# A SOFTWARE PROJECT DYNAMICS MODEL FOR PROCESS COST, SCHEDULE AND RISK ASSESSMENT

by

Raymond Joseph Madachy

# FACULTY OF THE GRADUATE SCHOOL

A Dissertation Presented to the

# UNIVERSITY OF SOUTHERN CALIFORNIA

In Partial Fulfillment of the Requirements for the Degree

## DOCTOR OF PHILOSOPHY

(Industrial and Systems Engineering)

December 1994

Copyright 1994 Raymond Joseph Madachy

# **Acknowledgements**

The author would like to acknowledge some of the many people who made this work possible. Sincere thanks to my dissertation committee of Dr. Barry Boehm, Dr. Behrokh Khoshnevis and Dr. Eberhardt Rechtin for their inspiration, guidance, encouragement and support through the years. Several other researchers also provided data and suggestions along the way. Thanks also to Litton Data Systems for their support of this research.

Many thanks are due to my patient wife Nancy who endured countless hours of my work towards this goal, and my parents Joseph and Juliana Madachy who provided my initial education.

# **Table of Contents**

Acknowledgements	ii
List of Figures	v
List of Tables	vi
Abstract	vii
CHAPTER 1 INTRODUCTION	1
1.1 Statement of the Problem	2
1.2 Purpose of the Research	3
CHAPTER 2 BACKGROUND	7
2.1 Software Engineering 2.1.1 Process Technology 2.1.1.1 Process Lifecycle Models 2.1.1.2 Process Modeling 2.1.1.3 Process Improvement 2.1.2 Cost Estimation 2.1.3 Risk Management 2.1.4 Knowledge-Based Software Engineering  2.2 Simulation 2.2.1 System Dynamics  2.3 Software Project Dynamics  2.4 Critique of Past Approaches	10 10 10 15 18 19 20 22 23 24 25
CHAPTER 3 MODELING OF AN INSPECTION-BASED PROCESS	30
3.1 Background	31
3.2 Industrial Data Collection and Analysis	33
3.3 Model Overview	35
CHAPTER 4 KNOWLEDGE-BASED RISK ASSESSMENT AND COST ESTIMATION	44
4.1 Background	44
4.2 Method	44
	iii

4.2.1 Risk assessment	46
4.2.2 Rule base	49
4.2.3 Summary and Conclusions	50
CHAPTER 5 MODEL DEMONSTRATION AND EVALUATION	52
5.1 Test Cases	55
5.1.1 Reference Test Case	55
5.1.1.1 Calibration Procedure	56
5.1.2 Additional Test Cases	56
5.2 Process Assessment	57
5.2.1 Example 1: Effects of Performing Inspections	57
5.2.2 Example 2: Staffing Policies	63
5.2.3 Example 3: Schedule Compression	65
5.2.4 Example 4: Monte-Carlo Simulation	66
5.2.5 Example 5: Experience Learning Curve	67
5.3 Integrated Risk Assessment and Simulation	68
5.4 Derivation of a Detailed COCOMO Cost Driver	71
5.5 Validation Against Industrial Data	72
5.6 Evaluation Summary	77
CHAPTER 6 CONCLUSIONS	78
6.1 Research Summary	78
6.2 Contributions	79
6.3 Directions for Future Research	80
BIBLIOGRAPHY	84
APPENDIX A SYSTEM DYNAMICS MODEL SUPPLEMENT	92
A.1 Reference Behavior	92
A.2 Test Case Results	106
A.3 Validation Summary	109
A.4 Equations	112

# **List of Figures**

Figure 2-1: Venn Diagram of Research Areas	8
Figure 2-2: Bibliographic Taxonomy	9
Figure 3-1: Experimental Paradigm	32
Figure 3.1-1: Effect of Inspections on Project Effort	34
Figure 3.1-2: Defects Found per Subject Type	36
Figure 3.4-1: Inspection Model Diagram	38
Figure 3.4-2: Correspondence Between Dynamic Model and COCOMO	40
Figure 3.4-3: High Level Model Boundary	43
Figure 4.2-1: Sample Input Screen	47
Figure 4.2.1-1: Assignment of Risk Levels	48
Figure 4.2.1-2: Sample Risk Outputs	50
Figure 4.2.1-3: Prioritized Risks	50
Figure 4.2.2-1: Rule Taxonomy	52
Figure 5.2.1-1: Manpower Rates With and Without Inspections	60
Figure 5.2.1-2: Error Generation Rate Effects	61
Figure 5.2.1-3: Error Multiplication Rate Effects	63
Figure 5.2.1-4: Net Return-on-investment for Different Inspection Policies	64
Figure 5.2.2-1: Rectangular Staffing Profile Input	66
Figure 5.2.2-2: Rectangular Staffing Simulation Results	66
Figure 5.2.3-1: Total Manpower Rate Curves for Relative Schedule	67
Figure 5.2.3-2: Cumulative Effort and Actual Schedule Time vs. Relative Schedule	67
Figure 5.2.4-1: Probability Distributions for Project Effort	68
Figure 5.2.5-1: Design Learning Curve	69
Figure 5.2.5-2: Design Productivity	69
Figure 5.2.5-3: Design Progress	69
Figure 5.3-1: Input Anomaly Warning	70
Figure 5.3-2: Revised Inputs for Nominal Project	70
Figure 5.3-3: Inputs for Risky Project	71
Figure 5.3-4: Expert COCOMO Output for Nominal Project	71
Figure 5.3-5: Expert COCOMO Output for Risky Project	72
Figure 5.3-6: Resulting Staffing Profiles	72
Figure 5.4-1: Effort Multipliers by Phase for <i>Use of Inspections</i>	74
Figure 5.5-1: Correlation Against Actual Cost	78
Figure 5.5-2: Project Risk by COCOMO Project Number	78
Figure A.1-1: Task Graphs	94
Figure A.1-2: Error Graphs	95
Figure A.1-3: Effort Graphs	96

# **List of Tables**

Table 4.2.2-1: Rule Base	51
Table 5-1: Summary Table of System Dynamics Model Validation Tests	54
Table 5.1.2-1: Test Cases	58
Table 5.2.1-1: Test Results Summary - Effects of Inspections	59
Table 5.4-1: Rating Guidelines for Cost Driver <i>Use of Inspections</i>	73
Table 5.2.4-1: Monte-Carlo Statistical Summary	68
Table 5.5-1: Inspection ROI Comparison	75
Table 5.5-2: Testing Effort and Schedule Comparison	76
Table 5.5-3: Rework Effort Ratio Comparison	76
Table 5.5-4: Softcost Effort Multiplier Comparison	77
Table A.2-1: Test Case Results	109
Table A.4-1: System Dynamics Model Equations	116

### **Abstract**

A dynamic model of an inspection-based software lifecycle process has been developed to support quantitative evaluation of the process. In conjunction with a knowledge-based method that has been developed for cost estimation and project risk assessment, these modeling techniques can support project planning and management, and aid in process improvement.

The model serves to examine the effects of inspection practices on cost, schedule and quality throughout the lifecycle. It uses system dynamics to model the interrelated flows of tasks, errors and personnel throughout different development phases and is calibrated to industrial data. It extends previous software project dynamics research by examining an inspection-based process with an original model, integrating it with the knowledge-based method for risk assessment and cost estimation, and using an alternative modeling platform.

While specific enough to investigate inspection practices, it is sufficiently general to incorporate changes for other phenomena. It demonstrates the effects of performing inspections or not, the effectiveness of varied inspection policies, and the effects of other managerial policies such as manpower allocation. The dynamic effects are tracked throughout the time history of a project to show resource usage, task completions and defect trends per phase. Cumulative metrics and development tradeoffs for decision making are also presented.

The knowledge-based method has been implemented on multiple platforms. As an extension to COCOMO, it aids in project planning by identifying, categorizing, quantifying and prioritizing project risks. It also detects cost estimate input anomalies and provides risk control advice in addition to conventional cost and schedule calculation. It extends previous work by focusing on risk assessment, incorporating substantially more rules, going beyond standard COCOMO, performing quantitative validation, and providing a user-friendly interface. The method is being used and enhanced in industrial environments as part of an integrated capability to assist in system acquisition, project planning and risk management.

Several types of validation tests are performed against industrial data, existing theory and other prediction models, and practitioners are used to evaluate the model. The results indicate a valid model that

can be used for process evaluation and project planning, and serve as a framework for incorporating other dynamic process factors.

