0.02	0.03	0.91	0.99	+
1	C_D	0.01	0.18	0.24	1.29	0.01	0.76	+
3	C_D	0.01	0.18	0.24	1.29	0.01	0.76	+
4	C_D	0.24	0.18	0.24	1.29	0.01	0.76	+
5	C_D	0.01	0.18	0.24	1.29	0.01	0.76	+

There are almost 3-4 actual data points to be compared with the BIM-utilized parameter distributions. All points fit in the 90% confidence range of the distributions except for one in D_K. The results shown in Table 24 are summarized in term of the project parameter categories in Table 25. The average validation passing rate for the entire model is 94%.

Table 25: validation passing rate for the project parameters

Parameter	Sample size	Passed	Passed%
D_P	3	3	100%
D_K	3	2	67%
D_D	3	3	100%
C_P	4	4	100%
C_K	4	4	100%
C_D	4	4	100%

Chapter 5. BIM impact analysis

5.1. Impact of BIM on project performance

The impact of BIM utilization on the project outcomes is measured by performance indexes (PI). The schedule performance index (Schedule PI), Equation 56 , and the cost performance index (Cost PI), Equation 57 , are the two popular performance indexes in the IT impact analysis in construction industry (El-Mshaleh et al. 2003,2006 and O'Conner et al. 2003, 2004).

$$\text{Schedule Performance Index} = \frac{\text{Planned Duration}}{\text{Actual Duration}} \tag{56}$$

$$\text{Cost Performance Index} = \frac{\text{Planned Cost}}{\text{Actual Cost}} \tag{57}$$

Both the Non-BIM and BIM-utilized project models were used to estimate the project outcomes of a hypothetical set of projects. The set of the 33 gathered projects is assumed as the sample which represents the industry projects. The project set is simulated by both models; Non-BIM and BIM-utilized models. The performance indexes, Schedule PI and Cost PI, are constructed from the simulation outcomes. Figure 56 shows the methodology of the BIM impact analysis.

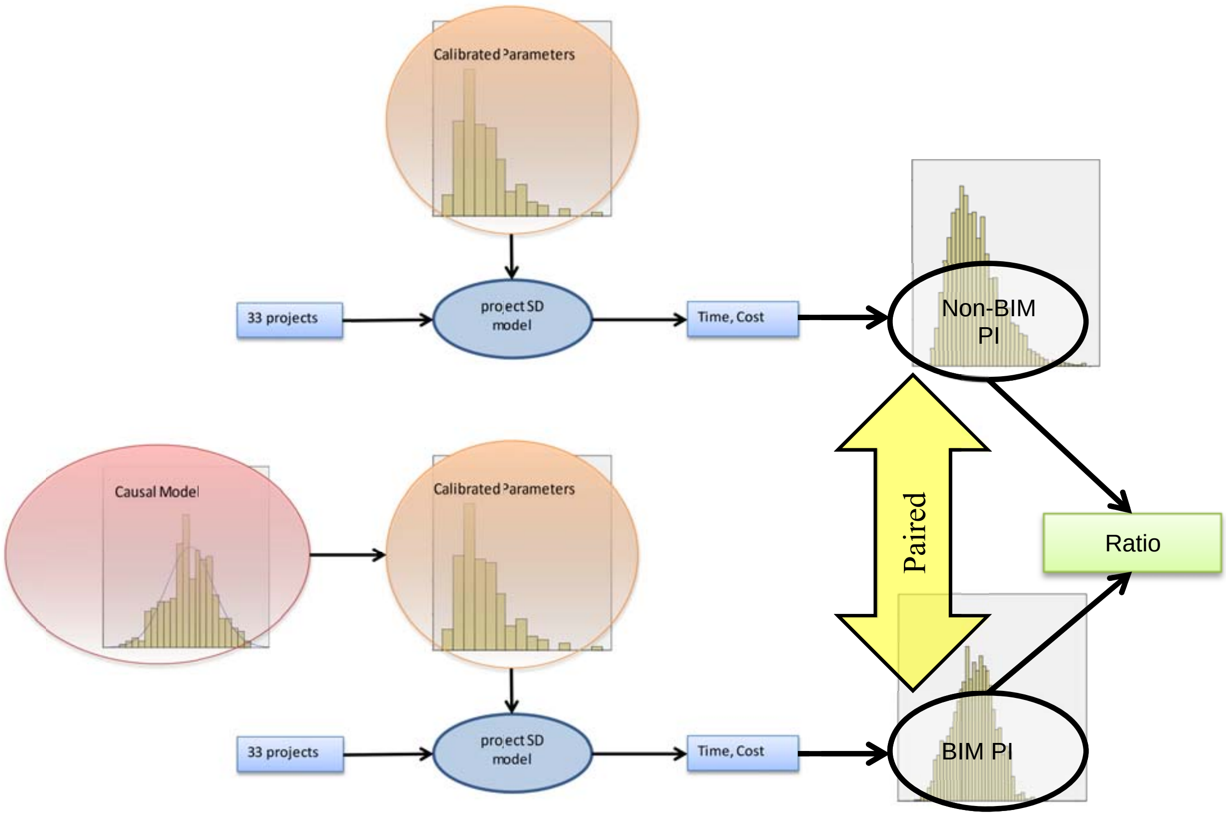

Figure 56: The methodology of analyzing the BIM impact on the project performance

The Non-BIM performance indexes along with the BIM-utilized performance indexes are paired for each project. The ratio of the BIM-utilized PI to Non-BIM PI is calculated for the simulation outcomes. The result is shown in Table 26 and Table 27. Table 28 and Table 29 summarize the results of the Schedule PI and Cost PI, respectively.

Table 26: Schedule PI impact ratio, statistical properties

Activity	PI	Statistics	Non-BIM	BIM-Utilized	Impact ratio
Design	Schedule	Stat_Mean	0.17	0.47	1.30
Design	Schedule	Stat_StdDev	5.57	3.85	0.21
Design	Schedule	Stat_Median	0.36	0.47	1.38
Design	Schedule	Stat_5	0.09	0.11	1.08
Design	Schedule	Stat_95	0.98	1.39	1.69
Construction	Schedule	Stat_Mean	0.75	0.81	1.09
Construction	Schedule	Stat_StdDev	1.19	1.25	0.09
Construction	Schedule	Stat_Median	0.62	0.66	1.08
Construction	Schedule	Stat_5	0.19	0.22	1.03
Construction	Schedule	Stat_95	1.29	1.41	1.16
Project	Schedule	Stat_Mean	0.35	0.47	1.16
Project	Schedule	Stat_StdDev	9.46	9.46	0.47
Project	Schedule	Stat_Median	0.65	0.74	1.14
Project	Schedule	Stat_5	0.27	0.31	1.05
Project	Schedule	Stat_95	1.30	1.53	1.39

Table 27: Cost PI impact ratio, statistical properties

Activity	PI	Statistics	Non-BIM	BIM-Utilized	Impact ratio
Design	Cost	Stat_Mean	0.90	0.94	1.08
Design	Cost	Stat_StdDev	0.25	0.15	0.13
Design	Cost	Stat_Median	0.87	0.92	1.07
Design	Cost	Stat_5	0.54	0.73	0.89
Design	Cost	Stat_95	1.38	1.22	1.35
Construction	Cost	Stat_Mean	0.99	1.00	1.03
Construction	Cost	Stat_StdDev	0.18	0.17	0.04
Construction	Cost	Stat_Median	0.99	1.00	1.01
Construction	Cost	Stat_5	0.70	0.75	0.98
Construction	Cost	Stat_95	1.31	1.31	1.07
Project	Cost	Stat_Mean	1.01	1.02	1.04
Project	Cost	Stat_StdDev	0.77	0.56	0.19
Project	Cost	Stat_Median	0.96	0.99	1.02
Project	Cost	Stat_5	0.72	0.76	0.99
Project	Cost	Stat_95	1.27	1.27	1.08

Table 28: The impact of BIM utilization of Schedule PI

Activity	NON SPI Mean	NON Schedule PI StdDev	BIM Schedule PI Mean	BIM Schedule PI StdDev	Impact rate
Design	17%	5.57	47%	3.85	30%
Construction	75%	1.19	81%	1.25	10%
Project	35%	9.46	47%	9.46	16%

Table 29: The impact of BIM utilization of Cost PI

Activity	NON Cost PI Mean	NON Cost PI StdDev	BIM Cost PI Mean	BIM Cost PI StdDev	Impact rate
Design	90%	0.25	94%	0.15	8%
Construction	99%	0.18	100%	0.17	3%
Project	101%	0.77	102%	0.56	4%

As the tables indicate, the design Schedule PI is the most impacted PI of projects by BIM with 30% improvement. The construction and project Schedule PI are improved only 10% and 16% respectively. The Cost PI shows 8% improvement in the design cost and relatively low improvement in the construction and entire project, 3% and 4%.

5.2. Impact of BIM features on project performance

One of the important outcomes of this research is identifying the magnitude of the impact of BIM features on project performance. As utilizing BIM features is a binary state, the model is analyzed in 5 utilization scenarios. Table 30 shows the details.

Table 30: 5 hypothetical scenarios of using BIM features

Scenario	BIM feature	Util-1	Util-2	Util-3	Util-4	Util-5
1	3D to 2D	1	0	0	0	1
2	Change	0	1	0	0	1
3	Clashes	0	0	1	0	1
4	IFC	0	0	0	1	0
5	All	0	0	0	0	1

The result of each scenario is compared to the scenario 5 to measure the impact of BIM on the project performance indexes, with or without the BIM feature. The results are organized in two formats. Figure 57 and Figure 58 show the magnitude of the impact of BIM features on the PIs. However, Figure 59 and Figure 60 demonstrate the contribution of BIM features in their impacts on the PIs.

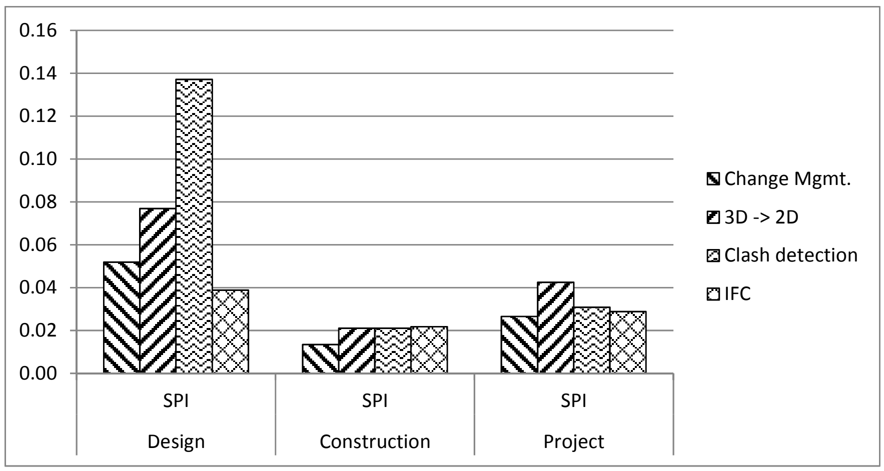

Figure 57: Magnitude of the BIM feature impacts on Schedule PI

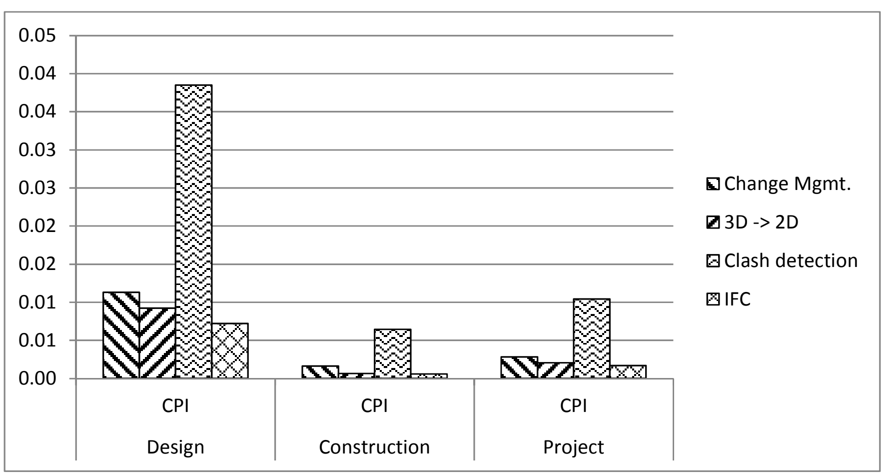

Figure 58: Magnitude of the BIM feature impacts on Cost PI

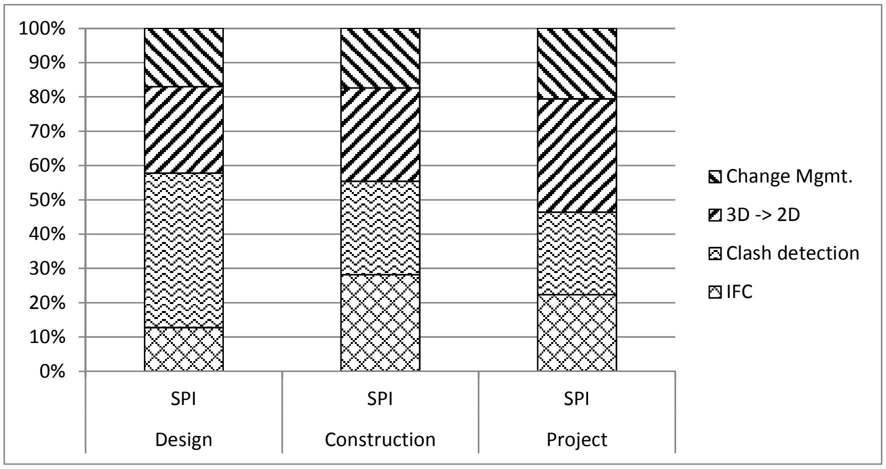

Figure 59: Participation of the BIM feature impacts on Schedule PI

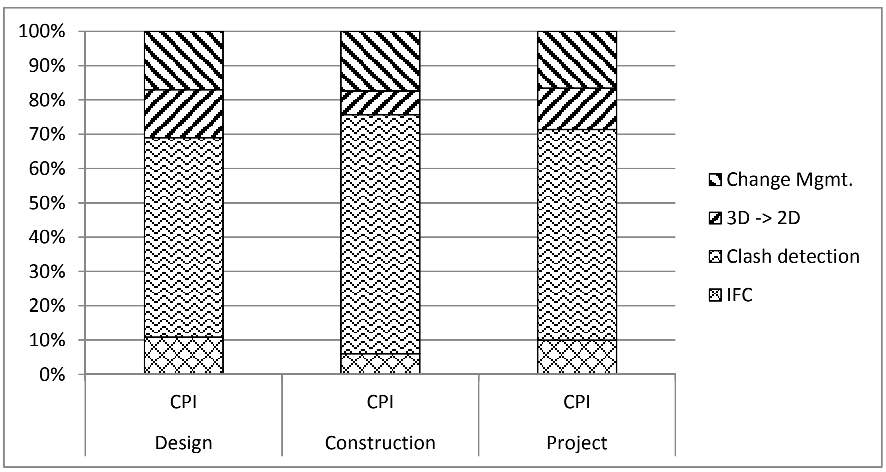

Figure 60: Participation of the BIM feature impacts on Cost PI

The "Clash detection" feature is found to be the most influential feature of the BIM software applications on design, construction and the entire project. It contributes in design Schedule PI, 45%; construction Schedule PI, 27%; and the project Schedule PI, 24%. However on Cost PI, it has 58%, 70% and 61% contribution in the design, construction and project respectively. The second most influential feature of Schedule PI and Cost PI is not the same. "Automated 3D to 2D drawing" is the second most influential feature on Schedule PI with the contribution of 25%, 27%, and 33% in the design, construction, and project, respectively. Automated 3D to 2D drawing" contributes in design, construction and project Cost PIs with 14%, 7%, and 12%. However, "Change management" is the second most influential factor in Cost PI with 17% contribution in design, construction and project. It also contributes 17%, 17% and 21% in the design, construction and project Schedule PIs. The "change management" and "IFC compatibility" features almost share the third place together in Schedule PI. They compete against each other on the design, construction and project, Schedule PIs and Cost PIs, for almost 20% share. "Change management" is found the least influential feature in Schedule PI with 18% contribution. The "IFC compatibility" and "Automated 3D to 2D drawing" are found to be the least influential feature with almost 10% contribution in Cost PI. Figure 61 and Figure 62 show the result in brief.