## **Chapter 1 Introduction**

This study extends knowledge in the fields of software project dynamics modeling, process technology, cost estimation and risk management. It is a significant contribution because explication of the dynamic interdependencies of software project variables fills in knowledge gaps in these fields to produce an integrated model of their relationships.

A large knowledge gap exists for measuring different software development practices and planning large software projects. There are virtually no methods of quantitatively comparing dynamic characteristics of software development processes and few for assessing project risk. Very little data exists on the tradeoffs of alternative software development process models, and expert knowledge is not utilized in tool assistants for cost and schedule estimation or project risk assessment.

This research investigates system dynamics modeling of alternative software development processes and knowledge-based techniques for cost, schedule and risk assessment of large software projects with a primary focus on cost. In particular, an inspection-based development process is modeled. By combining quantitative techniques with expert judgement in a common model, an intelligent simulation capability results to support planning and management functions for software development projects. This provides greater insight into the software development process, increased estimation and risk management capabilities to reduce project cost and schedule variances, and the capability to evaluate process improvement via process definition and analysis. The overall project assessment toolset provides a framework for software cost/schedule/risk management and process maturity improvement across software development organizations.

The system dynamics model employs feedback principles to simulate dynamic interactions of management decision-making processes and technical development activities. Dynamic modeling of the software development process has provided a number of useful insights, and can be used to predict the consequences of various management actions or test the impact of internal or external environmental factors. By having an executable simulation model, managers can assess the effects of changed processes and management policies before they commit to development plans.

A calibrated dynamic model enables a metrics-based continuous process improvement capability, and a basis for prioritizing organizational process improvement investments by providing a measure of software development processes. The process model can be used as a baseline for benchmarking process improvement metrics.

The knowledge-based component of this study incorporates expert heuristics to assess various facets of cost and schedule estimation and project risk assessment based on cost factors. Incorporation of expert system rules can place considerable added knowledge at the disposal of the software project planner or manager to help avoid high-risk development situations and cost overruns.

#### 1.1 Statement of the Problem

The main problem investigated in this research is what are the effects of changes to the software development process on cost, schedule and risk? In particular, the effects of performing inspections during the process are investigated. The rationale for this study is to improve software engineering practice.

Some general definitions are provided below before expanding on the problem and purpose:

<u>software engineering</u>: the discipline in which science and mathematics are applied in developing software <u>process</u>: a set of activities, methods, practices, and transformations that people use to develop and maintain software and the associated products [Paulk et al. 91]

<u>inspection</u>: a formal review of a software artifact such as design or code to efficiently find errors. An inspection requires training of participants, sufficient preparation time before an inspection meeting, a structured meeting with timing and defect recording protocols, specific roles executed during the meeting, and followup of fixing defects found during the inspection. See Chapter 3 for more details of inspections including the effort required to perform them.

cost estimation: prediction of both the person effort and elapsed time of a project

<u>risk</u>: the possibility of an unsatisfactory outcome on a project

<u>knowledge-based system</u>: a program that operates on captured knowledge and expertise using inference to emulate human reasoning.

The term "process model" has two distinct interpretations in this research. A process model refers to 1) a method of software development, i.e. a lifecycle process model that determines the order of the stages involved in software development and evolution, and establishes the transition criteria for progressing between stages and 2) an executable simulation model of the software development process. This research develops a simulation model of a software development method. Proper interpretation of the term will be made clear in context.

Some specific sets of questions addressed by this research include the following:

- 1) What are the *dynamic* effects of process changes on cost, schedule, risk and related factors? What are the quantitative and qualitative (heuristic) features of an inspection-based process from a cost/schedule/risk perspective?
- 2) Which expert heuristics using cost factors are useful for risk assessment? To what extent can they be quantified? Can knowledge-based project risk assessment in the form of heuristic rules be combined with a dynamic model? What are some common factors that can be used to link the risk assessment and dynamic modeling?
- 3) What are the relationships between dynamic and static models and how are they complementary? How can the results of static models contribute to dynamic models? Can a dynamic model be calibrated such that a point prediction will always match that of a static model?

To delimit the scope of this research, only medium to large size software projects are considered. These typically fall in the range of 50,000 to 1,000,000 delivered lines of code [Charette 89]. Only an inspection-based development processes will be modeled, as identified in subsequent sections.

The practice of software engineering is multi-faceted with a host of interrelated problems, and this research explores methods to help alleviate some of these problems. The remainder of this section describes these problems and the relevance of this study for helping to solve them.

#### 1.2 Purpose of the Research

The role of software in complex systems has increased dramatically over the last couple of decades. Software is often the critical factor in project success, and companies are recognizing software as the key to competitiveness. Software is normally the control center of complex architectures, provides system flexibility and increasingly drives hardware design. Though there have been substantial advancements in software practices, there are difficult development problems that will pose increasing challenges for a long time.

The magnitude of software development has increased tremendously; the annual cost is now estimated at \$200B in the United States alone. As the problems to be solved increase in complexity, systems grow in size and hardware performance increases, the task of software development for large and innovative systems becomes more difficult to manage. Despite these obstacles, the software demand continues to increase at a substantial rate.

The term *software crisis* refers to a set of various problems associated with the software development of large systems that meet their requirements and are cost effective, timely, efficient, reliable and modifiable. Escaping from a software crisis can be accomplished by improving the organizational process by which software is created, maintained and managed [Humphrey 89].

One of the first books to highlight the process problem was *The Mythical Man-Month* [Brooks 75] where the problems were identified as not just product failures but failures in the development process itself. In the ensuing years, software has become the medium of new systems in a much larger way. Development of complex systems is increasingly reliant on software development practices as the proportion of software to hardware development effort has transitioned from a small part to the sizable majority [Charette 89, Boehm 89].

Tools are needed to assist in alleviating the problems associated with the development of large, complex software systems. Planning and management are at the core of the problems due to a lack of understanding of the development process coupled with the increasing size and complexity demanded of systems. Much of the difficulty of development can be mitigated by effectively applying appropriate engineering methods and tools to management practices. Much focus is on improving technical

development activities, but without corresponding advances in software management tools and practices, software projects will continue to produce cost overruns, late deliveries and dissatisfied customers.

Many techniques have been developed and used in software development planning. Besides cost models, other well-known methods include Critical Path Method/Program Evaluation and Review Techniques (CPM/PERT), decision analysis and others [Boehm 89, Pressman 87]. These methods all have limitations. CPM/PERT methods can model the detailed development activities and cost estimation models produce estimates used for initial planning, but none of these techniques model the dynamic aspects of a project such as managerial decision making and software development activities in a micro-oriented integrative fashion.

Typical problems in software development include poor cost and schedule estimation, unreasonable planning, lack of risk identification and mitigation, constantly shifting requirements baselines, poor hiring practices, and various difficulties faced by developers prolonged by a lack of managerial insight. These problems are related in important ways, and explication of the interdependencies can provide knowledge and techniques for assistance.

A major research problem is how to identify and assess risk items. Risks on software projects can lead to cost overruns, schedule slip, or poorly performing software. Risk factors are frequently built into problem-ridden software projects via oversimplified assumptions about software development, such as assuming the independence of individual project decisions and independence of past and future project experience.

Project planners often overlook risk situations when developing cost and schedule estimates.

After the proposal or project plan is approved, the software development team must live with the built-in risk. These initial project plans are usually not revised until it's too late to influence a more favorable outcome. By incorporating expert knowledge, these risks can be identified during planning and mitigated before the project begins.

Many of the aforementioned problems can be traced to the development process. The traditional waterfall process has been blamed for many of the downfalls. It prescribes a sequential development cycle of activities whereby requirements are supposed to be fixed at the beginning. Yet requirements are

virtually never complete at project inception. The problems are exacerbated when this occurs on a large, complex project. Changes to requirements are certain as development progresses, thereby leading to substantial cost and schedule inefficiencies in the process. Other problems with the traditional waterfall include disincentives for reuse, lack of user involvement, inability to accommodate prototypes, and more [Agresti 86, Boehm 88].

In recent years, a variety of alternative process models have been developed to mitigate such problems. However, project planners and managers have few if any resources to evaluate alternative processes for a proposed or new project. Very few software professionals have worked within more than one or two types of development processes, so there is scant industrial experience to draw on in organizations at this time. Different process models, particularly the newer ones of interest, are described in section 2.1.1.1 Process Lifecycle Models.

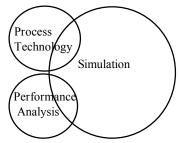
When considering potential process changes within the decision space of managers, it would be desirable to predict the impact via simulation studies before choosing a course of action. The use of a simulation model to investigate these different software development practices and managerial decision making policies will furnish managers with added knowledge for evaluating process options, provide a baseline for benchmarking process improvement activities, and more accurate prediction capability.