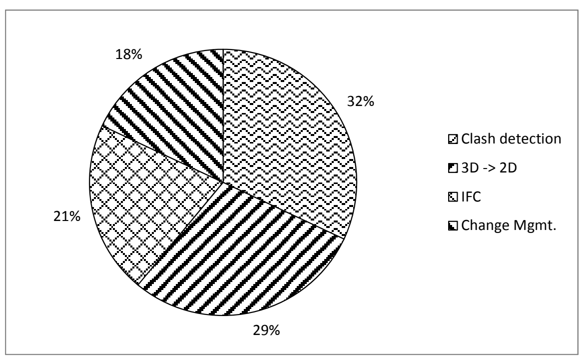

Figure 61: BIM feature ranking in Schedule PI

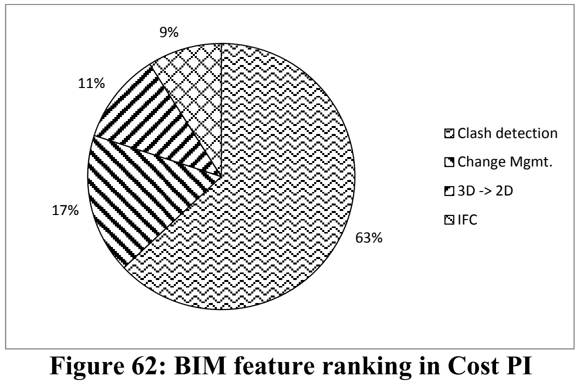

Figure 62: BIM feature ranking in Cost PI

Chapter 6. Sensitivity analysis

Sensitivity analysis (SA) is usually used for two purposes: 1) explaining the model behavior, 2) addressing the model output uncertainty due to the variations of model parameters. SA can be performed in the univariate or multivariate approach. The univariate SA is mostly used to plot the model outcome based on changing parameters in the valid ranges to explain the model behavior. Conversely, the multivariate SA is applied to measure the impact of the parameter variations projected on the model outcomes.

"Industry parameter", Parameter (β) and "novice score" are the only two parameters assumed constant in the Non-BIM and BIM-utilized project models. The impact of the variation of these parameters on the model outcomes is analyzed using the multivariate SA technique. As discussed, Maturity measures the expert general background and Proficiency measures the current valuable expertise which is most related to the scope under study. "Novice score" divided by 10 is approximately the combinatorial factor that explain how many percentage of Maturity is added to DOE score. BIM technology is new in the AEC industry and we believe Maturity that represents the general experience of expert shall not contribute in DOE score more than 30%. The impact of "novice score" in the range of 0 and 3 was measured on the BIM-ICM outcome. The impact was found to be negligible, less than 1%, on the BIM-utilized parameters. As a matter of fact, "novice score" was ignored in the sensitivity analysis.

As Parameter (β) is influenced by the random sampling in calibration, the impact of the random sampling to select the calibration sample on the model outcome needs to be investigated as well. 7 samples were selected randomly with two different sample sizes; 10 and 18. Surprisingly, the impact of random sampling on the calibrated project parameters is negligible. However, the calibrated Parameter (β) was found to change slightly in the range of 1.148 to 1.391 (-7% to 13% of the optimal parameter), with the mean of 1.222 and standard deviation of 0.08. Table 31 shows the results.

Table 31: The impact of random sampling on Parameter (β)

Sample #	Size	(β)
1	33	1.148
2	10	1.155
3	10	1.391
4	10	1.222
5	18	1.233
6	18	1.186
7	18	1.218

The impact of variation of (β) on Non-BIM project model is computed in four cases β = 0.0, 1.0, 1.239(optimum), and 2.0. The PI outcome of each case is scaled with the optimum PI to calculate the variation ratio. Figure 63 shows the results. Note that design PIs are not affected by changing (β).

As Figure 63 indicates, the absolute variation of construction and project PIs where (β) varies between 1.148 and 1.391 is less than 1%. Although the impact of (β) variation is relatively small, it influences the impact rates of construction and project Cost PIs by 30% and 25%, respectively. As a result, the impact rates of BIM are 2%-4% for construction Cost PI, and 3%-5% for project Cost PI.

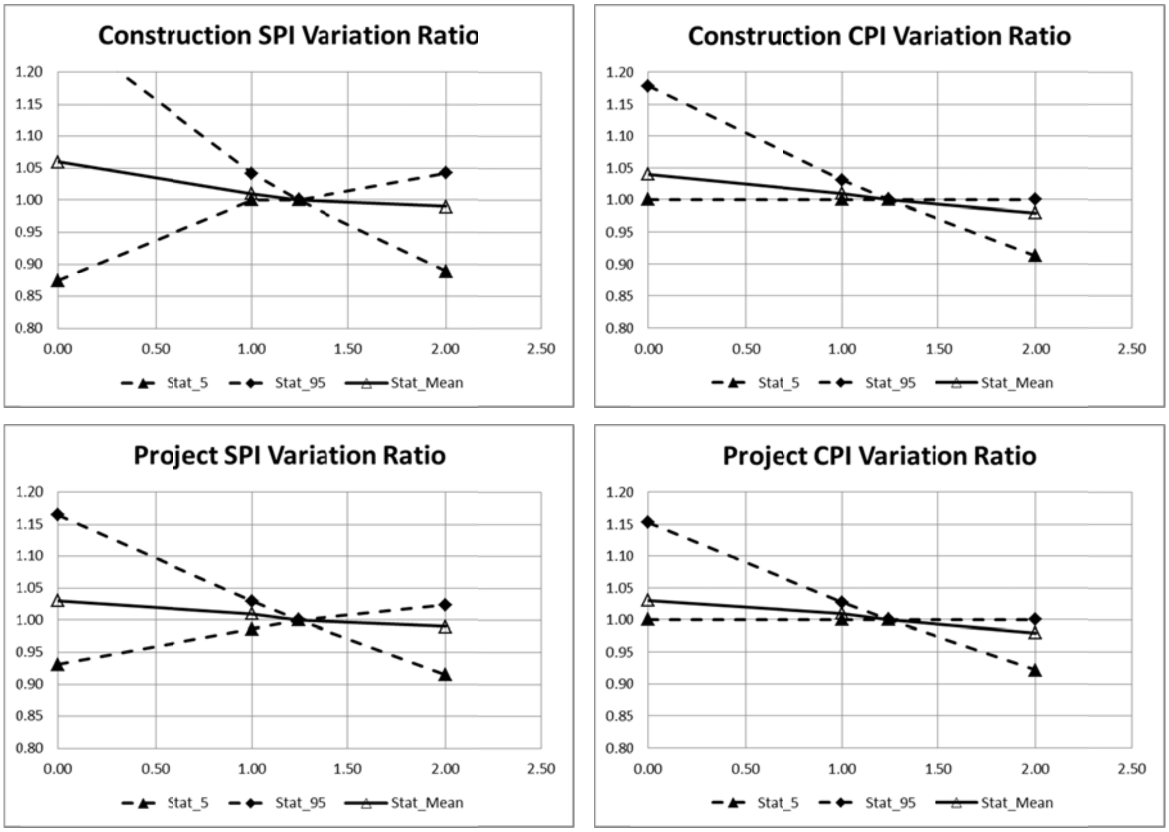

Figure 63: Sensitivity of PIs based on (β) variation

Furthermore, the sensitivity of payoff function based on the parameter (β) is analyzed to ensure that the optimum solution is not local optimality. Parameter (β) changes between 0 and 2 with the increment of 0.2. The payoff values of each case are scaled by the payoff values of the optimal solution at β = 1.239. The payoff value is the sum of the simulated payoffs of the 33 projects. The results are presented in Figure 64. Since the calibrated project parameters are nearly the same for each randomly selected calibration sample, calibration is only dependent on the parameter (β). Figure 64 demonstrates that the payoff is convex around the optimal (β). As the matter of fact, the optimum is the general optimal point in the feasible range of (β) = [0, 2]

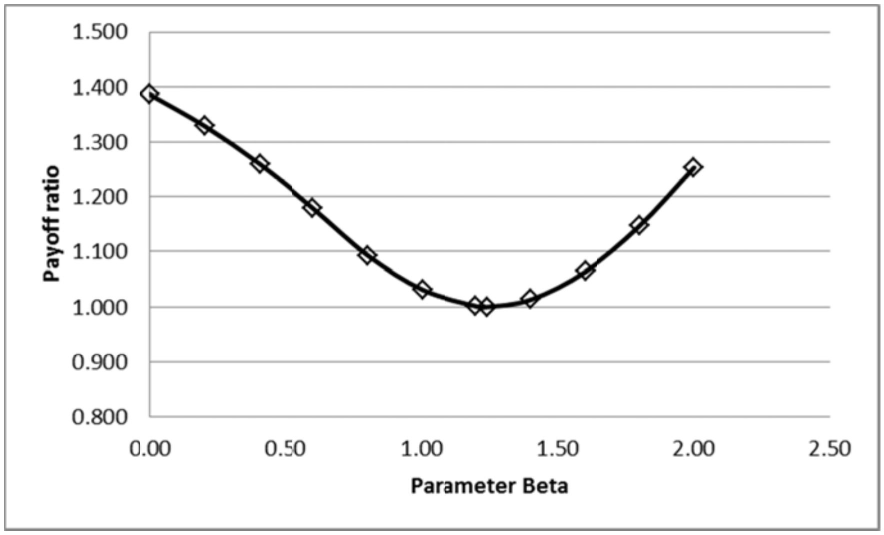

Figure 64: Sensitivity of (β)

Finally, the sensitivity of the calibration model on error weights is investigated. There are 3 types of error weights for design and construction in the payoff function: 1) error weights of the time term (SSEP[T]), 2) error weights of the cost overrun term (SSEP[CO1]), and error weights of the cost overrun curve (SSEP[CO2]). 5 sets of error weights are defined in 5 scenarios along with the base scenario which is the set of error weights selected in accordance with the calibration and validation chapter. Table 32 indicates the scenarios.

Table 32: Scenarios of error weight sensitivity analysis

Case	EW[T]	EW[CO1]	EW[CO2]
Base	2	1	1
1	1	1	1
2	1	2	1
3	1	1	2
4	+100	1	1
5	1	+100	1

The calibration is performed for each scenario. The average change percentage for each parameter and also the payoff function calculated and are shown in Figure 65. As shown, the impact of error weights on the calibrated parameters and the payoff is less than 10% in most cases.

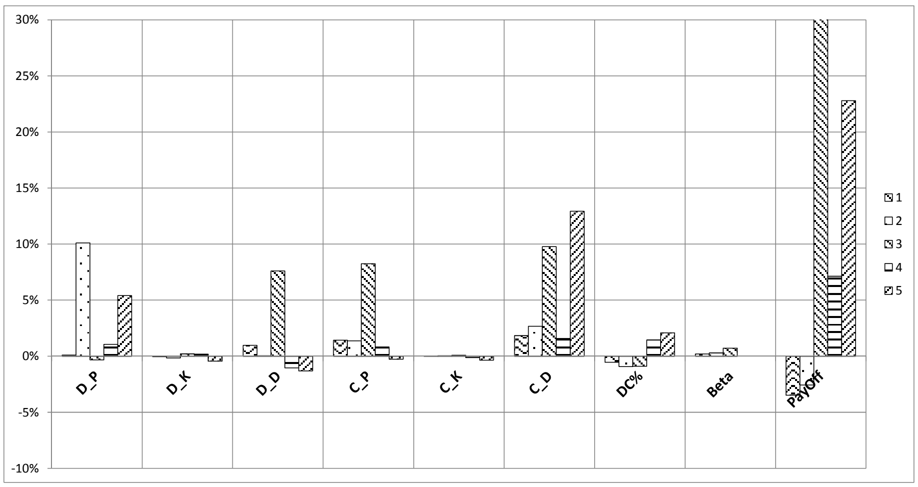

Figure 65: Error weights sensitivity analysis results

Chapter 7. Conclusion and Direction for Future Research

The proposed project supply chain model was found to be a promising tool to simulate and predict the performance of construction projects. The model has potentials to include other project factors such project size, construction type and so on. Also, the existing system dynamics project management models which have been developed with the focus on managerial factors can easily be combined with the project supply chain model to analyze the impact of decision making rules and strategies in a more realistic way.

The impact of design phase undiscovered rework on construction phase quality of work has been hypothesized as influential in project dynamics by many. However few empirical studies have measured this impact. This dissertation provided one of the first estimates for a feedback mechanism that has been hypothesized by previous researchers but has not been captured empirically yet.

Overall, it seems that BIM is contributing in design more than construction. As BIM impacts schedule performance index (Schedule PI) more than the cost performance index (Cost PI), time which is the essence of the design business is affected more than cost which controls the construction

Among all parties who are involved in the design process, architects are exploiting BIM more than the others. The MEP design also is shifting fully to BIM. Although, it seems BIM features are well-developed in structural design but surprisingly the use of BIM is rare in this discipline. The BIM-MEP is the most popular application of the BIM family of software applications in the construction activity. The interoperability of BIM and the automated manufacturing machinery has made BIM roll to the center of the mechanical sub-contractor fabrication.

Besides, construction administration is using BIM to coordinate interference of different disciplines. It prevents clash-based errors before starting the job and also reduces the number of RFIs. RFI is known as the factor that diminishes construction productivity.

The 16% improvement in the schedule performance is a significant impact on the project schedule and project administration. However, 4% cost saving in construction should not be neglected when construction management cost is almost 5% of the total contract cost. More recently, Chelson (2010) studied the effects of BIM on construction site productivity. He reported a 4 to 7% cost saving in construction. This research obtained 2 to 4% improvement in cost performance. It seems 4% construction cost saving is a reliable estimate consistent between this research and that of Chelson's.

BIM also has some disadvantages. The disadvantages of BIM utilization has not been discussed well in the literature yet. The cost was found to be the most important factor in preventing small building projects to adopt BIM. BIM is not handy to sketch new ideas. BIM software restrictions, such as lots of the data entry at the very early stage of the project when there is no information available, hassle architects to start drafting their ideas with BIM. Experience is a very subtle factor that makes utilizing BIM successful. Experience is more crucial in utilizing BIM rather than CAD software applications. The pre-defined constraints of the virtual model elements make ad hoc changes impossible in BIM software. That is the major disadvantage of BIM software applications versus CADs. The lack of adequate experience in BIM software features and functionalities make BIM a nightmare for inexperienced practitioners.

At this moment, multiuser collaboration in BIM software applications is being implemented based on file sharing techniques while the need for server-based multiuser collaboration will be felt in the near future.

AEC and BIM software developer companies are the two sectors of the construction industry, which benefit from this research outcomes. One of the applications of this research is to help the AEC company decision makers and investors to better understand the impact of the BIM utilization dynamics in terms of savings in cost and time. The model is capable of being adjusted for each AEC company based on their historical data. The model is quite flexible to consider projects with different levels of BIM utilization. For example, if only the architectural design or the MEP design is using BIM, the model is able to take these preferences into account. Besides, the model is able to not only predict the project final time and cost but also the project cost curve during the design and construction.

The other application is to help BIM software developer companies to measure the effectiveness of their solution in the construction industry business. They can use this methodology to measure the impact of their BIM software features on project performance to not only evaluate their product effectiveness on the project performance but also identify new solutions that have the most impact on the project outcomes.

The concept of utilization of system dynamics to model project supply chain is not well-developed in the literature. This research is a ground breaking study to introduce system dynamics to model project supply chain in detailed level of activities. Besides, to the author's best knowledge, this research is the first attempt to employ a model-based approach utilizing a model to represent project dynamic behaviors to analyze the impact of IT advancement in the construction industry.

Those two areas are not explored well yet. During this study, the author came across many issues and details that need to be addressed further in the future work. The main goal of this research is introducing a new methodology to approach similar problems in the construction industry research area. Addressing all those issues is out of the scope of this study. However, these areas are opportunities for the people who are interested in this type of research in the future.