As described, methods are needed to provide automated assistance in the areas of process evaluation and risk assessment to support planning and management of large projects. Given the magnitude of software development, even incremental and partial solutions can provide significant returns.

# **Chapter 2 Background**

The background of this study is multi-disciplinary, and Figure 2-1 shows a Venn diagram of relevant major research areas <sup>1</sup>. To assist in categorizing specific work and to illustrate the intertwining of research, Figure 2-2 shows a taxonomy of the bibliography. The disciplines of software engineering and software metrics provide wide coverage, and their references supply general background for this research. Software metrics is highly relevant to the other subdisciplines since measurement is essential to each. This section is divided up along the different research areas in Figure 2-1, so some cited works will be relevant in multiple sections due to the disciplinary overlap. Sections *2.1 Software Engineering* and *2.2 Simulation* both lead to section *2.3 Software Project Dynamics*, which is a new field of research that uses system dynamics simulation to explore software engineering issues.

<sup>&</sup>lt;sup>1</sup> To simplify the diagram, overlap of software engineering and simulation is not shown. In particular, process technology - the focus of this research, and performance analysis are two aspects of software engineering that heavily use simulation as shown below.



Also, the discipline of artificial intelligence is a superset of knowledge-based systems and is not shown separately.

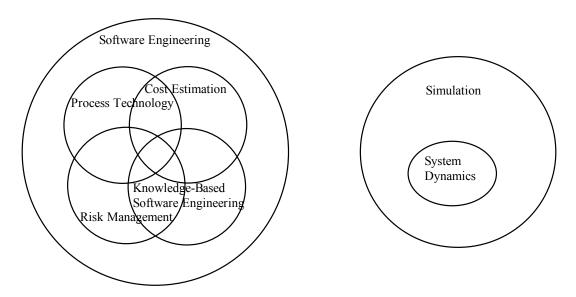
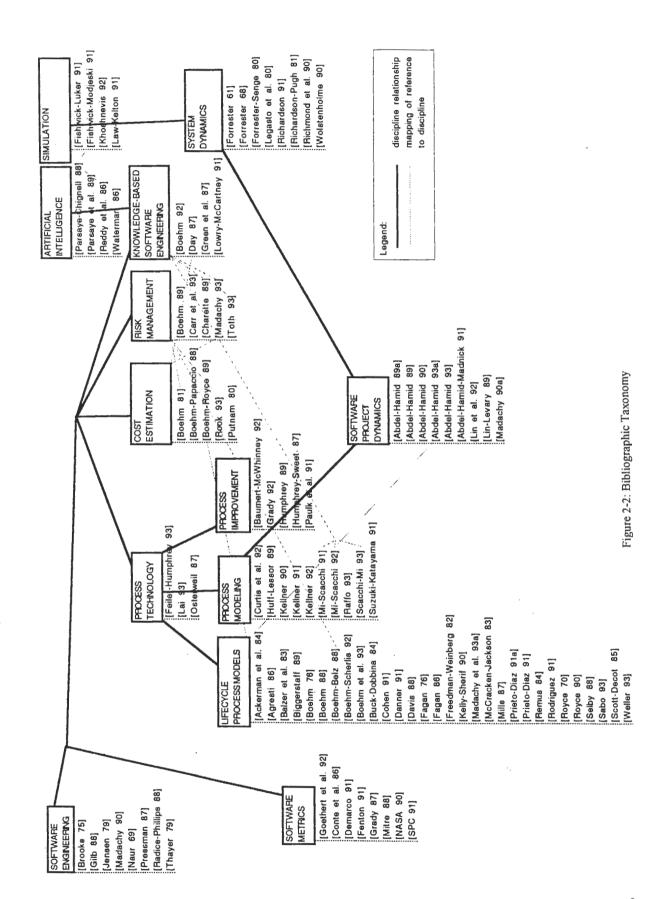


Figure 2-1: Venn Diagram of Research Areas



#### 2.1 Software Engineering

An early definition of software engineering was "the establishment and use of sound engineering principles in order to obtain economically software that is reliable and works efficiently on real machines" [Naur 69]. Boehm adds the provision of human utility in the definition "software engineering is the application of science and mathematics by which the capabilities of computer equipment are made useful to man via computer programs, procedures and associated documentation" [Boehm 81]. In practice, the engineering principles are applied as a combination of different methods. This research investigates new methods to assist in software engineering, and the following subsections provide background on relevant subdisciplines.

#### 2.1.1 Process Technology

Software process technology is a new field being used to address several critical issues in software engineering, where a process is a sequence of software development activities using associated tools and methods. Process technology encompasses three general classes of research: new process lifecycle models, process modeling and process improvement. This research involves all of these, since modeling of lifecycle processes is used to achieve process improvement. Background for each of these areas is described in separate sections.

#### 2.1.1.1 Process Lifecycle Models

A process lifecycle model determines the order of the stages involved in software development, and establishes the transition criteria between stages. The process used in the initial days of software development is now called the "code-and-fix" model [Boehm 88]. It essentially contained two steps: 1) write code and 2) fix the problems in the code. Requirements, design, test and maintenance were not considered before coding began. This type of development led to poorly structured code that was expensive to fix and did not match users' requirements. These problems led to the recognition of the testing and maintenance phases, and early planning. The stagewise model, where software was to be developed in successive stages, came about to address the deficiencies of the code-and-fix model [Boehm 88].

The waterfall model was first documented by Royce [Royce 70]. It offered two primary enhancements to the stagewise model: 1) feedback loops between stages and 2) a "build it twice" step parallel with requirements analysis [Boehm 88]. Variations of the waterfall model all contain the essential activities of specification, design, code, test and operations/maintenance. The lifecycle model was further popularized by Boehm in a version that contained verification, validation or test activity at the end of each phase to ensure that the objectives of the phase were satisfied [Boehm 76]. In this model, the phases are sequential, none can be skipped and baselines are produced throughout the phases. No changes to baselines are made unless all interested parties agree. The economic rationale for the model is that to achieve a successful product, all of the subgoals within each phase must be met and that a different ordering of the phases will produce a less successful product [Boehm 81]. Another primary virtue of the waterfall model is its recognition of design as a critical activity [Agresti 86].

However, the waterfall model implies a sequential approach to product development, which is often impractical for large projects due to shifting requirements. Some other critiques of the waterfall model include: a lack of user involvement, ineffectiveness in the requirements phase, inflexibility to accommodate prototypes, unrealistic separation of specification from design, inability to accommodate reuse, and various maintenance related problems [Agresti 86], [Boehm 88]. In [Swartout-Balzer 82], it is argued that specification and design are inevitably intertwined, which implies that process models should reflect this reality. Agresti claims that the fundamental weakness of the waterfall model is the imbalance of analysis versus synthesis due to the influence of the systems approach and the reality of software practices when the model was formulated [Agresti 86]. An annotated bibliography of critiques of the conventional lifecycle is provided in [Agresti 86].

Some of the difficulties of the conventional (waterfall) lifecycle have been addressed by extending it for incremental development, parallel developments, evolutionary change and other revisions and refinements [Boehm 88, Agresti 86]. Agresti describes the prototyping, operational specification and transformational paradigms as alternatives to the waterfall [Agresti 86]. These are shown to respond to the inadequacies of the waterfall by delivering executable objects early to the user and increasing the role of automation. The following sections describe selected enhancements and alternatives to the waterfall model.

Note that process models can be synthesized into hybrid approaches depending on the development situation.

Prototyping is a process that enables the developer to create a quick initial working model of the software to be built, and is similar to the "build it twice" step in Royce's 1970 waterfall model. A formal definition of prototyping is "a full-scale model and functional form of a new system or subsystem. (A prototype does not have to be the complete system - only the part of interest)" [Thayer-Dorfman 1990]. The objective of prototyping is to clarify the characteristics and operation of a system [Agresti 86]. This approach may be used when there is only a general set of objectives, or other uncertainties exist about algorithmic efficiencies or the desired form of an interface. A quick design occurs focusing on software aspects visible to the user, and the resulting prototype is evaluated to refine the requirements [Boehm 89, Pressman 87].

The incremental process approach develops a system in increments, whereby all requirements are determined up front and subsets of requirements are allocated to separate increments. The increments are developed in sequential cycles, with each incremental release adding functionality. One example is as the Ada process model [Boehm 89a, Royce 90] which uses salient features of Ada to mitigate risks, such as the ability to compile specifications of design early on. The incremental approach reduces overall effort and provides an initial system earlier to the customer. The effort phase distributions are different and the overall schedule may lengthen somewhat [Boehm 81]. The Ada process model prescribes more effort in requirements analysis and design, and less for coding and integration.

Inspections are a formal, efficient and economical method of finding errors in design and code [Fagan 76]. They are a form of peer review, as are structured walkthroughs. An inspection-based process uses inspections at a number of points in the process of project planning and system development, and thus can be used for requirements descriptions, design, code, test plans, or virtually any engineering document.

Inspections are carried out in a prescribed series of steps including preparation, having an inspection meeting where specific roles are executed, and rework of errors discovered by the inspection.

By detecting and correcting errors in earlier stages of the process such as design, significant cost reductions can be made since the rework is much less costly compared to later in the testing and integration phases

[Radice-Phillips 88, Grady 92, Madachy et al. 93a]. Further background and a model of the inspection-based process is discussed in *Chapter 3 Modeling of an Inspection-Based Process*.

The transform model automatically converts a formal software specification into a program [Balzer et al. 83]. Such a model minimizes the problems of code that has been modified many times and is difficult to maintain. The steps involved in the transform process model identified in [Boehm 88] are: 1) formally specify the product, 2) automatically transform the specification into code (this assumes the capability to do so), 3) iterate if necessary to improve the performance, 3) exercise the product and 4) iterate again by adjusting the specification based on the operational experience. This model and its variants are often called operational specification or fourth-generation language (4GL) techniques.

The evolutionary model was developed to address deficiencies in the waterfall model related to having fully elaborated specifications [McCracken-Jackson 83]. The stages in the evolutionary model are expanding increments of an operational product, with evolution being determined by operational experience. Such a model helps deliver an initial operational capability and provides a real world operational basis for evolution; however, the lack of long-range planning often leads to trouble with the operational system not being flexible enough to handle unplanned paths of evolution [Boehm 88].

The spiral model can accommodate previous models as special cases and provides guidance to determine which combination of models best fits a given situation [Boehm 88]. It is a risk-driven method of development that identifies areas of uncertainties that are sources of project risk. The development proceeds in repeating cycles of determining objectives, evaluating alternatives, prototyping and developing, and then planning the next cycle. Each cycle involves a progression that addresses the same sequence of steps for each portion of the product and for each level of elaboration. Development builds on top of the results of previous spirals. This is in contrast to the waterfall model which prescribes a single shot development where documents are the criteria for advancing to subsequent development stages. The spiral model prescribes an evolutionary process, but explicitly incorporates long-range architectural and usage considerations in contrast to the basic evolutionary model [Boehm 88].

A number of proposed reuse process models have been published. Some are risk-driven and based on the spiral model, while others are enhanced waterfall process models. Those based on the spiral

model have only mapped partial activities onto the spiral [Prieto-Diaz 91a], or adapted the model to a specific application domain [Danner 91]. A set of process models has been proposed by Cohen at the Software Engineering Institute for different levels of reuse: adaptive, parameterized and engineered [Cohen 91].

A process for reusing software assets provides reduced development time, improved reliability, improved quality and user programmability [Boehm-Scherlis 92]. A software process model for reuse and re-engineering must provide for a variety of activities and support the reuse of assets across the entire lifecycle. Such assets may include requirements, architectures, code, test plans, QA reviews, documents, etc. It must support tasks specific to reuse and re-engineering, such as domain analysis and domain engineering [Prieto-Diaz 91]. Re-engineering differs from reuse in that entire product architectures are used as starting points for new systems, as opposed to bottom-up reuse of individual components. In [Boehm-Scherlis 92], the term megaprogramming is given to the practice of building and evolving software component by component. It incorporates reuse, software engineering environments, architecture engineering and application generation to provide a product-line approach to development [Boehm-Scherlis 92].

The cleanroom process approach [Mills 87] certifies the reliability of a software system based on a certification model, and is being used in several companies and government agencies. In this process, programmers can't even compile their own code as it's done by independent workers. Much of the traditional programming task work shifts to certification activities in this process model.

In summary, primary differences between some major models are: prototyping develops small working models to support requirements definition, transformational approaches specify the software and employ automatic code generation, incremental development defines all requirements up front and then allocates requirement subsets to individual releases, evolutionary approaches also develop software in increments except that requirements are only defined for the next release, reuse-based development uses previously developed software assets and the spiral model is a risk-driven variation of evolutionary development that can function as a superset process model. Some of the other identified process changes provide alternative methods for implementing subprocesses of the more encompassing lifecycle models.

Few guidelines have been published to aid in selecting an appropriate process model for a given project, though Boehm has developed a process structuring table [Boehm 89] and Sabo has developed a knowledge-based assistant for choosing a process [Sabo 93]. One application of the spiral model was for process generation itself [Boehm-Belz 88]. The spiral model provided an approach for determining the requirements, architecture and design of a software development process. This research develops methods for evaluating alternative processes including risk analysis, which are critical activities called for by the risk-driven spiral approach to process development.

There have been a couple small experiments comparing different programming processes in terms of productivity, resulting product size and quality. In [Boehm 88a], an experiment was performed comparing development teams that used prototyping versus writing requirements specifications. In [Davis 88], an initial framework was developed for comparing lifecycle models. The comparison framework was a non-quantitative approach for visualizing differences between models in terms of the ability to meet user's functional needs. These studies were both preliminary, did not consider dynamic project interactions, provided little data and no tool support that project planners can utilize, and stressed the need for further research to quantify the tradeoffs.

#### 2.1.1.2 Process Modeling

Osterweil has argued that we should be as good at modeling the software process as modeling applications [Osterweil 87]. Process modeling is representing a process architecture, design or definition in the abstract [Feiler-Humphrey 93]. Software process modeling supports process-driven development and related efforts such as process definition, process improvement, process management and automated process-driven environments [Curtis et al. 92, Kellner 92]. As a means of reasoning about software processes, process models provide a mechanism for recording and understanding processes, evaluating, communicating and promoting process improvements. Thus, process models are a vehicle for improving software engineering practice.

To support the above objectives, process models must go beyond representation to support analysis of a process including the prediction of potential process changes and improvements [Kellner 91,

Feiler-Humphrey 93]. Unfortunately, there is no standard approach for process modeling. A variety of process definition and simulation methods exist that answer unique subsets of process questions.

Software process modeling is distinguished from other types of modeling in computer science because many of the phenomena are enacted by humans [Curtis et al. 92]. Research on software process modeling supports a wide range of objectives including facilitating human understanding and communication, supporting process improvement, supporting process management, automating process guidance and automating execution support [Curtis et al. 92]. A background of process improvement is provided in the next section, *2.1.1.3 Process Improvement*.

This research uses process modeling to support several of the aforementioned objectives, particularly process improvement and process management. It will also help facilitate human understanding and communication of the process, but does not explicitly consider automated process guidance or automated execution support.

Process modeling languages and representations usually present one or more perspectives related to the process. Some of the most commonly represented perspectives are functional, behavioral, organizational and informational. They are analogous to different viewpoints on an observable process. Although separate, these representations are interrelated and a major difficulty is tying them together [Curtis et al. 92, Kellner 91, Kellner 92].

There have been a host of language types and constructs used in software process modeling to support the different objectives and perspectives. Five approaches to representing process information, as described and reviewed in [Curtis et al. 92] are programming models (process programming), functional models, plan-based models, Petri-net models (role interaction nets) and quantitative modeling (system dynamics). The suitability of a modeling approach depends on the goals and objectives for the resulting model. No current software process modeling approach fully satisfies the diverse goals and objectives previously mentioned [Kellner 91].

Functional models have been developed with the Hierarchical and Functional Software Process (HFSP) description and enaction language [Suzuki-Katayama 91]. HFSP is primarily a declarative and textual language. A process is defined as a set of mathematical relationships among inputs (such as

specifications) and outputs (such as source code). HFSP is primarily oriented towards the functional and behavioral perspectives.

Plan-based models have been implemented in a constraint-based language called GRAPPLE [Huff-Lessor 89]. It models software development as a set of goals, subgoals, preconditions, constraints and effects. An effective plan-based process model requires coding information of the environment and the goal hierarchies of the process.

The role interaction structure of a project can be represented by a Petri-net based representation. Interaction nets can be used to coordinate the routing of artifacts among interacting roles and can be used to track progress as the completions of role interactions. There have been problems with scalability and using the technique if a basic description of the organization process does not already exist [Curtis et al. 92].