There are many characteristics and features such as project size, location, complexity, contract type and delivery method as well as the parties' performance and business size, that have not been considered in the project model due to lack of data. However, project parameters such as production rate (P), coefficient of change (Kc) and time to detect undiscovered change (D) are the aggregation of those factors in the most compacted way. Analyzing the impact of those factors on the project parameters would be a very exciting topic of research.

There are several hypotheses about how the design and construction processes interact in a construction project. This research adopted the scenario of "the undiscovered change in design affects the construction quality of work" which has been studied by some researchers. Other scenarios can be identified, analyzed and tested for future research.

Utilizing causal model built by expert elicitation technique was found to be a very useful tool to understand the underlying causes and the problem structure at the very early stage of the research. As “hard data” (actual project data) collection is difficult and costly in the construction industry, the author believes this technique combined with the model-based approaches or even the statistical methods is going to provide a big advantage for researchers to collect data. Exploring expert elicitation method in the context of construction industry is another area for future research.

Due to lack of information, in this research production rate was assumed constant from beginning to end, which is not necessarily true in reality. In theory, production rate is a result of multiplication of the labor force and the productivity. Projects usually start with a few activities. Their Gantt chart schedules get expanded in the middle of the projects and slim down at the end. This feature causes the labor force resource allocation to behave as a bell-shaped curve. Considering this matter into account would be a good study to improve the project supply chain model concept.

The author found that scope cut and scope change by unforeseen conditions are different, in terms of their driving causes, from other changes initiated by A/E designer and constructor to improve defected jobs caused by negligence or availability of new opportunity. Due to lack of detailed information and sufficient number of projects, this study was not able to address this issue. A future study to model unforeseen scope changes using a different concept instead of the coefficient of change (Kc) is also a fruitful area of research.

In this research, it was assumed that time saving and error reduction corresponds to BIM user who has enough experience working with the software. Enough experience is defined as 1) the user knows which feature is appropriate for what purposes, and 2) the user is aware of how to use the feature in an efficient way. As the utilization of BIM technology is new in the AEC industry, there are evidences that suggest the experience of the user to use BIM in an efficient way is sometimes the big issue in BIM utilization success. BIM user experience can be integrated into the BIM impact causal model. This is yet another area for future research.

Appendix A: Expert responses

Seq	Expert	Scope	Cause	Time saving %	Error reduction %
1	2	Arch	3D interface	0.01	0.01
2	2	Arch	3D to 2D	0.10	0.05
3	2	Arch	Clashes	0.20	0.40
4	2	Arch	Change Mgmt.	0.10	0.05
5	2	MEP	3D interface	0.01	0.01
6	2	MEP	3D to 2D	0.10	0.05
7	2	MEP	Clashes	0.10	0.20
8	2	MEP	IFC	0.15	0.20
9	2	MEP	Change Mgmt.	0.10	0.20
10	3	Arch	3D interface	0.01	0.01
11	3	Arch	3D to 2D	0.10	0.10
12	3	Arch	Clashes	0.30	0.50
13	3	Arch	Change Mgmt.	0.05	0.10
14	3	MEP	3D interface	0.01	0.01
15	3	MEP	3D to 2D	0.10	0.10
16	3	MEP	Clashes	0.20	0.20
17	3	MEP	IFC	0.30	0.30
18	3	MEP	Change Mgmt.	0.05	0.20
19	4	Arch	3D interface	0.05	0.05
20	4	Arch	3D to 2D	0.20	0.10
21	4	Arch	Clashes	0.20	0.50
22	4	Arch	Change Mgmt.	0.05	0.05
23	5	Shop	3D interface	0.05	0.05
24	5	Shop	3D to 2D	0.20	0.20
25	5	Shop	Clashes	0.20	0.20
26	5	Shop	Change Mgmt.	0.10	0.10
27	5	Shop	IFC	0.15	0.20
28	6	MEP	3D interface	0.05	0.05
29	6	MEP	3D to 2D	0.20	0.10
30	6	MEP	Clashes	0.10	0.20
31	6	MEP	IFC	0.20	0.30
32	6	MEP	Change Mgmt.	0.10	0.10
33	7	Shop	3D interface	0.01	0.01
34	7	Shop	3D to 2D	0.20	0.30
35	7	Shop	Clashes	0.30	0.20
36	7	Shop	Change Mgmt.	0.10	0.10
37	7	Shop	IFC	0.30	0.30
38	8	Shop	3D interface	0.01	0.01
39	8	Shop	3D to 2D	0.10	0.20
40	8	Shop	Clashes	0.20	0.30
41	8	Shop	Change Mgmt.	0.10	0.20
42	8	Shop	IFC	0.20	0.30
43	9	Arch	3D interface	0.05	0.05
44	9	Arch	3D to 2D	0.20	0.20
45	9	Arch	Clashes	0.20	0.40
46	9	Arch	Change Mgmt.	0.10	0.20
47	10	Shop	3D interface	0.10	0.10
48	10	Shop	3D to 2D	0.20	0.20
49	10	Shop	Clashes	0.30	0.50
50	10	Shop	Change Mgmt.	0.10	0.20
51	10	Shop	IFC	0.10	0.10

Seq	Expert	Scope	Importance%
1	2	Arch-Inf	0.400
2	3	Arch-Inf	0.500
3	2	MEP-Inf	0.200
4	3	MEP-Inf	0.150
5	8	Shop-Inf	0.150
6	10	Shop-Inf	0.100

Appendix B: Generating correlated random parameters

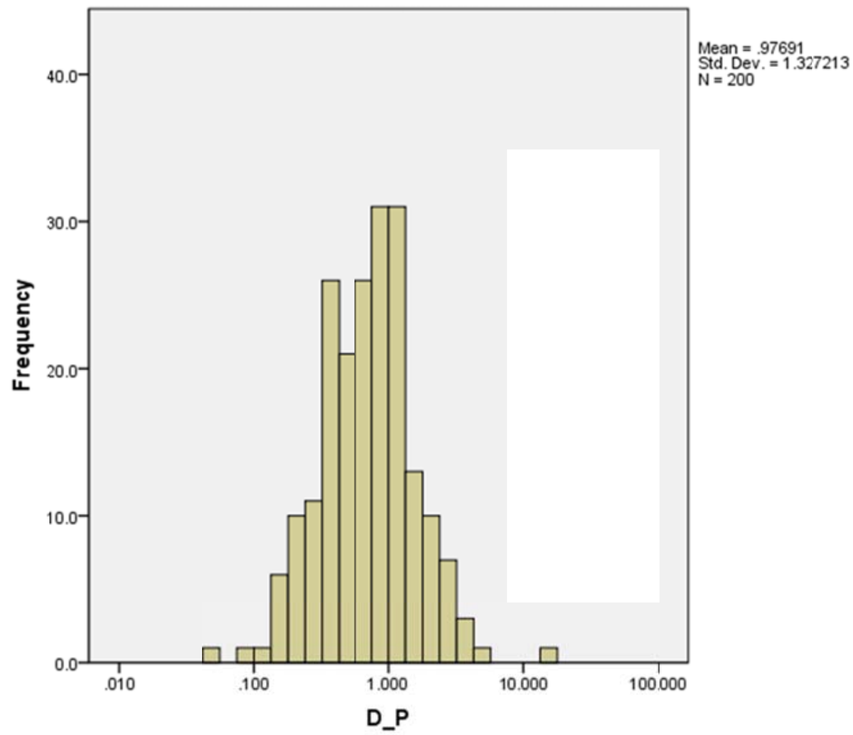

Figure 66.1: Distribution of 200 random samples of the design production rate parameter (D_P).

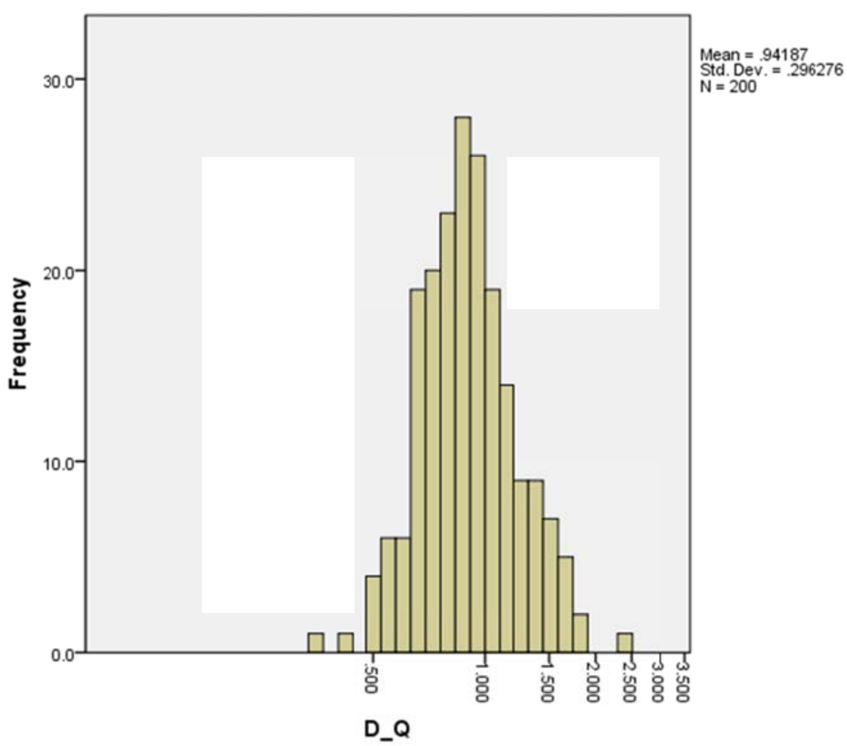

Figure 66.2: Distribution of 200 random samples of the design quality of work parameter (D_Q).

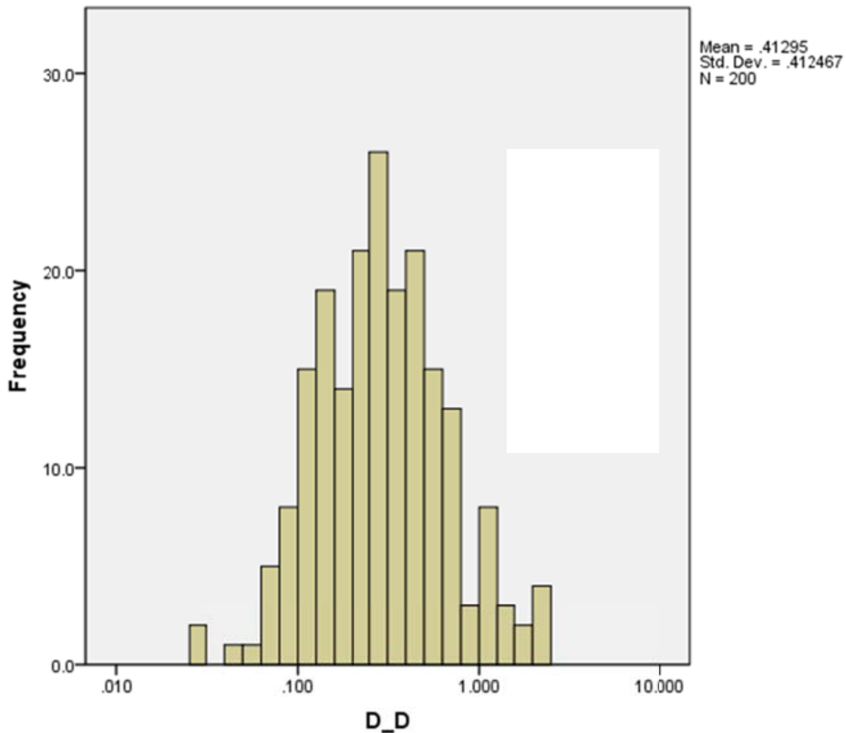

Figure 66.3: Distribution of 200 random samples of the design time to detect rework (D_D).

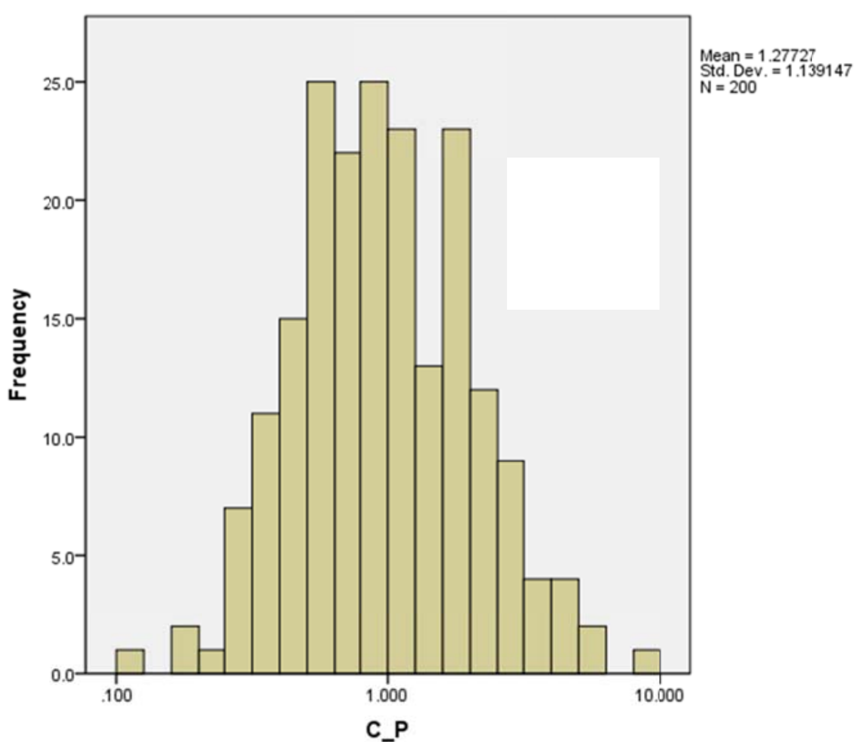

Figure 66.4: Distribution of 200 random samples of the construction production rate (C_P).

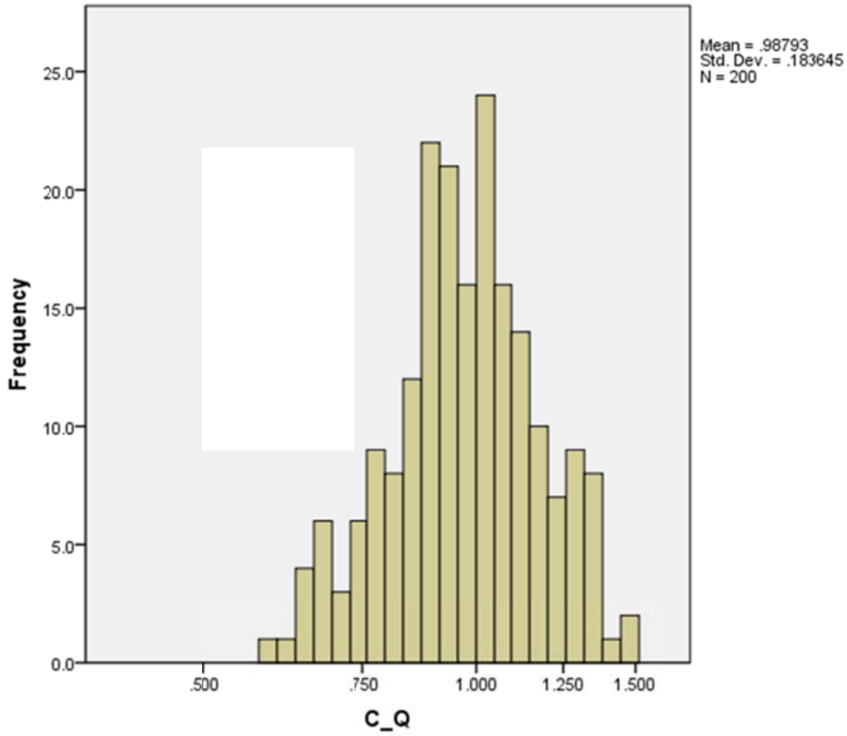

Figure 66.5: Distribution of 200 random samples of the construction quality of work (C_Q).

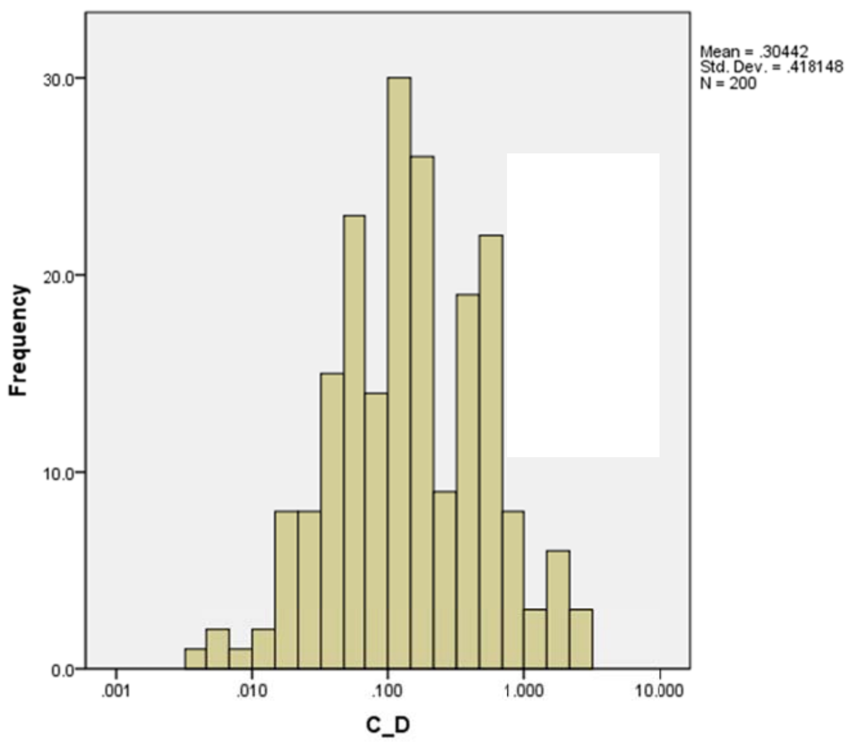

Figure 66.6: Distribution of 200 random samples of the construction time to detect rework (C_D).

Figure 66: Distributions of the random project parameters (sample size=200)

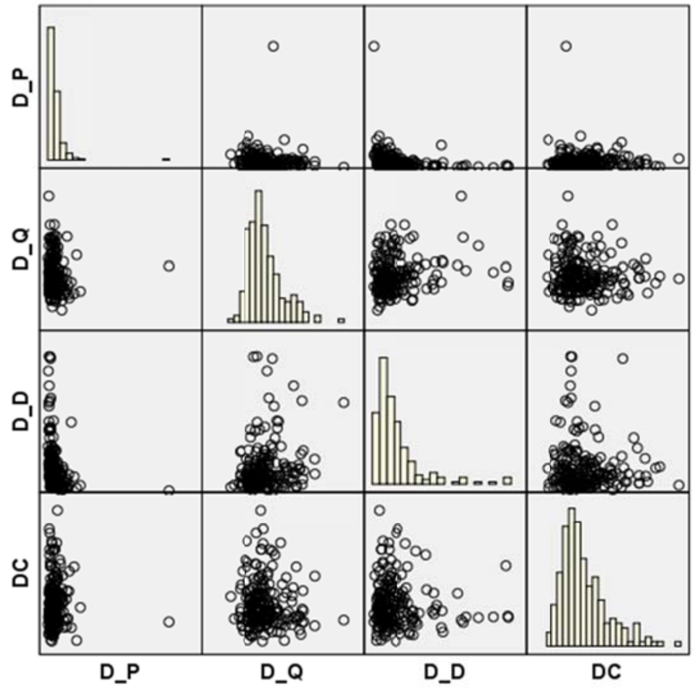

Figure 67: Matrix scattered diagram of the random parameters, Design

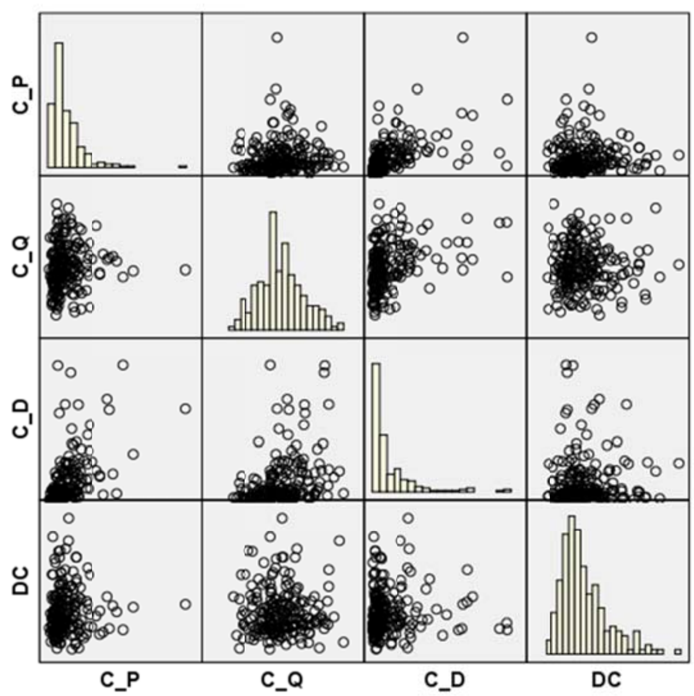

Figure 68: Matrix scattered diagram of the random parameters, Construction

Appendix C: Simulation Model Formulation in Vensim

This appendix includes the model definition in Vensim 5.8 script language.

Model Inputs

```
"Design>W0"[project]
"Design>T0"[project]
"Construction>W0"[project]
"Construction>T0"[project]
"Design>Start"[project]
```

Parameters

Project-specific parameters

- Design

```
"Design>P"[project]
"Design>Kc"[project]
"Design>TDUC"[project]
"Design>ActualCompletionToStartConstuction"[project]
```

- Construction

```
"Construction>P"[project]
"Construction>Kc"[project]
"Construction>TDUC"[project]
```

Industry parameter

```
"FA>P1"
```

Normalized project parameters

```
"Design>Norm P"[project]

"Design>Norm TDUC"[project]

"Construction>Norm P"[project]

"Construction>Norm TDUC"[project]


"Design>P"[project]="Design>Norm
     P"[project]*"Design>W0"[project]/"Design>T0"[proj
     ect]

"Design>TDUC"[project]="Design>Norm
     TDUC"[project]*"Design>T0"[project]

"Construction>P"[project]="Construction>N
     P"[project]*"Construction>W0"[project]/"Construct
     ion>T0"[project]

"Construction>TDUC"[project]="Constructon>Norm
     TDUC"[project]*"Construction>T0"[project]
```

Essential variables and equations

The design and construction change loops along with the “Factor A” relation are the main components of the model. The following list of codes describes the model equations in Vensim.

- Design

```
"Design>W"[project]=INTEG("Design>r2"[project]-
     "Design>r1"[project],"Design>W0"[project])

"Design>A"[project]=INTEG("Design>(Kc)r1"[project],0)

"Design>UC"[project]=INTEG("Design>(1-Kc)r1"[project]-
     "Design>r2"[project],0)

"Design>r1"[project]="Design>P"[project]*"Design
     Active"[project]*IF THEN
     ELSE("Design>W"[project]>0, 1 , 0)

"Design>(Kc)r1"[project]="Design>r1"[project]*"Design>
     Kc"[project]
```

```
"Design>(1-Kc)r1"[project]="Design>r1"[project]*(1-
     "Design>Kc"[project])

"Design>r2"[project]="Design>UC"[project]/"Design>TDUC
     "[project]

"Design>Norm UC"[project]=Abs("Design>UC"[project])/
     "Design>W0"[project]
```

- Construction

```
"Construction>W"[project]=INTEG("Construction>r2"[proj
     ect]-
     "Construction>r1"[project],"Construction>W0"[proj
     ect])

"Construction>A"[project]=INTEG("Construction>(Kc)r1"[
     project],0)

"Construction>UC"[project]=INTEG("Construction>(1-
     Kc)r1"[project]-"Construction>r2"[project],0)

"Construction>r1"[project]="Construction>P"[project]*"
     Construction Active”[project]*IF THEN
     ELSE("Construction>W"[project]>0, 1 , 0)

"Construction>(Kc)r1"[project]="Construction>r1"[proje
     ct]*"Construction>Kc"[project]

"Construction>(1-
     Kc)r1"[project]="Construction>r1"[project]*(1-
     "Construction>Kc"[project])

"Construction>r2"[project]="Construction>UC"[project]/
     "Construction>TDUC"[project]
```

- Factor A

```
Factor A[project]=1/(1+"Design>Norm
     UC"[project])^"FA>P1"
```

Auxiliary variables and equations.

```
"Design>Work
     done"[project]=INTEG("Design>r1"[project],0)

"Design>Perceived Completion"[project]= "Design>Work
     done"[project]/"Design>W0"[project]



"Construction>Work
     done"[project]=INTEG("Construction>r1"[project],0
     )
```

```
"Construction>Perceived
     Completion"[project]="Construction>Work
     done"[project]/"Construction>W0"[project]
```

Control variables

The events such as "Design Finish" and "Construction Start" are essential elements in the SD models. The control variables are used to trigger and handle the events.

- Design control variables

```
Design Active[project]=  IF THEN ELSE(Time <
     "Design>start"[project], 0, IF THEN ELSE(
     "Design>Actual Completion"[project]>0.99 :AND:
     "Design>Rework Gap"[project]<=0.01, 0, 1))

"Design>Actual
     Completion"[project]="Design>A"[project]/"Design>
     W0"[project]

"Design>Rework
     Gap"[project]=Abs("Design>UC"[project]/"Design>W0
     "[project])
```

- Construction control variables

```
Construction Active[project]= IF THEN
     ELSE(Time<"Construction>start"[project], 0, IF
     THEN ELSE("Construction>Actual
     Completion"[project]>0.99 :AND:
     "Construction>Rework Gap"[project]<=0.01, 0, 1))

"Construction>Actual
     Completion"[project]="Construction>A"[project]/"C
     onstruction>W0"[project]

"Construction>Rework
     Gap"[project]=Abs("Construction>UC"[project]/"Con
     struction>W0"[project])
```

Outputs

- Design outputs

```
"D>EndT"[project]=INTEG("D>ChEndT"[project],0)

"D>ChEndT"[project]=IF THEN ELSE((("Design>Actual
     Completion"[project]>0.99 :AND: "Design>Rework
     Gap"[project]<=0.01) :OR: Time=FINAL TIME-TIME
     STEP) :AND: "D>EndT"[project]=0,Time/TIME STEP,0)
```

```
"Design>CO"[project]=INTEG("Design>r2"[project],0)
```

- Construction outputs

```
"C>EndT"[project]=INTEG("C>ChEndT"[project],0)

"C>ChEndT"[project]=IF THEN
     ELSE((("Construction>Actual
     Completion"[project]>0.99 :AND:
     "Construction>Rework Gap"[project]<=0.01) :OR:
     Time=FINAL TIME-TIME STEP) :AND:
     "C>EndT"[project]=0,Time/TIME STEP,0)

"Construction>CO"[project]=INTEG("Construction>r2"[pro
     ject],0)
```

Appendix D: Calibration Model Formulation in Vensim

This appendix includes the calibration model definition in Vensim 5.8 script language.

Objective function

```
Payoff = "D>Total POE"[project] + "C>Total
     POE"[project]

"D>Total POE"[project]=("D>POE
     T"[project]*"D>WeightErrorT"+"D>POE
     CO1"[project]*"D>WeightErrorCO1"+"D>POE
     CO2"[project]*"D>WeightErrorCO2")*"D>WeightError"

"C>Total POE"[project]=("C>POE
     T"[project]*"C>WeightErrorT"+"C>POE
     CO1"[project]* "C>WeightErrorCO1" +"C>POE
     CO2"[project]*
     "C>WeightErrorCO2")*"C>WeightError"
```

Error Weights

- Design error weights

```
"D>WeightErrorT"= 2

"D>WeightErrorCO1"=1

"D>WeightErrorCO2"=1
```

- Construction error weights

```
"C>WeightErrorT"= 2

"C>WeightErrorCO1"=1

"C>WeightErrorCO2"=1
```

Parameter space

The calibration parameter space is a seven dimensional real space including the design and construction normalized production rate (P), coefficient of change (Kc), and the time to detect undiscovered change (TDUC) along with the industry parameter (β).

- Project parameters

```
0.1<="Design>Norm P"[project]<=10
0.1<="Design>Kc"[project]<=10
0.01<="Design>Norm TDUC"[project]<=10
0.1<="Construction>Norm P"[project]<=10
0.1<="Construction>Kc"[project]<=10
0.01<="Construction>Norm TDUC"[project]<=10
0.01<="Design>ActualCompletionToStartConstuction"[project]<=1
```

- Industry parameter

```
-10<="FA>P1"<=10
```

Inputs

- Calibration design module inputs

```
"Design>Finish"[project]
"Design>CO Total"[project]
"Design>CO TS Data"[project]
```

- Calibration construction module inputs

```
"Construction>Finish"[project]
"Construction>CO Total"[project]
"Construction>CO TS Data"[project]
```

Essential variables and equations

The essential variables are the variables incorporated to calculate the payoff function.

(1) Squared error percentage of project final time

```
"D>POE T"[project]=IF THEN
     ELSE("D>ChEndT"[project]>0,(Abs("Design>Finish"[p
     roject]-
     Time)/"Design>Finish"[project])^ErrPwr[project]/T
     IME STEP*Max(Time,"Design>Finish"[project]),0)

"C>POE T"[project]=IF THEN
     ELSE("C>ChEndT"[project]>0,(Abs("Construction>Fin
     ish"[project]-
     Time)/"Construction>Finish"[project])^ErrPwr[proj
     ect]/ TIME
     STEP*Max(Time,"Construction>Finish"[project]),0)
```

(2) Squared error percentage of project final cost change

```
"D>POE CO1"[project]=IF THEN
     ELSE("D>ChEndT"[project]>0,(XIDZ(Abs("Design>CO
     Total"[project]-
     "Design>CO"[project]),Max(Abs("Design>CO
     Total"[project]),Abs("Design>CO"[project])),0))^E
     rrPwr/TIME
     STEP*Max(Time,"Design>Finish"[project]),0)

"C>POE CO1"[project]=IF THEN
     ELSE("C>ChEndT"[project]>0,(XIDZ(Abs("Constructio
     n>CO Total"[project]-
     "Construction>CO"[project]),Max(Abs
     ("Construction>CO Total"[project]),
     Abs("Construction>CO"[project])),0))^ErrPwr[proje
     ct]/TIME
     STEP*Max(Time,"Construction>Finish"[project]),0)
```

(3) SEP of the project cost change behavior

```
"D>POE CO2"[project]=(XIDZ(Abs("Design>CO TS
     Data"[project]-
     "Design>CO"[project]),"D>MaxCO"[project],0))^ErrP
     wr*IF THEN
     ELSE(Time>Max("Design>Finish"[project],IF THEN
     ELSE("D>EndT"[project]=0, Time,
     "D>EndT"[project])),0,1)

"C>POE CO2"[project]=(XIDZ(Abs("Construction>CO TS
     Data"[project]-
     "Construction>CO"[project]),"C>MaxCO"
     [project],0))^ErrPwr[project]*IF THEN
     ELSE(Time>Max("Construction>Finish"[project],IF
     THEN ELSE("C>EndT"[project]=0, Time,
     "C>EndT"[project])),0,1)
```

Appendix E: Calibrated cost curves

The cost overrun curves of the 18 calibrated projects including: P008, P010, P011, P016, P017, P019, P021, P023, P027, P040, P054, P055, P058, P061, P062, P065, P066 and P067 are shown in series.