System dynamics is one of the few modeling techniques that involves quantitative representation. Feedback and control system techniques are used to model social and industrial phenomena. See section 2.2.1 System Dynamics for more background on system dynamics and section 2.3 Software Project Dynamics for research that uses system dynamics to model behavioral aspects of software projects.

Dynamic behavior, as modeled through a set of interacting equations, is difficult to reproduce through modeling techniques that do not provide dynamic feedback loops. The value of system dynamics models are tied to the extent that constructs and parameters represent actual observed project states [Curtis et al. 92].

A process modeling approach that combines several language paradigms has been developed by Kellner and colleagues at the Software Engineering Institute (SEI) [Kellner 90, Kellner 91, Kellner 92]. It utilizes the STATEMATE tool that includes state transitions with events and triggers, systems analysis and design diagrams and data modeling to support representation, analysis and simulation of processes. This approach enables a quantitative simulation that combines the functional, behavioral and organizational perspectives.

The modeling approach was used for an example process, investigating quantitative aspects of managerial planning [Kellner 91]. In the micro-level study, specific coding and testing tasks with assumed task durations and outcomes were used to derive schedules, work effort and staffing profiles.

Another technique for process modeling is the Articulator approach developed by Mi and Scacchi [Mi-Scacchi 91, Mi-Scacchi 92, Scacchi-Mi 93]. They have developed a knowledge-based computing environment that uses artificial intelligence scheduling techniques from production systems for modeling, analyzing and simulating organizational processes. Classes of organizational resources are modeled using an object-oriented knowledge representation scheme. The resource classes characterize the attributes, relations, rules and computational methods used. The resource taxonomy serves as a meta-model for constructing process models consisting of agents, tools and tasks. Consistency, completeness and traceability of the process can be analyzed with the Articulator approach, and simulation takes place through the symbolic performance of process tasks by assigned agents using tools and other resources.

#### 2.1.1.3 Process Improvement

In order to address software development problems, the development task must be treated as a process that can be controlled, measured and improved [Humphrey 89]. This requires an organization to understand the current status of their processes, identify desired process change, make a process improvement plan and execute the plan.

Humphrey has developed a model of how software organizations can mature their processes and continually improve to better meet their cost and schedule goals called the Capability Maturity Model (CMM) [Humphrey 89]. The CMM framework identifies five levels of organizational maturity, where each level lays a foundation for making process improvements at the next level. The framework utilizes a set of key practices including requirements management, project planning and control, quality assurance, configuration management, process focus and definition, process measurement and analysis, quality management and others. The SEI, tasked by the government to improve software engineering practices, is using the CMM as a basis for improving the software processes of organizations [Paulk et al. 91].

At level one in the CMM, an organization is described as ad-hoc, whereby processes are not in place and a chaotic development environment exists. The second level is called the repeatable level. At

this level, project planning and tracking is established and processes are repeatable. The third level is termed the defined level, whereby processes are formally defined. Level 4 is called the managed level, whereby the defined process is instrumented and metrics are used to set targets. Statistical quality control can then be applied to process elements. At level 5, the optimized level, detailed measurements are used to guide programs of continuous process improvement, technology innovation and defect prevention.

To make the process predictable, repeatable and manageable, an organization must first assess the maturity of the processes in place [Paulk et al. 91]. By knowing the maturity level, organizations can identify problem areas to concentrate on and effect process improvement in key practice areas. The SEI has developed assessment procedures based on the CMM [Humphrey-Sweet 87].

Software process modeling is essential to support process improvements at levels 4 and 5 through process definition and analysis. Process models can represent the variation among processes, encapsulate potential solutions and can be used as a baseline for benchmarking process improvement metrics [Lai 93]. In [Grady 92], guidelines for collecting and analyzing metrics to support process improvement are provided.

#### 2.1.2 Cost Estimation

Cost models are commonly used for project planning and estimation. The most widely accepted and thoroughly documented software cost model is Boehm's COnstructive COst MOdel (COCOMO) presented in his landmark book on software engineering economics [Boehm 81]. The model is incorporated in many of the estimation tools used in industry and research. The multi-level model provides formulas for estimating effort and schedule using cost driver ratings to adjust the estimated effort. It is also used to compute the initial project plan for Abdel-Hamid's dynamic project simulation [Abdel-Hamid-Madnick 91].

The COCOMO model estimates software effort as a nonlinear function of the product size and modifies it by a geometric product of effort multipliers associated with cost driver ratings. The cost driver variables include product attributes, computer attributes, personnel attributes and project attributes. In the most detailed version of COCOMO, the effort multipliers are phase-sensitive, thus taking on different

values throughout the various phases of the project. The revised Ada COCOMO model adds some more cost drivers, including process attributes [Boehm-Royce 89].

In terms of prediction capability against the COCOMO database, the Basic version of COCOMO which does not incorporate cost drivers estimates within 20% of project actuals only 25% of the time. The Intermediate version incorporating cost drivers predicts within 20% of actuals 68% of the time. The prediction increases to 70% of the time for the Detailed version. This prediction performance represents the approximate upper range of current cost models [Boehm 81, Conte et al. 86, Charette 89].

While COCOMO is an empirical model incorporating analytic equations, statistical data fitting and expert judgement, other cost models are more theoretically based [Conte et al. 86]. Putnam's resource allocation model called SLIM assumes that manpower utilization follows a Rayleigh-type curve [Putnam 80]. Jensen's model is similar to Putnam's model, but it attempts to soften the effect of schedule compression on effort. The RCA PRICE S is another composite model like COCOMO geared towards embedded system applications. Several other models have been proposed throughout the years that are algorithmic, top-down, bottom-up, Parkinsonian and other types.

#### 2.1.3 Risk Management

Risk is the possibility of undesirable outcome, or a loss. Risk impact, or risk exposure is defined as the probability of loss multiplied by the cost of the loss. Risk management is a new discipline whose objectives are to identify, address and eliminate software risk items before they become either threats to successful software operation or major sources of software rework [Boehm 89].

Examples of risk in software development include exceeding budget, schedule overrun, or delivering an unsuitable product. Boehm identifies the top 10 generic software risk items in [Boehm 89], and Charette provides documented evidence of many software development failures to highlight the need for risk management practice [Charette 89].

Software risk management involves a combination of methods used to assess and control risk, and is on ongoing activity throughout a development project. Some common techniques used include performance models, cost models, network analysis, decision analysis, quality factor analysis and others [Boehm 89, Rook 93]. Risk management involves both risk assessment and risk control [Boehm 89,

Charette 89]. The substeps in risk assessment are risk identification, risk analysis and risk prioritization, whereas risk control entails risk management planning, risk resolution and risk monitoring.

Risk identification produces a list of risk items, risk analysis evaluates the magnitudes of loss probability and consequence, and risk prioritization produces an ordered list of the risk items by severity. Risk management planning is the creation of plans to address specific risk items, risk resolution is creating a situation that eliminates or lessens a given risk, and risk monitoring is tracking of the risk resolution activities [Boehm 89].

Risk management attempts to balance the triad of cost-schedule-functionality [Charette 89, Boehm 89]. Though cost, schedule and product risks are interrelated, they can also be analyzed independently. Some methods used to quantify cost, schedule and performance risk include table methods, analytical methods, knowledge based techniques, questionnaire-based methods and others.

A risk identification scheme has been developed by the SEI that is based on a risk taxonomy [Carr et al. 93]. A hierarchical questionnaire is used by trained assessors to interview project personnel.

Different risk classes are product engineering, development environment and program constraints [Carr et al. 93].

Knowledge-based methods can be used to assess risk and provide advice for risk mitigation. In Chapter 4, a risk assessment scheme is described that uses cost factors from COCOMO to identify risk items from [Madachy 94]. Toth has developed a method for assessing technical risk based on a knowledge base of product and process needs, satisfying capabilities and capability maturity factors [Toth 94]. Risk areas are inferred by evaluating disparities between needs and capabilities.

Risk management is heavily allied with cost estimation [Boehm 89, Charette 89, Rook 93]. Cost estimates are used to evaluate risk and perform risk tradeoffs, risk methods such as Monte Carlo simulation can be applied to cost models, and the likelihood of meeting cost estimates depends on risk management.

The spiral model is often called a risk-driven approach to software development [Boehm 88], as opposed to a document-driven or code-driven process such as the waterfall. Each cycle through the spiral entails evaluation of the risks. Thus, the spiral model explicitly includes risk management in the process.

Risk management bridges concepts from the spiral model with software development practices [Boehm 88].