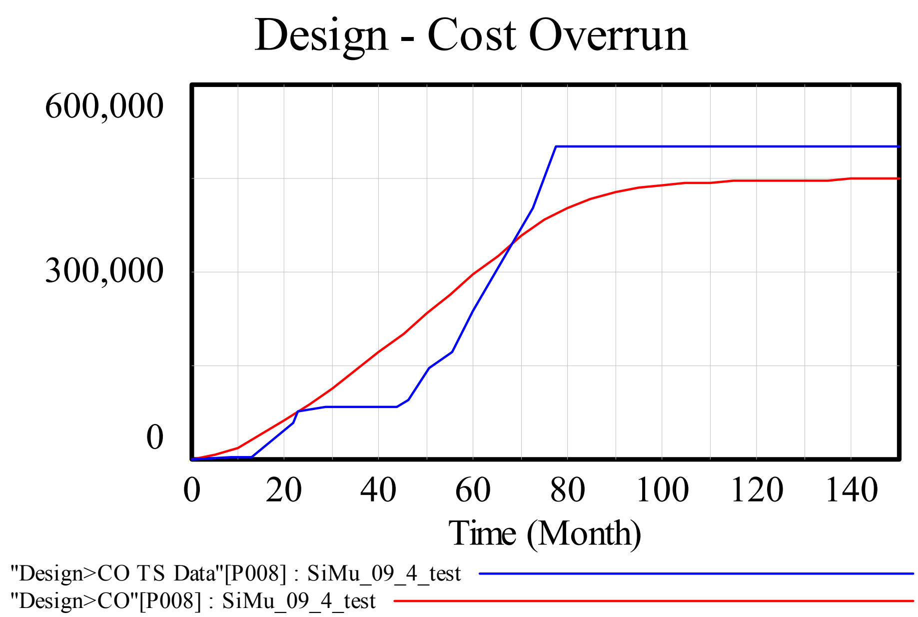

Figure 69.1: Design cost overrun, Project [P008], Actual data blue line, Simulation red line.

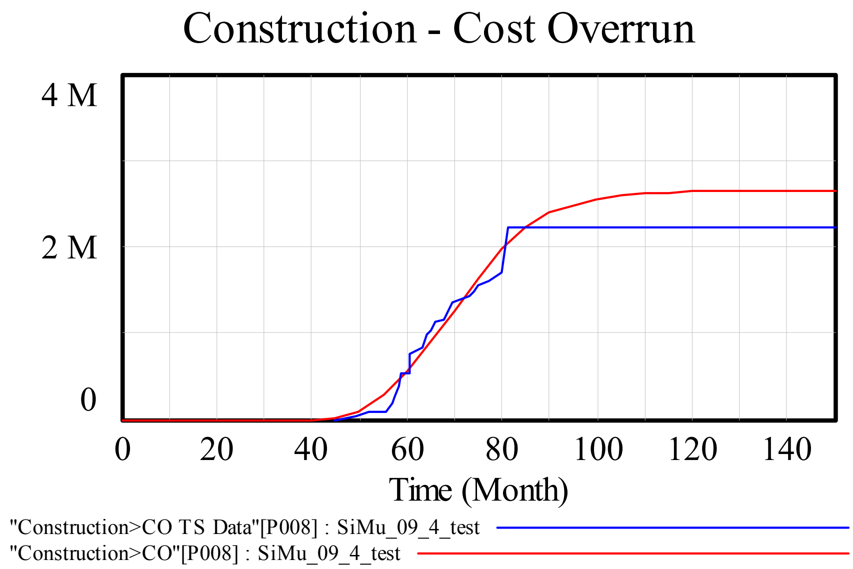

Figure 69.2: Construction cost overrun, Project [P008], Actual data blue line, Simulation red line.

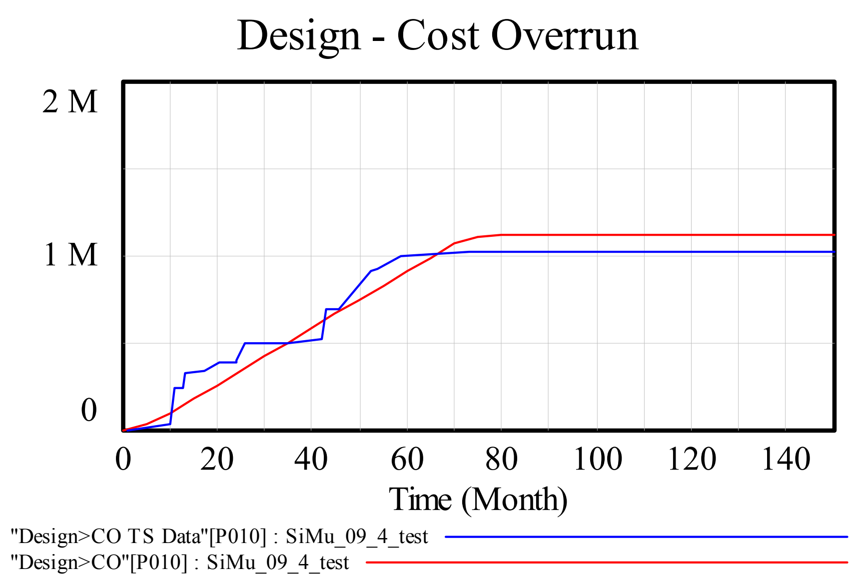

Figure 69.3: Design cost overrun, Project [P010], Actual data blue line, Simulation red line.

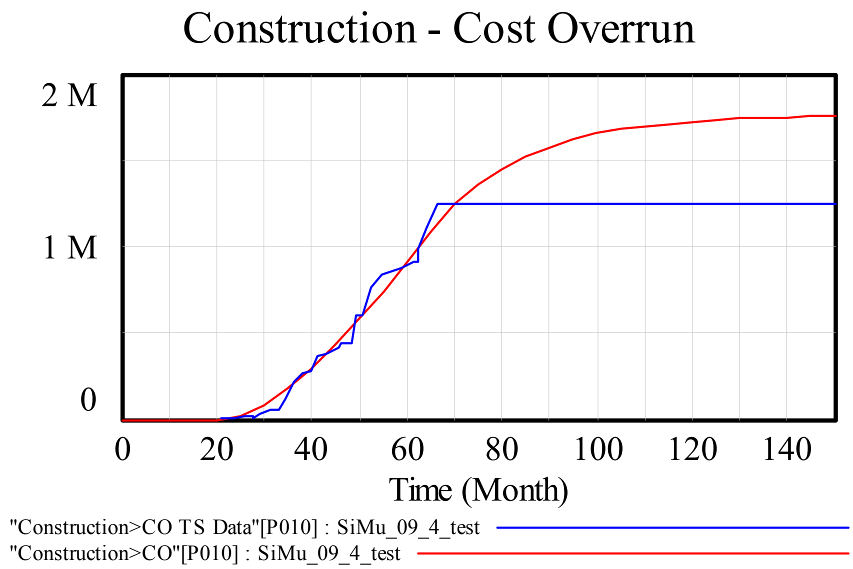

Figure 69.4: Construction cost overrun, Project [P010], Actual data blue line, Simulation red line.

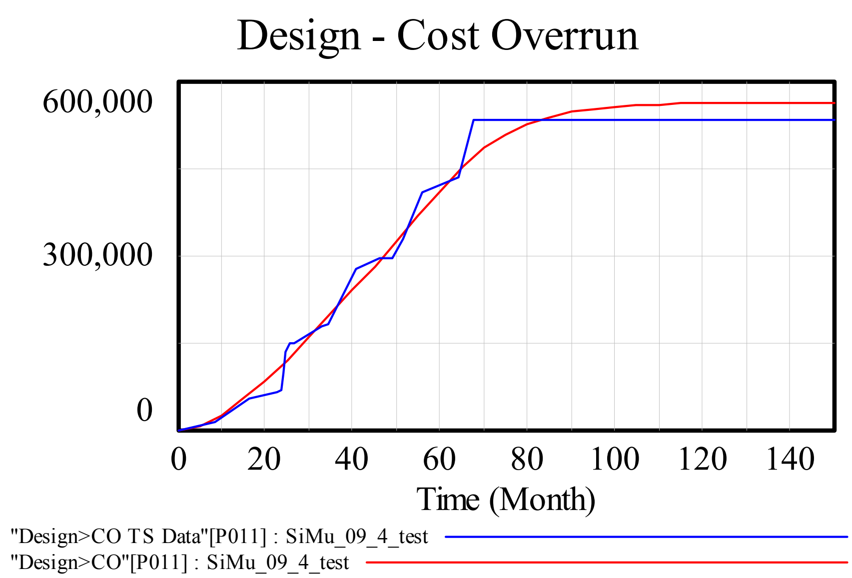

Figure 69.5: Design cost overrun, Project [P011], Actual data blue line, Simulation red line.

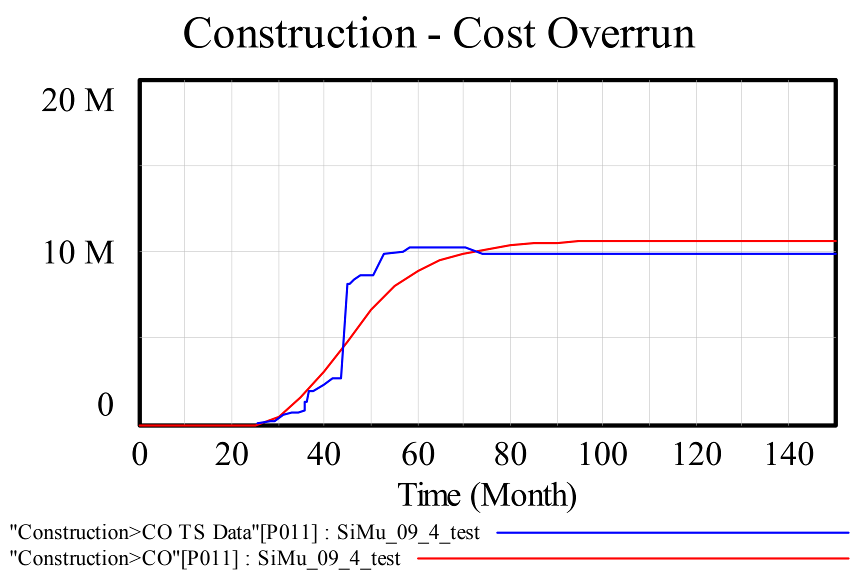

Figure 69.6: Construction cost overrun, Project [P011], Actual data blue line, Simulation red line.

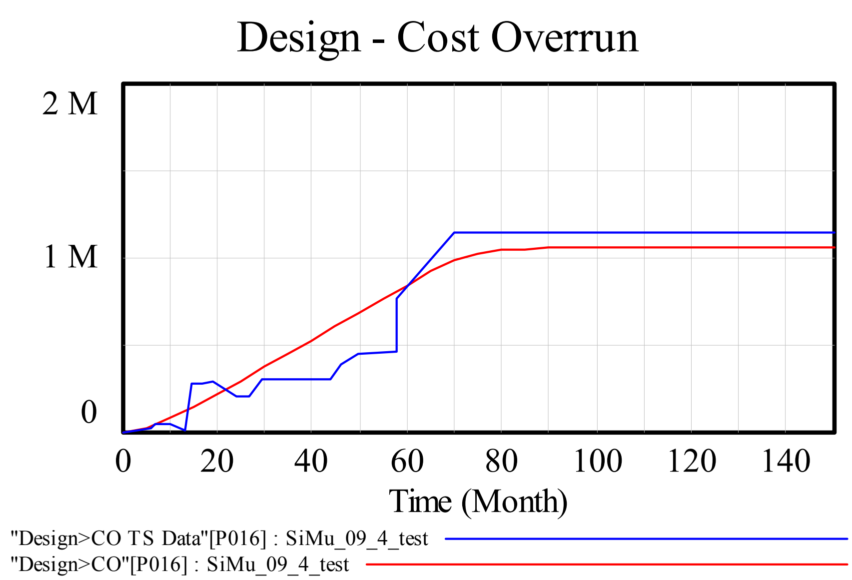

Figure 69.7: Design cost overrun, Project [P016], Actual data blue line, Simulation red line.

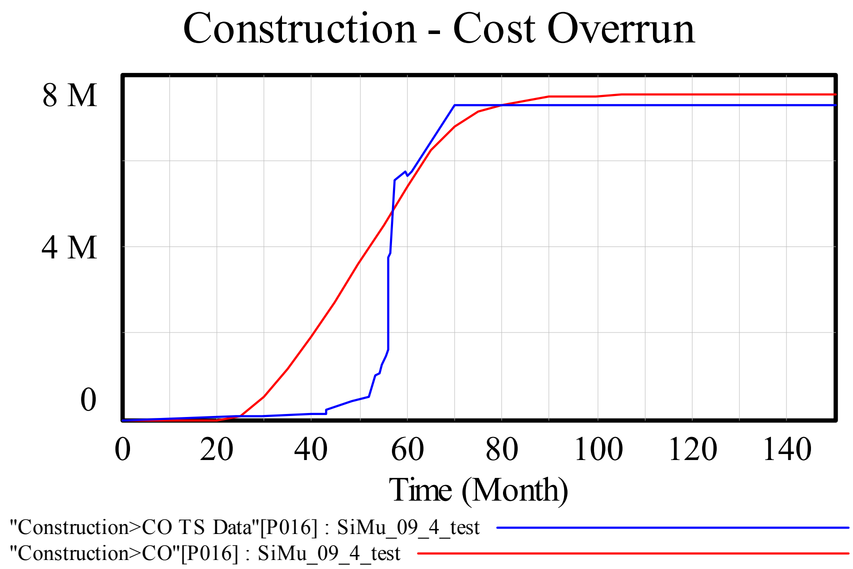

Figure 69.8: Construction cost overrun, Project [P016], Actual data blue line, Simulation red line.

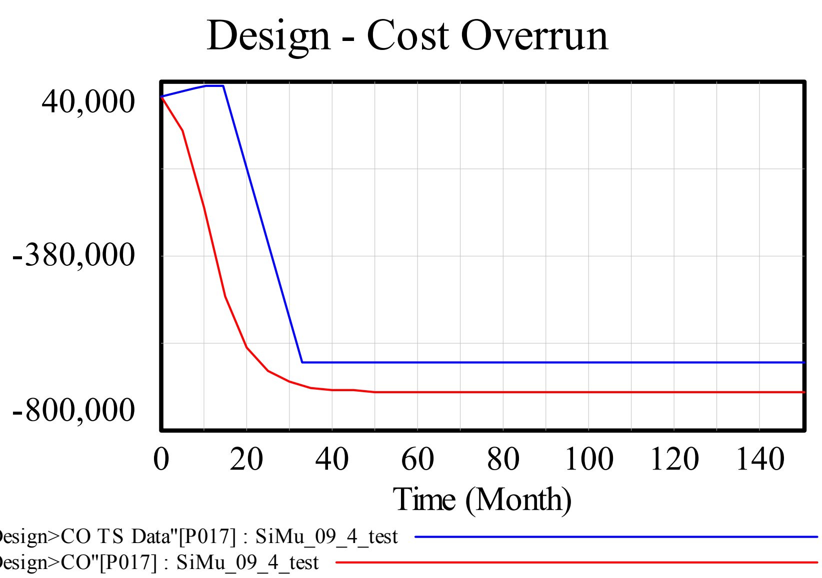

Figure 69.9: Design cost overrun, Project [P017], Actual data blue line, Simulation red line.

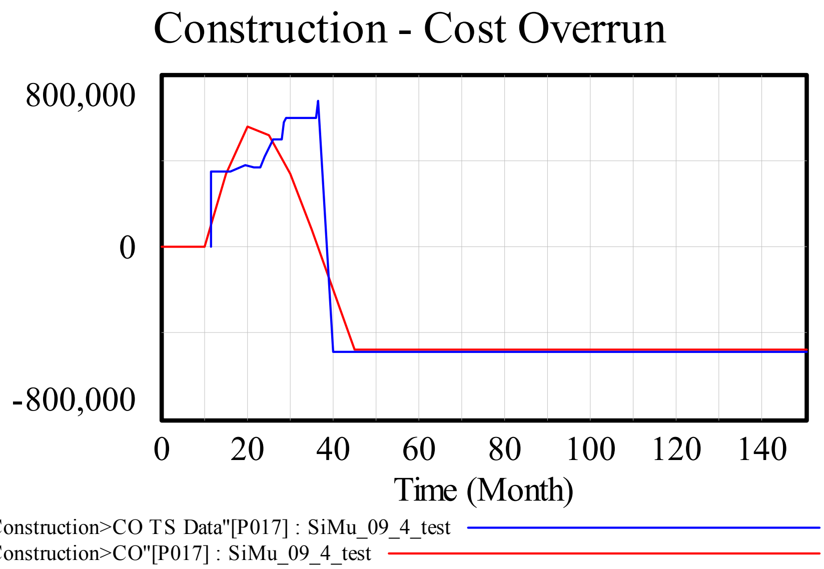

Figure 69.10: Construction cost overrun, Project [P017], Actual data blue line, Simulation red line.