Performing inspections is a method of reducing risk. By reviewing software artifacts before they are used in subsequent phases, defects are found and eliminated beforehand. If practiced in a rigorous and formal manner, inspections can be used as an integral part of risk management.

#### 2.1.4 Knowledge-Based Software Engineering

Recent research in knowledge-based assistance for software engineering is on supporting all lifecycle activities [Green et al. 87], though much past work has focused on automating the coding process. Progress has been made in transformational aids to development, with much less progress towards accumulating knowledge bases for large scale software engineering processes [Boehm 92]. Despite the potential of capturing expertise to assist in project management of large software developments, few applications have specifically addressed such concerns. Knowledge-based techniques have been used to support automatic programming [Lowry-McCartney 91], risk analysis, architecture determination, and other facets of large scale software development. Some recent work has been done on relevant applications including risk management and process structuring.

Using a knowledge base of cost drivers for risk identification and assessment is a powerful tool. Common patterns of cost and schedule risk can be detected this way. An expert systems cost model was developed at Mitre [Day 87] employing about 40 rules with the COCOMO model, though it was used very little. Expert COCOMO is a knowledge-based approach to identifying project risk items related to cost and schedule and assisting in cost estimation [Madachy 94]. This work extends [Day 87] to incorporate substantially more rules and to quantify, categorize and prioritize the risks. See Chapter 4 *Knowledge-Based Risk Assessment and Cost Estimation* for more details on Expert COCOMO.

Toth has also developed a knowledge-based software technology risk advisor (STRA) [Toth 94], which provides assistance in identifying and managing software technology risks. Whereas Expert COCOMO uses knowledge of risk situations based on cost factors to identify and quantify risks, STRA uses a knowledge base of software product and process needs, satisfying capabilities and maturity factors. STRA focuses on technical product risk while Expert COCOMO focuses on cost and schedule risk.

A knowledge-based project management tool has also been developed to assist in choosing the software development process model that best fits the needs of a given project [Sabo 93]. It also performs remedial risk management tasks by alerting the developer to potential conflicts in the project metrics. This work was largely based on a process structuring decision table in [Boehm 89], and operates on knowledge of the growth envelope of the project, understanding of the requirements, robustness, available technology, budget, schedule, haste, downstream requirements, size, nucleus type, phasing, and architecture understanding.

#### 2.2 Simulation

Simulation is the numerical evaluation of a model, where a model consists of mathematical relationships describing a system of interest. Simulation can be used to explain system behavior, improve existing systems, or to design new systems [Khoshnevis 92]. Systems are further classified as static or dynamic, while dynamic systems can be continuous, discrete or combined depending on how the state variables change over time. A discrete model is not always used to model a discrete system and vice-versa. The choice of model depends on the specific objectives of a study.

#### 2.2.1 System Dynamics

System dynamics refers to the simulation methodology pioneered by Forrester, which was developed to model complex continuous systems for improving management policies and organizational structures [Forrester 61, Forrester 68]. Models are formulated using continuous quantities interconnected in loops of information feedback and circular causality. The quantities are expressed as levels (stocks or accumulations), rates (flows) and information links representing the feedback loops.

The system dynamics approach involves the following concepts [Richardson 91]:

-defining problems dynamically, in terms of graphs over time

-striving for an endogenous, behavioral view of the significant dynamics of a system

-thinking of all real systems concepts as continuous quantities interconnected in information feedback loops and circular causality

-identifying independent levels in the system and their inflow and outflow rates

-formulating a model capable of reproducing the dynamic problem of concern by itself

-deriving understandings and applicable policy insights from the resulting model

-implementing changes resulting from model-based understandings and insights.

The mathematical structure of a system dynamics simulation model is a system of coupled, nonlinear, first-order differential equations,

$$\mathbf{x}'(\mathbf{t}) = \mathbf{f}(\mathbf{x}, \mathbf{p}),$$

where **x** is a vector of levels, **p** a set of parameters and **f** is a nonlinear vector-valued function. State variables are represented by the levels. Implementations of system dynamics include DYNAMO [Richardson-Pugh 81], and ITHINK [Richmond et al. 90]. DYNAMO is a programming language that requires the modeler to write difference equations. ITHINK uses visual diagramming for constructing dynamic models, allows for graphical representation of table functions and also provides utilities for modeling discrete components.

Although the applicability of feedback systems concepts to managerial systems has been studied for many years, only recently has system dynamics been applied in software engineering. The following section provides background on the use of system dynamics for modeling software development.

#### 2.3 Software Project Dynamics

When used for software engineering, system dynamics provides an integrative model which supports analysis of the interactions between related activities such as code development, project management, testing, hiring, training, etcetera [Abdel-Hamid-Madnick 91]. System dynamics modeling of project interactions has been shown to replicate actual project cost and schedule trends when the simulation model is properly initialized with project parameters [Abdel-Hamid 89a, Lin et al. 92]. A dynamic model could enable planners and managers to assess the cost and schedule consequences of alternative strategies such as reuse, re-engineering, prototyping, incremental development, evolutionary development, or other process options.

In [Abdel-Hamid 89] and [Abdel-Hamid 89a], the dynamics of project staffing was investigated and validation of the system dynamics model against a historical project was performed. In the book *Software Project Dynamics* [Abdel-Hamid-Madnick 91], previous research is synthesized into an overall framework. A simulation model of project dynamics implemented in DYNAMO is also supplied in the book. Aspects of this model are further described in Chapter 3, as it constitutes a baseline for comparison.

Subsequently work was done in [Abdel-Hamid 93], where the problem of continuous estimation throughout a project was investigated. Experimental results showed that up to a point, reducing an initial estimate saves cost by decreasing wasteful practices. However, the effect of underestimation is counterproductive beyond a certain point because initial understaffing causes a later staff buildup.

Others are testing the feasibility of such modeling for in-house ongoing development [Lin-Levary 89, Lin et al. 92]. In [Lin-Levary 89], a system dynamics model based on Abdel-Hamid's work was integrated with an expert system to check input consistency and suggest further changes. In [Lin et al. 92], some enhancements were made to a system dynamics model and validated against project data.

Most recently, Abdel-Hamid has been developing a model of software reuse [Abdel-Hamid 93a]. The focus of the work is distinct from the goals of this research, as his model is for a macro-inventory perspective instead of an individual project decision perspective. It captures the operations of a development organization as multiple software products are developed, placed into operation and

maintained over time. Preliminary results show that a positive feedback loop exists between development productivity, delivery rate and reusable component production. The positive growth eventually slows down from the balancing influence of a negative feedback loop, since new code production decreases as reuse rates increase. This leads to a decreasing reuse repository size since older components are retired in addition to less new code developed for reuse.

After the initial planning phase of a software project, development starts and managers face other problems. In the midst of a project, milestones may slip and the manager must assess the schedule to completion. There are various experiential formulas [NASA 90] or schedule heuristics such as Brooks' law or the "rubber Gantt chart" heuristic [Rechtin 91] used to estimate the completion date.

Dynamic modeling can be used to experimentally examine such heuristics. Brooks stated one of the earliest heuristics about software development: "Adding more people to a late software project will make it later" [Brooks 75]. This principle violated managerial common sense, yet has been shown to be valid for many historical projects. This pointed out that management policies were not founded on the realities of software development.

Abdel-Hamid investigated Brooks' law through simulation and found that it particularly applies when hiring continues late into the testing phases, and that extra costs were due to the increased training and communication overhead [Abdel-Hamid-Madnick 91]. This is an example of dynamic simulation used to investigate managerial heuristics and quantitatively and qualitatively refine them.

#### 2.4 Critique of Past Approaches

Past approaches for planning and management of software projects have largely ignored the time dynamic aspects of project behavior. Software project plans, even when based on validated cost models, assume static values for productivity and other important project determinants. Activities are interrelated in a dynamic fashion, thus productivity can vary tremendously over the course of a project depending on many factors such as schedule pressure or time devoted to training of new personnel. The remainder of this section critiques past approaches for investigating the problems of this research, and is decomposed into different disciplines.

#### **Process Modeling**

Discrete event based process representations (such as Petri-nets) used in [Kellner 90, Kellner 91, Kellner 92] and others change state variables at discrete time points with non-uniform time intervals. They don't model the phenomena of interest varying between the time points, though software project behavior often consists of gradual effects. A typical example is the learning curve exhibited at the start of projects. This continuously varying effect cannot easily be captured through discrete event simulation. A continuous representation such as system dynamics captures the time-varying interrelationships between technical and social factors, while still allowing for discrete effects when necessary.

The approach used by Kellner presents a micro view of project coding activities, and outputs a staffing profile too discrete to plan for. Additionally, the micro view is unscalable for large projects where dozens or hundreds of people are involved. System dynamics provides a framework to incorporate diverse knowledge bases in multiple representations (functional, tabular, etc.) which are easily scalable, since differential equations are used to describe the system of interest. These representations also contribute to the development of static cost models.

A model of software development activities should be discrete if the characteristics of individual tasks are important. If however, the tasks can be treated "in the aggregate", the tasks can be described by differential equations in a continuous model. This is the perspective taken by planners and high-level managers. Front-end planning does not concern itself with individual tasks; in fact the tasks are not even identifiable early on. Likewise, managers desire a high-level, bottom-line view of software development where tracking of individual tasks is not of immediate concern, and is generally handled by subordinate management. Dynamic system behavior on a software project is therefore best modeled as continuous for the purposes of this research.

As this research is not concerned with low level details of software implementation, process models such as the Articulator [Mi-Scacchi 91] that analyze process task/resource connectivities provide more process detail than is necessary and also do not model effects of internal behavior over time. For

instance, there is no easy way to implement a learning curve or the effect of *perceived* workload on productivity.

#### Cost Estimation

Most cost models provide point estimates and are static whereby cost parameters are independent of time. They are not always well-suited for midstream adjustments after a project starts and cost estimation is often done poorly. Consistency constraints on the model may be violated or an estimator may overlook project planning discrepancies and fail to realize risks.

Current cost models such as COCOMO do not provide a representation of the internal dynamics of software projects. Thus the redistribution of effort to different phases for various project situations cannot be ascertained, except as a function of size and development mode. Other methods are needed to account for dynamic interactions involved in managerial adjustment strategies, and to provide the effort and schedule distribution as a function of environmental factors and managerial decisions.

The staffing profile provided by COCOMO is a discrete step function, and is not realistic for planning purposes. Though it can be transformed into a continuous function, the model does not directly provide a continuous staffing curve.

#### Risk Management

Very few risk management approaches for software projects have employed knowledge captured from experts in an automated fashion. Techniques that identify risks before any development begins still require subjective inputs to quantify the risks. There is little consistency between personnel providing these inputs and many do not have adequate experience to identify all the risk factors and assess the risks. Approaches for identifying risks are usually separate from cost estimation, thus a technique that identifies risks in conjunction with cost estimation is an improvement.

#### Software Project Dynamics

Abdel-Hamid and others [Abdel-Hamid 89, Abdel-Hamid 89a, Abdel-Hamid 90, Abdel-Hamid-Madnick 91, Abdel-Hamid 93, Lin et al. 92] have taken initial steps to account for dynamic project interactions. The current system dynamic models have primarily investigated the post-requirements development phases for projects using a standard waterfall lifecycle approach. They have been predicated on and tested for narrowly defined project environments for a single domain where the project development is based on the traditional waterfall process model. As such, the models are not applicable to all industrial environments. Only the post requirements phases have been investigated but the initial requirements and architecting phases provide the highest leverage for successful project performance. As the waterfall process model has a relatively poor track record and current research concentrates on different process models and architectures, researchers and practitioners need models of alternative processes. Enhancements are needed for alternative lifecycle models and for the high leverage initial phases of a project.

Abdel-Hamid's model is highly aggregated, as only two levels are used to model the stages of software development. Less aggregation is needed to examine the relationships between phases. The model also glosses over important interactions, such as the effectiveness of error reduction techniques. For instance, a single measure of QA effectiveness is used, although there are important internal behavioral interactions that contribute to the overall error removal rates.

More granularity is needed for managerial decision-making and planning purposes, such as what proportion of effort should be devoted to error removal activities, what is the optimal size of inspection teams, at what rates should documents and code be inspected for optimal error removal effectiveness, etc. Additionally, the QA effort formulation is inaccurate for modern organizations that institute formal methods of error detection, such as inspections or cleanroom techniques. See Chapter 3 for how this research models error removal activities on a more detailed level.

# **Chapter 3 Modeling of an Inspection-Based Process**

This chapter describes the development of an inspection-based process model that has drawn upon extensive literature search, analysis of industrial data, and expert interviews. The working hypothesis is that a system dynamics model can be developed of various aspects of an inspection-based lifecycle process. An inspection-based development process is one where inspections are performed on artifacts at multiple points in the lifecycle to detect errors, and the errors are fixed before the next phase. Examples of artifacts include requirements descriptions, design documents, code and testing plans. Specific process aspects of concern are described below.

The purpose of the modeling is to examine the effects of inspection practices on effort, schedule and quality during the development lifecycle. Both dynamic effects and cumulative project effects are investigated. When possible, these effects are examined per phase. Quality in this context refers to the absence of defects. A defect is defined as a flaw in the specification, design or implementation of a software product. Defects can be further classified by severity or type. The terms defect and error are synonymous throughout this dissertation.

The model is validated per the battery of tests for system dynamics models described in *Chapter 5 Model Demonstration and Evaluation*. Specific modeling objectives to test against include the ability to predict inspection effort broken down by inspection meeting and rework; testing effort; schedule; and error levels as a function of development phase. Validation has been performed by comparing the results against collected data and other published data. See [Madachy et al. 93a] for the initial industrial data collection and analysis aspect of this work which contains items not included in this dissertation.

The experimental paradigm used is shown in Figure 3-1. This work covers all of the research activities portrayed in the figure: literature search, expert interviews, analysis of industrial data and system dynamics model development including validation. One goal of the literature search is to help identify reference modes of the system. Reference modes help to define a problem, help to focus model conceptualization, and are important in later validation phases [Richardson-Pugh 81]. Reference behavior modes are identified at the outset as patterns over time, and used during validation to check the simulation

output. After experimental validation of the process model, knowledge of software phenomenology results as well as having a testbed for further experiments.

Development of this inspection process model was done in an incremental fashion, where model subsets were developed separately, validated and integrated into successively larger pieces. When parts were integrated together or the model revised, the entire suite of validation tests was performed again as regression testing.

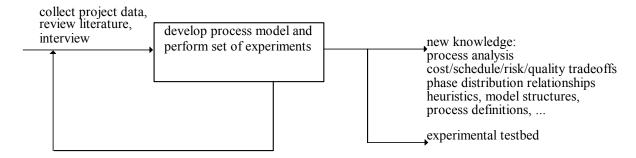


Figure 3-1: Experimental Paradigm

# 3.1 Background

Inspections were devised by Fagan at IBM as a formal, efficient and economical method of finding errors in design and code [Fagan 76]. Since their introduction, the use of inspections has been extended to requirements, testing plans and more [Fagan 86], [Gilb 88], [Radice-Phillips 88]. Thus, an inspection-based process would use inspections throughout project planning and system development for requirements descriptions, design, code, test plans, user guides or virtually any engineering document.

Inspections are a form of peer review, as are structured walkthroughs. Inspections are carried out in a prescribed series of steps including preparation, having an inspection meeting where specific roles are executed, and rework of errors discovered by the inspection. Specific roles include moderator, scribe, inspectors and author. The meeting itself normally does not last more than two hours. A typical inspection including preparation and followup might take 10-30 person-hours of effort. During the meeting, about 2-10 errors might be found.

By detecting and correcting errors in earlier stages of the process such as design, significant cost reductions can be made since the rework is much less costly compared to fixing errors later in the testing and integration phases [Fagan 86], [Radice-Phillips 88], [Grady 92], [Madachy et al. 93a]. For instance, only a couple hours are used to find a defect during an inspection but 5-20 hours might be required to fix it during system test.

Authors have reported a wide range of inspection metrics. For example, guidelines for the proper rates of preparation and inspection often differ geometrically as well as overall effectiveness (defects found per person-hour). There have been simplistic static relationships published for net return-on-investment or effort required as a function of pages or code, but none integrated together in a dynamic model. Neither do any existing models provide guidelines for estimating inspection effort as a function of product size, or estimating schedule when incorporating inspections.

In general, results have shown that extra effort is required during design and coding for inspections and much more is saved during testing and integration. This reference behavioral effect is shown in Figure 3.1-1 from [Fagan 86] that represents a goal of this modeling; to be able to demonstrate this effect on effort and schedule as a function of inspection practices.