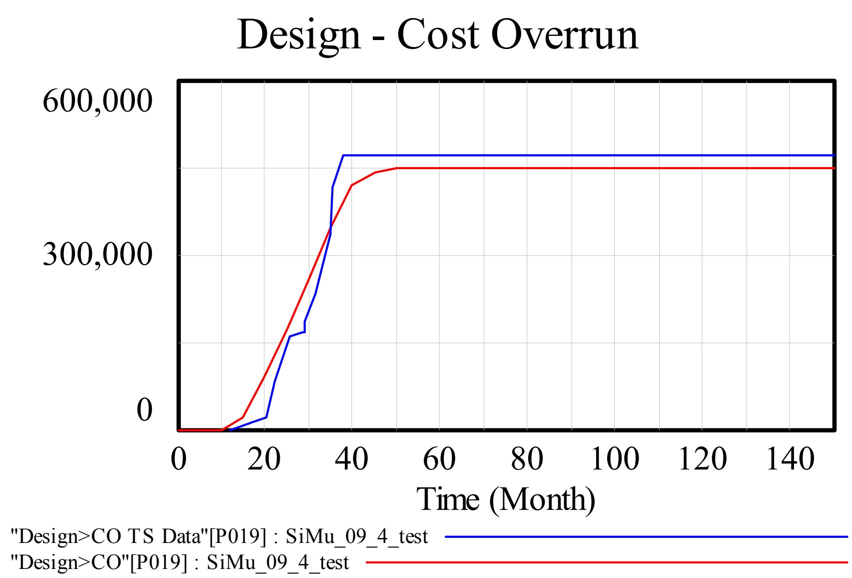

Figure 69.11: Design cost overrun, Project [P019], Actual data blue line, Simulation red line.

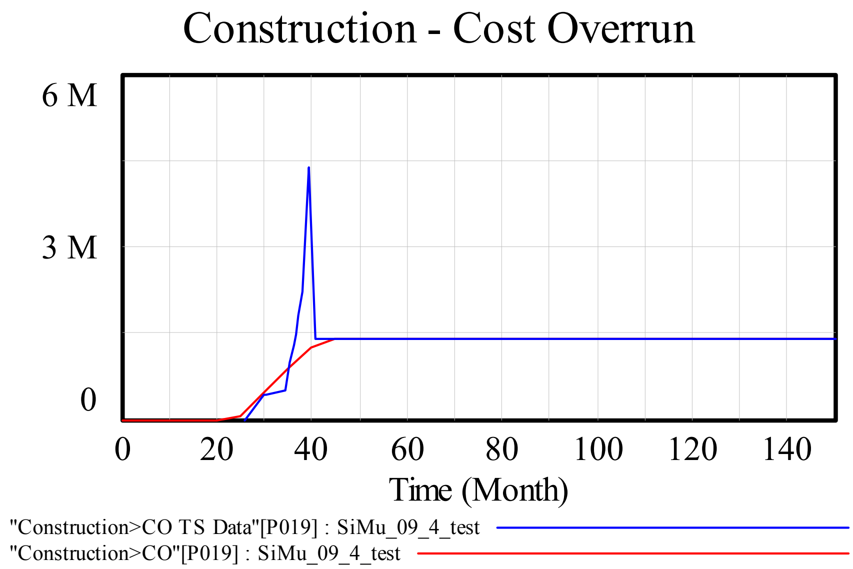

Figure 69.12: Construction cost overrun, Project [P019], Actual data blue line, Simulation red line.

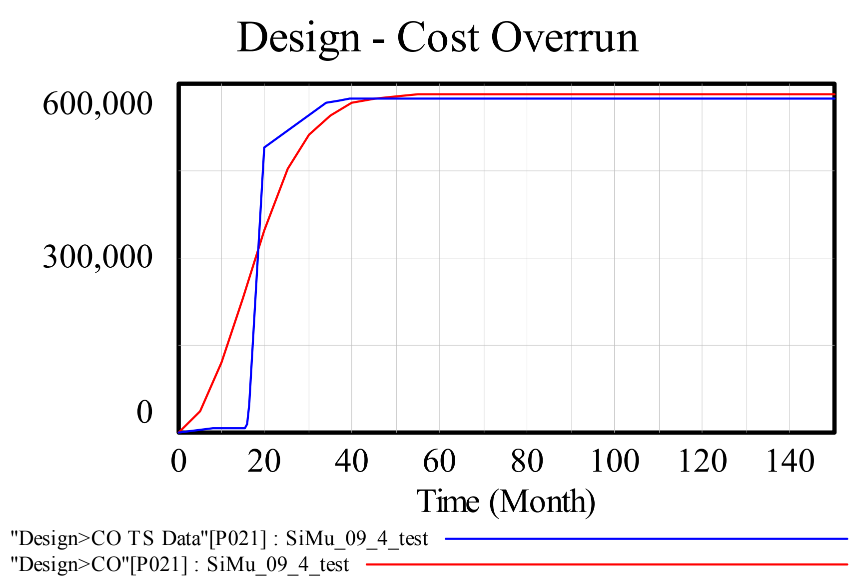

Figure 69.13: Design cost overrun, Project [P021], Actual data blue line, Simulation red line.

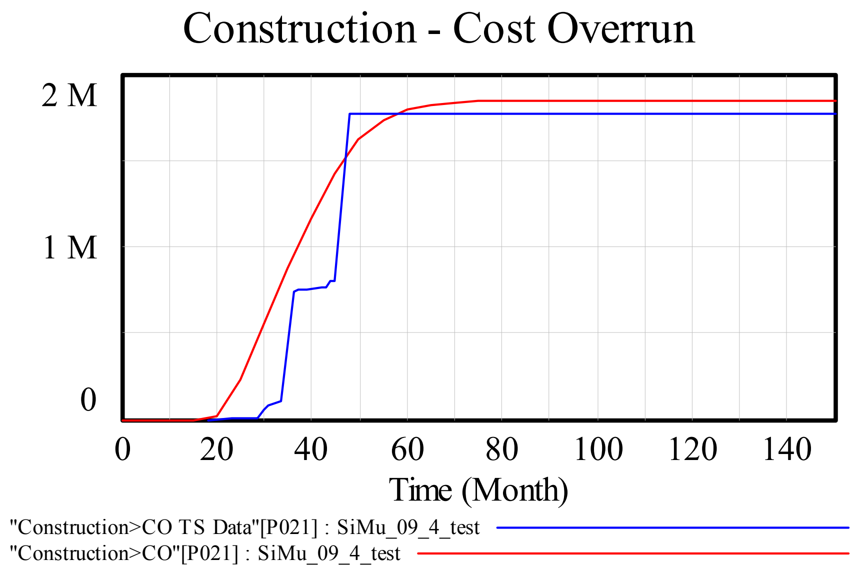

Figure 69.14: Construction cost overrun, Project [P021], Actual data blue line, Simulation red line.

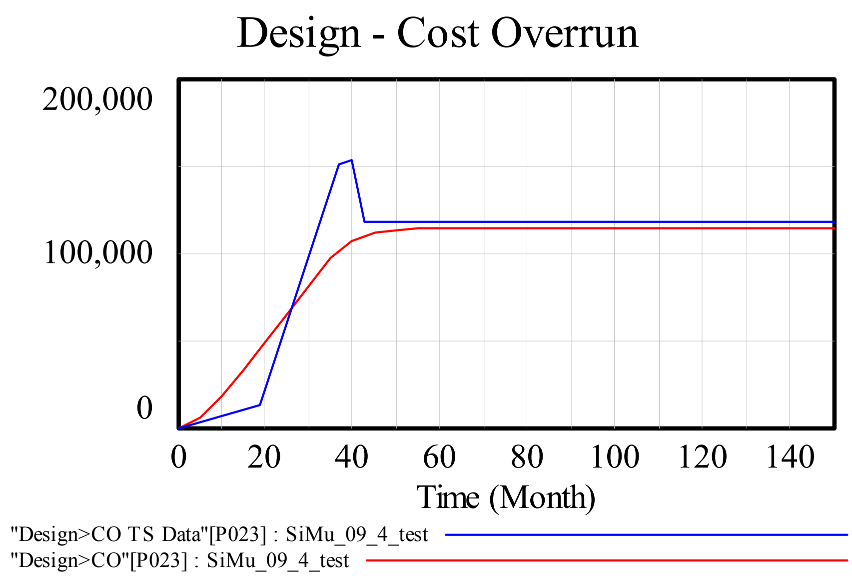

Figure 69.15: Design cost overrun, Project [P023], Actual data blue line, Simulation red line.

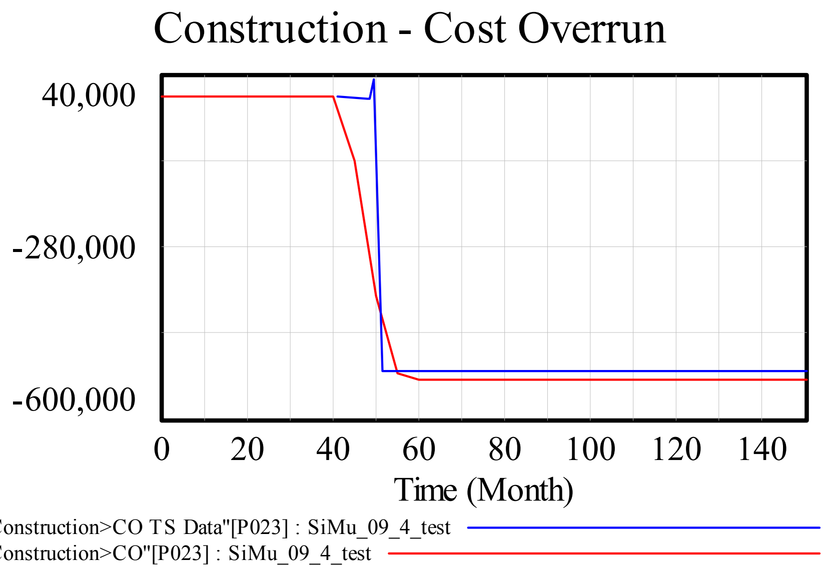

Figure 69.16: Construction cost overrun, Project [P023], Actual data blue line, Simulation red line.

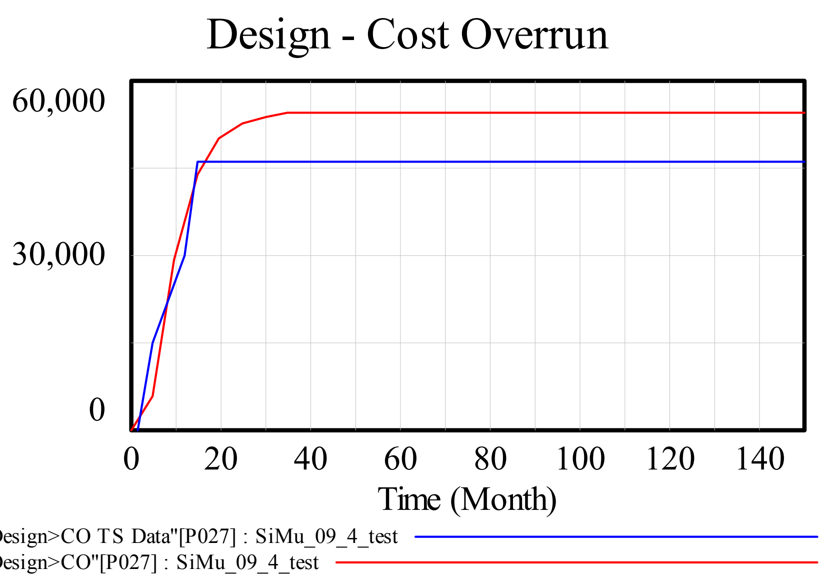

Figure 69.17: Design cost overrun, Project [P027], Actual data blue line, Simulation red line.

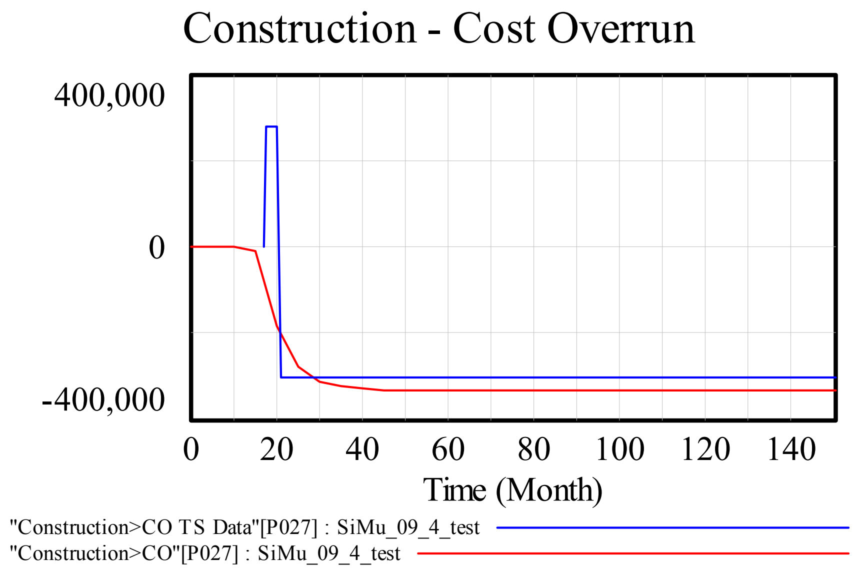

Figure 69.18: Construction cost overrun, Project [P027], Actual data blue line, Simulation red line.

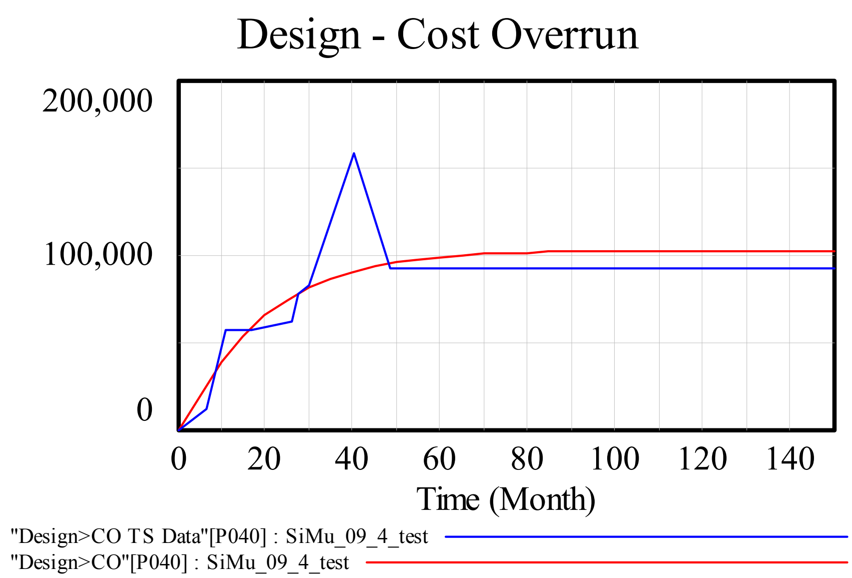

Figure 69.19: Design cost overrun, Project [P040], Actual data blue line, Simulation red line.

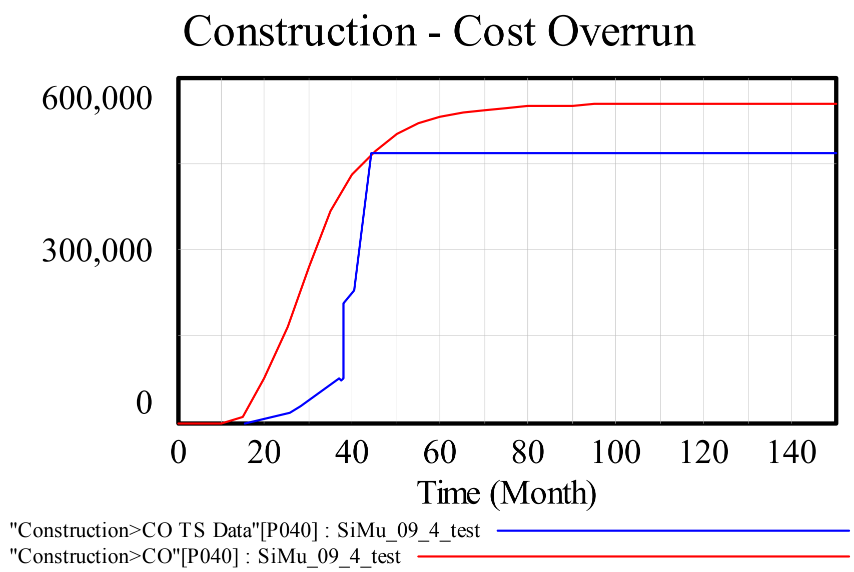

Figure 69.20: Construction cost overrun, Project [P040], Actual data blue line, Simulation red line.

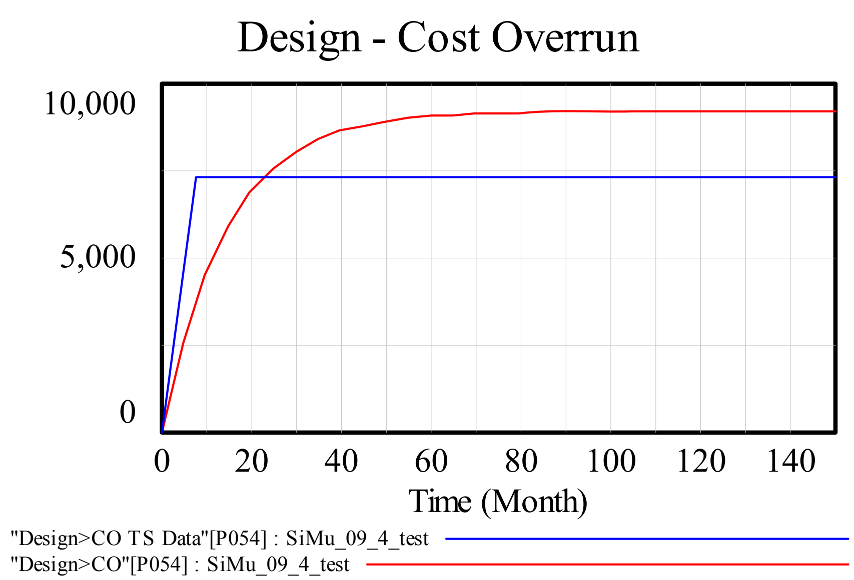

Figure 69.21: Design cost overrun, Project [P054], Actual data blue line, Simulation red line.

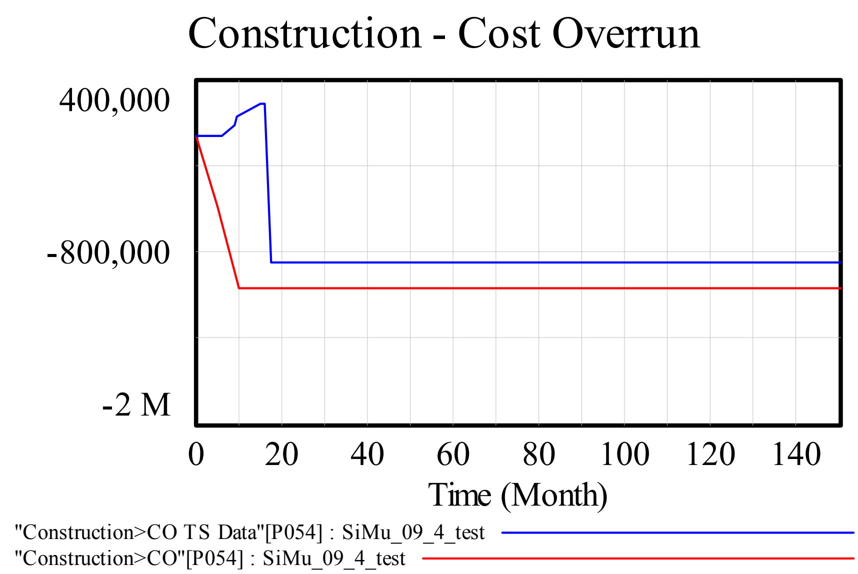

Figure 69.22: Construction cost overrun, Project [P054], Actual data blue line, Simulation red line.

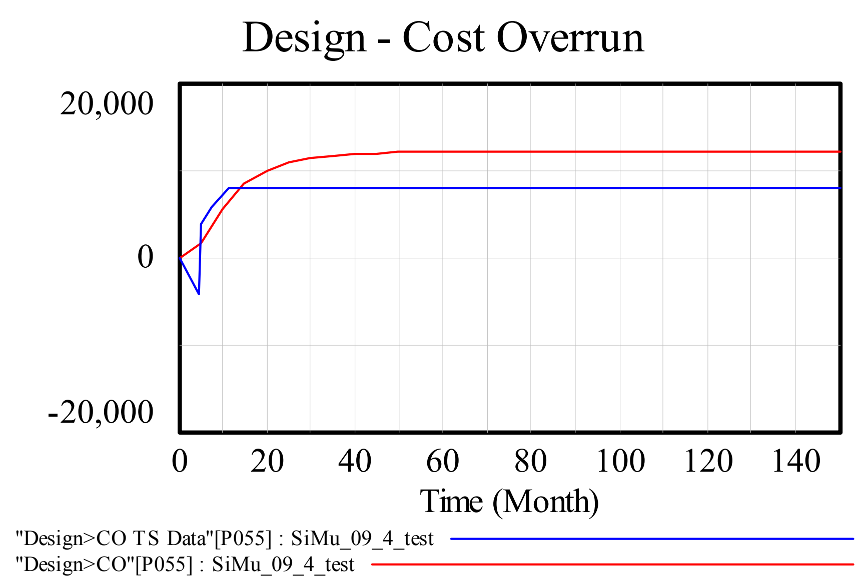

Figure 69.23: Design cost overrun, Project [P055], Actual data blue line, Simulation red line.

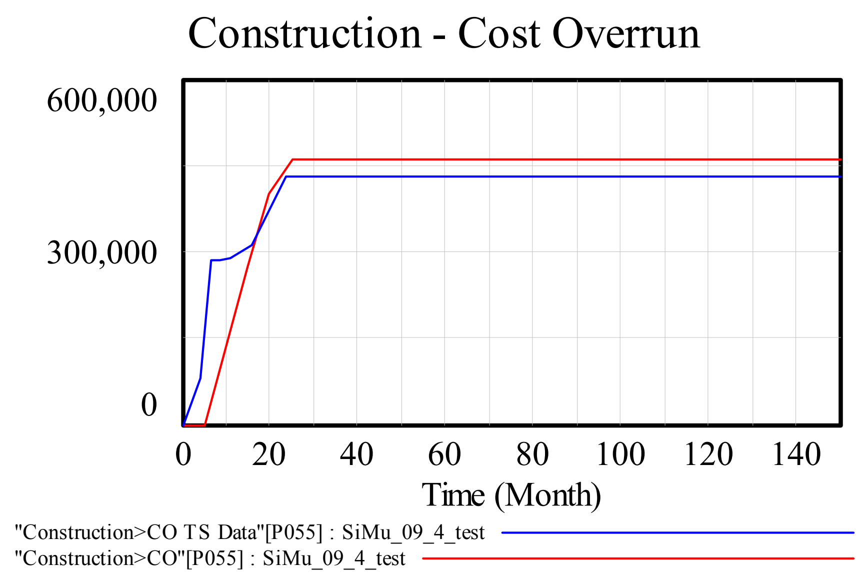

Figure 69.24: Construction cost overrun, Project [P055], Actual data blue line, Simulation red line.

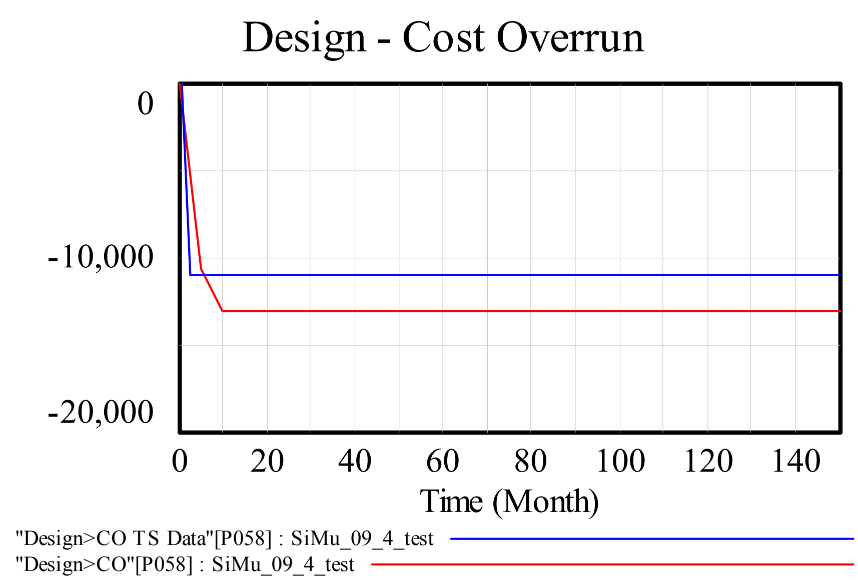

Figure 69.25: Design cost overrun, Project [P058], Actual data blue line, Simulation red line.

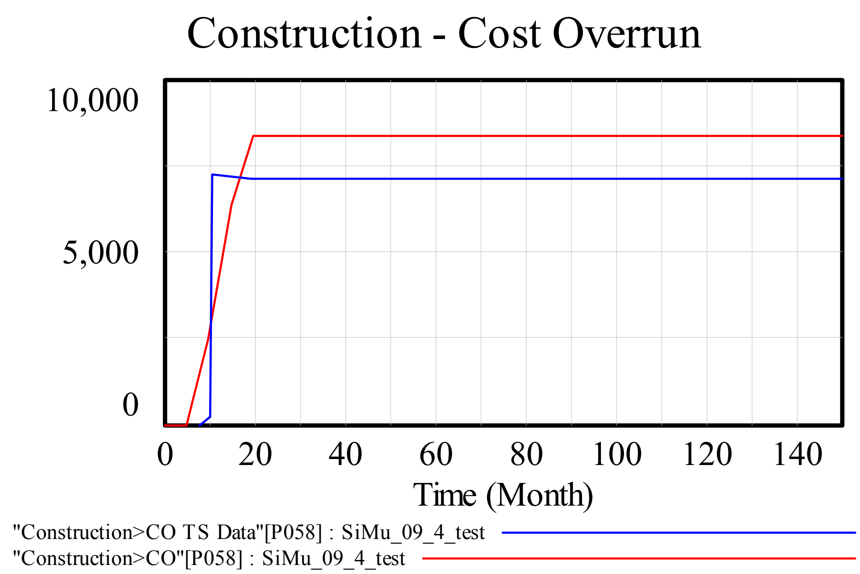

Figure 69.26: Construction cost overrun, Project [P058], Actual data blue line, Simulation red line.

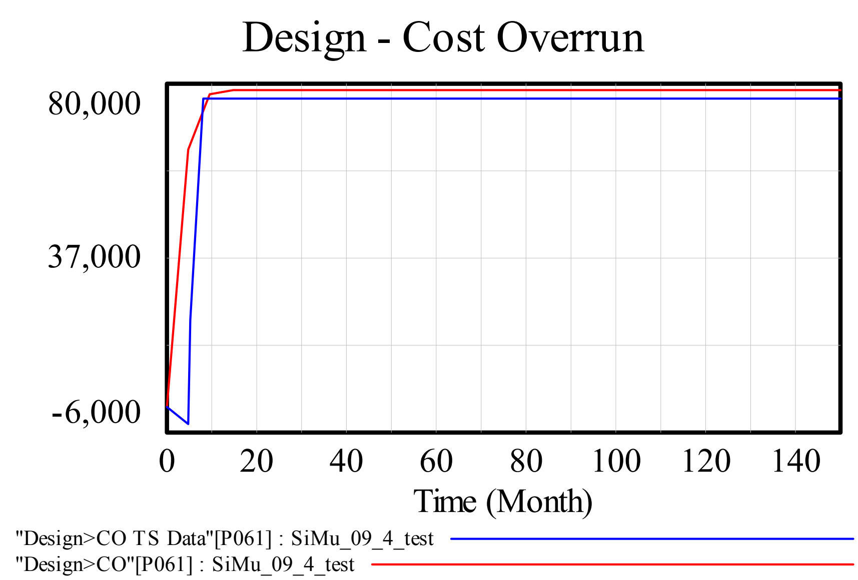

Figure 69.27: Design cost overrun, Project [P061], Actual data blue line, Simulation red line.

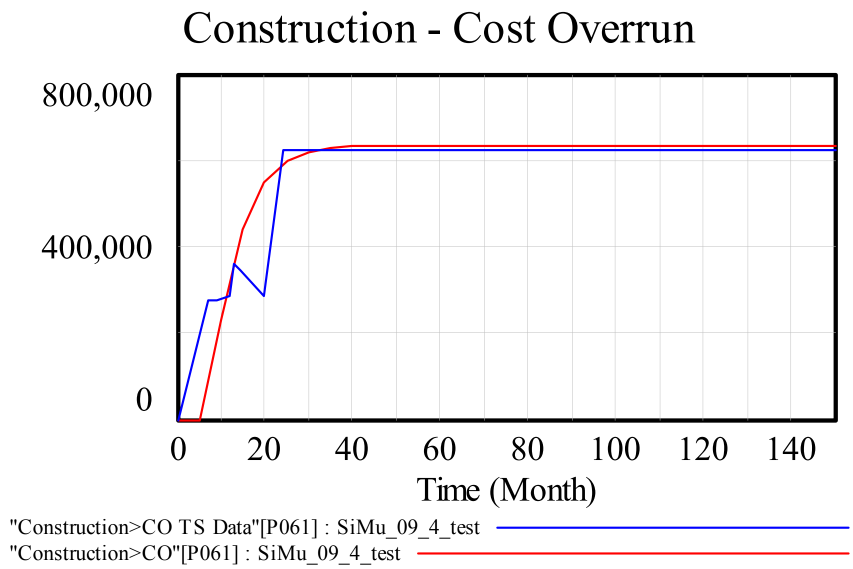

Figure 69.28: Construction cost overrun, Project [P061], Actual data blue line, Simulation red line.

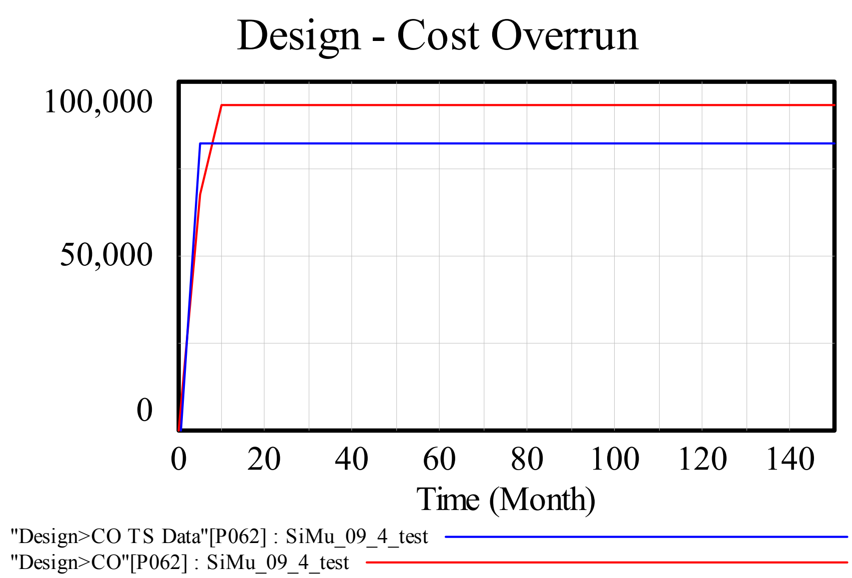

Figure 69.29: Design cost overrun, Project [P062], Actual data blue line, Simulation red line.

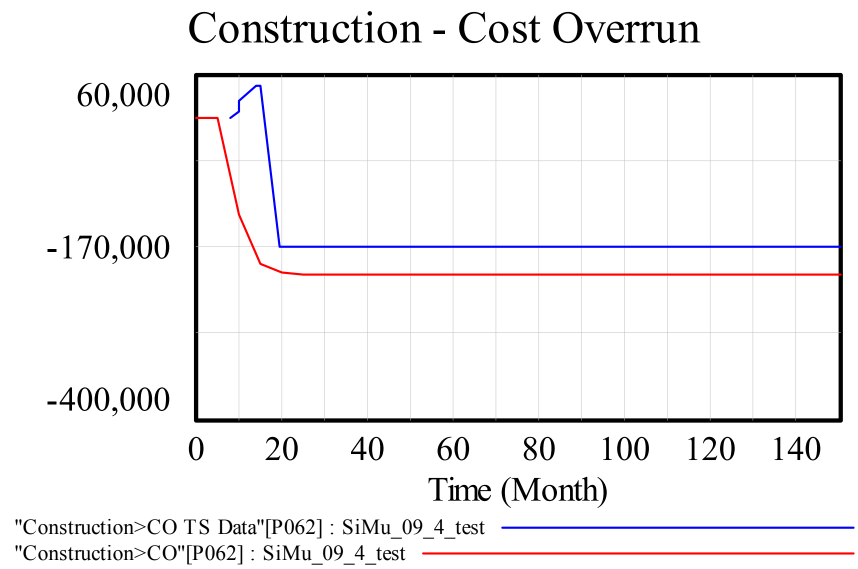

Figure 69.30: Construction cost overrun, Project [P062], Actual data blue line, Simulation red line.

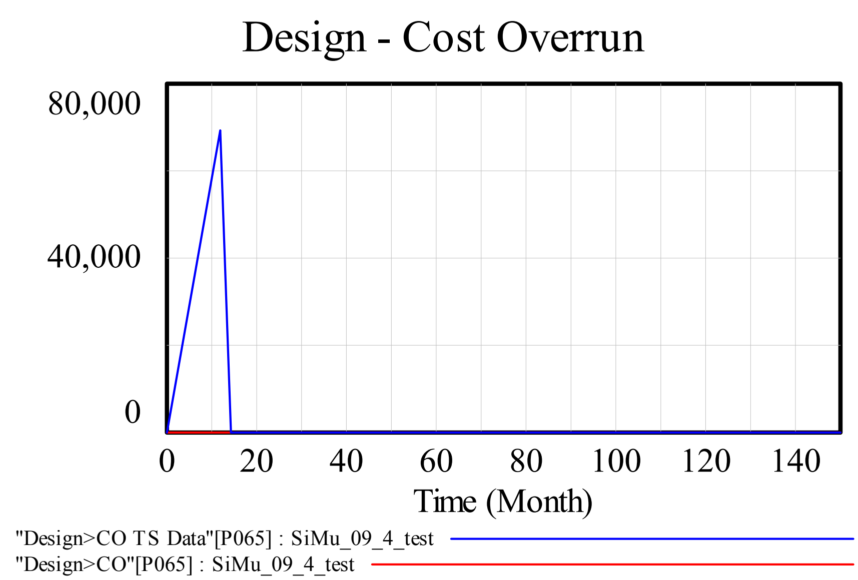

Figure 69.31: Design cost overrun, Project [P065], Actual data blue line, Simulation red line.

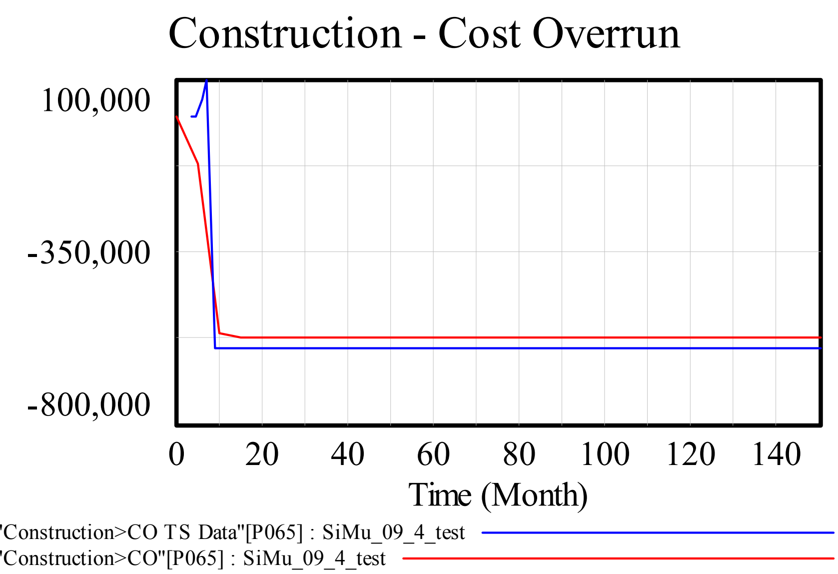

Figure 69.32: Construction cost overrun, Project [P065], Actual data blue line, Simulation red line.

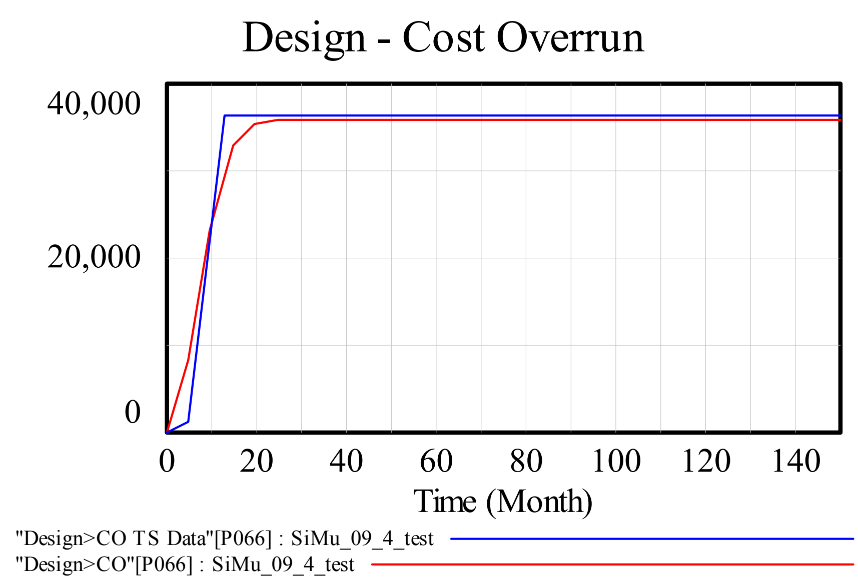

Figure 69.33: Design cost overrun, Project [P066], Actual data blue line, Simulation red line.

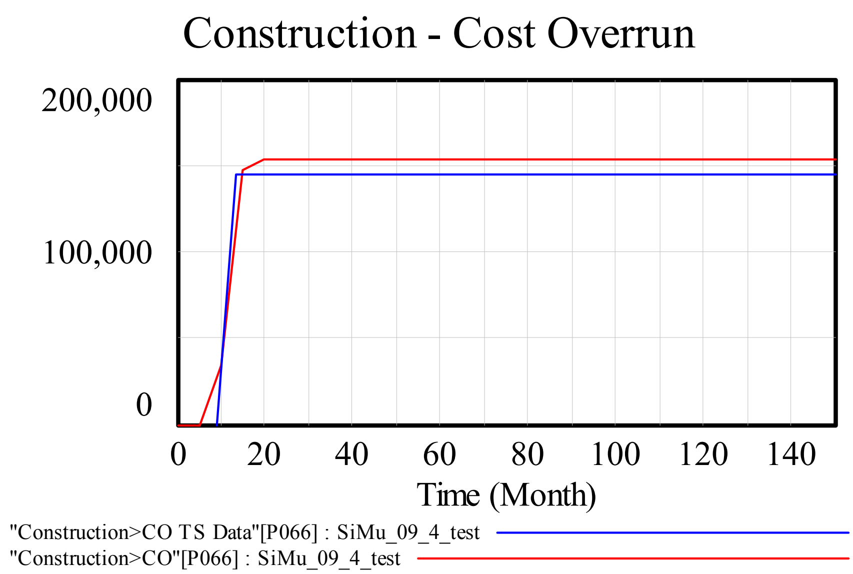

Figure 69.34: Construction cost overrun, Project [P066], Actual data blue line, Simulation red line.

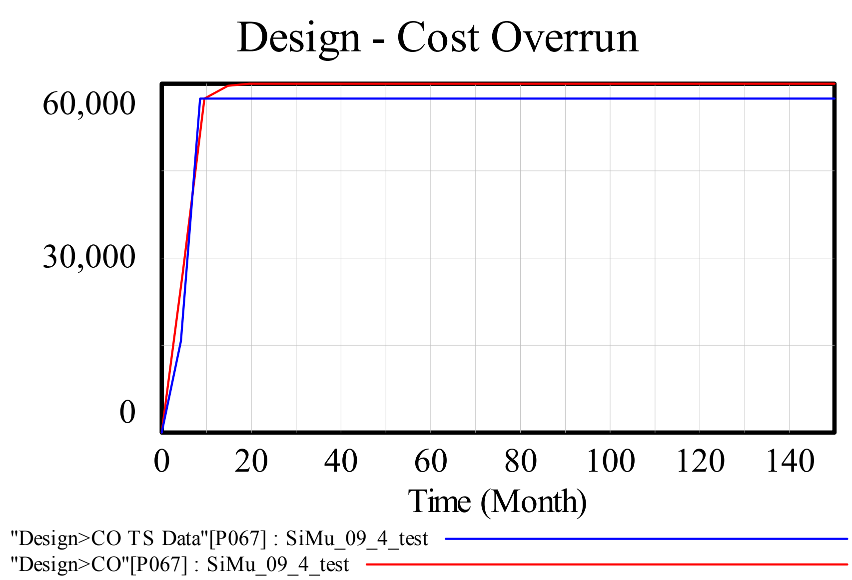

Figure 69.35: Design cost overrun, Project [P067], Actual data blue line, Simulation red line.

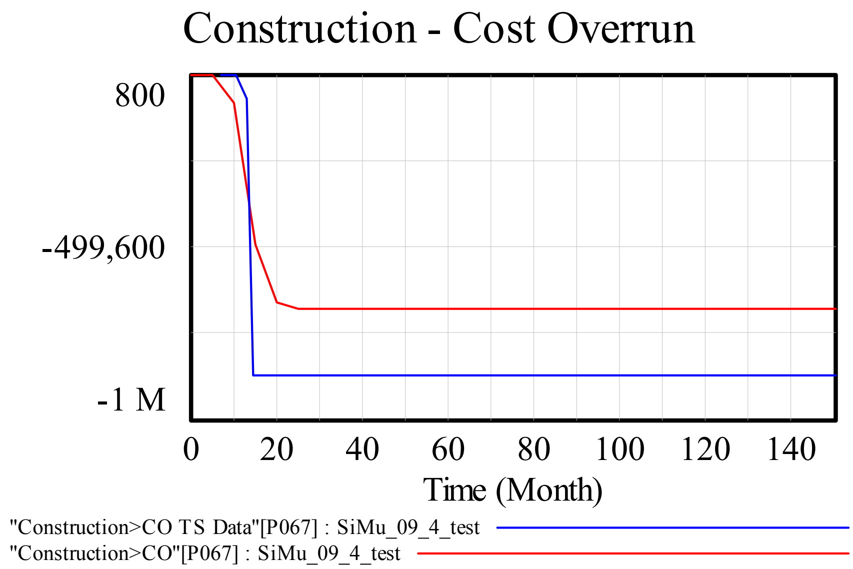

Figure 69.36: Construction cost overrun, Project [P067], Actual data blue line, Simulation red line.

Appendix F: Bayes' Theorem

Bayes' theory is based on the conditional probability, Equation 58.

$$P(B|A) = \frac{P(A \cap B)}{P(A)} \tag{58}$$

In general, event B may have different states. Let's assume "n" states. The states of event B are mutually exclusive events by definition. As a result:

$$\bigcup_{i=1}^{n} B_i = U \tag{59}$$

$$B_i \cap B_j = \emptyset \tag{60}$$

$$\forall i, j = 1, \dots, n \; and \; i \neq j$$

Figure 70 demonstrates the example of event B with 4 states along with event A. The four states of the event B partition the universe U.

$$P(B_i|A) = \frac{P(A \cap B_i)}{P(A)} \tag{61}$$

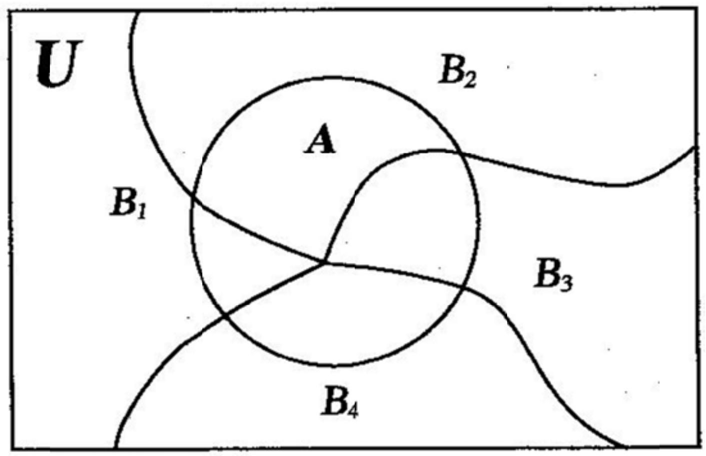

Figure 70: The example of event B with four states along with event A, Ref: Introduction to Bayesian Statistics by William M. Bolstad 2007 (2nd edition)

In this case, the conditional probability equation is expanded as shown in Equation 61

The intersection of set A with the two sides of Equation 59 along with Equation 60 results inEquation 62. It is also called “Law of Total Probability”. It basically means the marginal probability of event A is found by adding up its disjoint parts.

$$P(A) = \sum_{j=1}^{n} P(A \cap B_j) \tag{62}$$

The probability of A, given B_j, based on the conditional probability can be written as:

$$P(A|B_j) = \frac{P(A \cap B_j)}{P(B_j)} \tag{63}$$

Equation 64 which is restated form of the conditional probability is also known as the multiplication rule for probability.

$$P(A \cap B_j) = P\big(A\big|B_j\big).P(B_j) \tag{64}$$

Using the multiplication rule in the numerator of Equation 61along with the law of total probability in its denominator gives Equation 65known as the Bayes’ theorem.

$$P(B_i|A) = \frac{P(A|B_i).P(B_i)}{\sum_{j=1}^{n} P(A|B_j).P(B_j)} \tag{65}$$

Bayes' theorem is basically a restated form of the conditional probability where the multiplication rule is used to define the joint probability in the numerator and the marginal probability is reformed by the law of total probability followed by the multiplication rule in the denominator (William M. Bolstad (2007)).

Bayes' theorem provides a powerful methodology to construct the probability distributions of the unobservable events (B) which partition the universe based on the observable evidence (A). The conditional probability of the evidence (A) given the unobservable event B_i is also called the likelihood of the unobservable event (B_i), (Equation 66). Basically, the likelihood functions as the weight to each event (B_i) in the presence of the occurrence of event (A). $P(B_i)$ is called the prior probability of the unobservable event (B). Updating the prior probability of the event (B) in the presence of the evidence (A) constructs the new version of the probability of the event B which is called posterior probability P(B|A).

$$L(A|B_i) = P(A|B_i) \tag{66}$$

Equation 23 shows the Bayes' theorem in the continuous form, where (b) is the continuous variable that represents different states of the event (B), and (a) is the observed evidence in discrete or continuous form.

$$P(b|a) = \frac{L(a|b).P(b)}{\int L(a|b).P(b)\ db} \quad (67)$$

In the general state, where the likelihood function is unknown, there is no closed-form formulation to estimate the posterior probability distribution of event (B). The Markov Chain Monte Carlo (MCMC) simulation is the technique to resolve this issue. However, knowing the likelihood function does not completely help either. Calculating the denominator of the Bayes' theorem in continuous form (Equation 23) yields the closed-form formulation in some special cases. It has been found that there exist pairs of the distributions which if the prior distribution and likelihood are the members of the pair, then the posterior distribution will be member of the same pair. These pairs of distributions are called conjugate distributions.

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