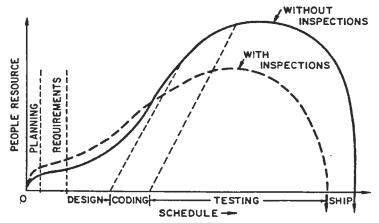


Figure 3.1-1: Effect of Inspections on Project Effort (from [Fagan 86])

The effort saved is due to the reduction of work to fix errors. Individual error removal production functions exist for inspection, unit test and other error removal techniques, and there is overlap between methods for removing some classes of errors [Boehm 81]. A general error flow model is presented in [Boehm 81], where errors are introduced at different phases and removed by various methods at appropriate phases. In [Pressman 87], a defect amplification model is presented, where some errors pass through phases while others get multiplied into more errors. These types of models can be used to demonstrate the effect of inspections on error flow and amplification. Defect amplification from design to code is modeled in this implementation as described in section 3.4.

As inspections can be used to instrument the development process by collecting defect data, patterns of defects can be tracked. For example, the defect density of artifacts through the lifecycle has been shown to decrease [Kelly-Sherif 90], [Madachy et al. 93a]. This phenomenon is discussed in the next section.

## 3.2 Industrial Data Collection and Analysis

Data collection and analysis for a project using an inspection-based process was performed at Litton Data Systems [Madachy et al. 93a]. Analysis of additional projects is documented in subsequent internal reports and [Madachy 94b]. Some results with important ramifications for a dynamic model include defect density and defect removal effectiveness lifecycle trends and activity distribution of effort.

Calibrations are made to match the model to these defect density trends and activity distributions in selected test cases.

Data for the previous project at Litton in the same product line and having identical environmental factors except for the use of inspections was also collected. It provides several parameters used in development and calibration of the system dynamics model, and also enables a comparison to judge the relative project effects from performing inspections.

Trouble report data from the project show an average defect density of about 48 defects/KSLOC found during testing. The trouble report data also provides the average cost in person-hours to fix a defect found during testing. This value is used for calculating the net return from inspections on the more recent project.

When the defect densities for different document types are ordered by lifecycle activity, the results show that the defects steadily decrease since the predecessor artifacts were previously inspected and less defects are introduced as the project progresses. This is shown in Figure 3.2-1, overlayed with similar results from JPL [Kelly-Sherif 90]. The trend corroborates the previous results. Code is not shown because of inconsistencies in reporting the document size. These results strongly support the practice of inspecting documents early as possible in the lifecycle, and can be used to calibrate defect rates for the different development activities when inspection efficiency and page counts are known.

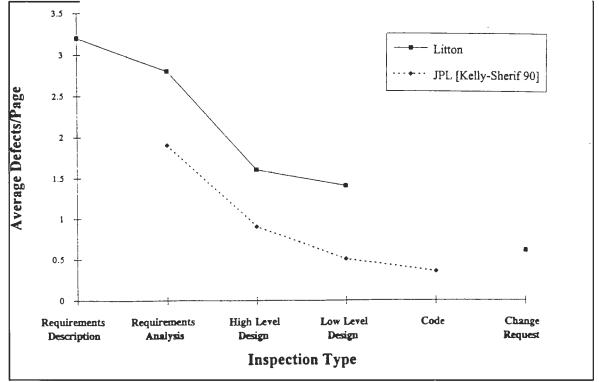


Figure 3.2-1: Defects Found per Subject Type

Summary statistics from Litton indicate the relative proportions of effort for preparation, inspection meeting, rework and other development activities. The model is validated against this data. Additional sources of insight from Litton data include inspection effort profiles for deadline dates, frequency of different inspection types and other data not easily quantified or fitting for the model at this time. See [Madachy et al. 93a] and [Madachy 94b] for additional analysis of inspection data.

Several senior personnel serving as experts have been interviewed: a division software director, a project manager responsible for status and cost reporting, the SEPG peer review coordinator, senior engineers collecting project tracking data and high-level inspection statistics, and other practitioners.

During the interviews, data and heuristics were obtained for process delays, manpower allocation policies and general project trends relevant to inspection practices. Followups and additional interviews with other personnel were performed as needed.

The interviewees and other international experts on inspections have also been involved in assessing and critiquing the model.

#### 3.3 Model Overview

The model covers design through testing activities including inspections of design and code. It assumes that inspections and system testing are the only defect removal activities, as practiced in a number of organizations. It also assumes a team trained in inspections such that inspections can be inserted into the process without associated training costs. Its staffing policy structure is based on mature software organizations (SEI level 2 or above) that are fairly repeatable in terms of productivity such that the effect of underestimation feedback does not play a major role in project behavior (though it could be incorporated as such).

The ITHINK modeling package is used to implement the system dynamics method [Richmond et al. 90]. It uses visual diagramming for constructing dynamic models, provides levels of abstraction, allows for graphical representation of table functions and provides utilities for sophisticated model components beyond previous implementations of system dynamics. Figure 3.4-1 is a diagram of the system dynamics model of an inspection-based process. Source code for the model is provided in Appendix A.

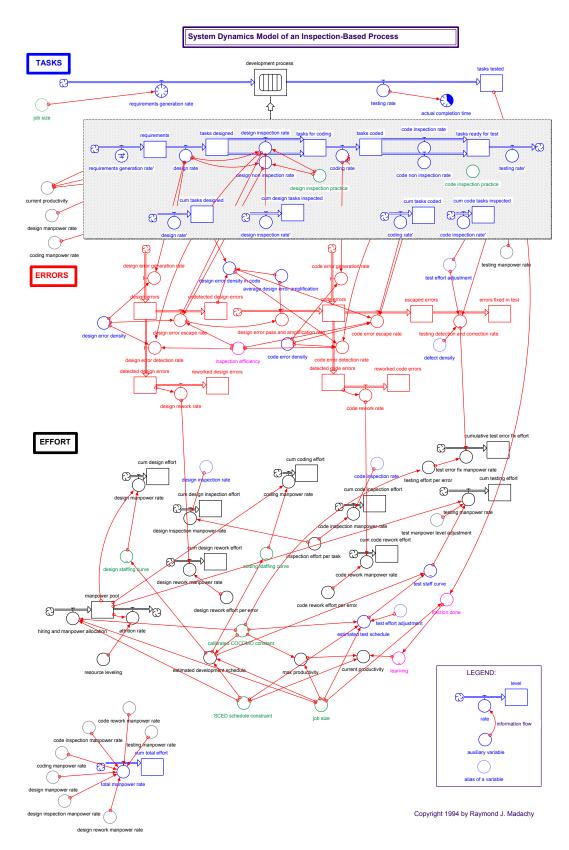


Figure 3.4-1: Inspection Model Diagram

Project behavior is initiated with the influx of requirements. Rates for the different phase activities are constrained by the manpower allocations and current productivity, and are integrated to determine the state variables, or levels of tasks in design, code, inspection, testing, etc. The tasks are either inspected or not during design or code activities as a function of inspection practices.

Errors are generated as a co-flow of design and coding activities, and eventually detected by inspections or passed onto the next phase. The detection of errors is a function of inspection practices and inspection efficiency. All errors detected during inspections are then reworked. Note that escaped design errors are amplified into coding errors. Those errors that still escape code inspections are then detected and corrected during integration and test activities. The effort and schedule for the testing phase is adjusted for the remaining error levels.

Other sectors of the model implement management policies such as allocating personnel resources and defining staffing curves for the different activities. Input to the policy decisions are the job size, productivity, schedule constraints and resource leveling constraints. Effort is instrumented in a cumulative fashion for all of the defined activities. Learning takes place as a function of the job completion, and adjusts the productivity. Schedule compression effects are approximated similar to the COCOMO cost driver effects for relative schedule.

The actual completion time is implemented as a cycle time utility whose final value represents the actual schedule. It instruments the maximum in-process time of the tasks that are time-stamped at requirements generation rate and complete testing.

Correspondence between the dynamic model and COCOMO is illustrated in Figure 3.4-2. It is based on the phase effort and schedule of a 32 KSLOC embedded mode reference project. For the nominal case of no inspections performed, the manpower allocation policy employs the curves to match the rectangular COCOMO effort profiles as a calibration between the models. Thus the area under the design curve matches the aggregated COCOMO preliminary and detailed design, and likewise for the coding and testing curves.

The resulting staffing profiles are scaled accordingly for specific job sizes and schedule constraints. The integration and test phase also depends on the level of errors encountered, and the curve shown is calibrated to an error rate of 50 errors/KSLOC during testing.

Because of the discretization procedure and table extrapolation algorithm in ITHINK that necessitates endpoints of zero for the staffing curves, the areas under the curves do not match COCOMO exactly. It will be shown in Chapter 5 that these differences are less than 3% and are not a drawback since cost estimation error goes well beyond 3% for the best calibrated models and that individual organizations have different phase productivities than the COCOMO tables.

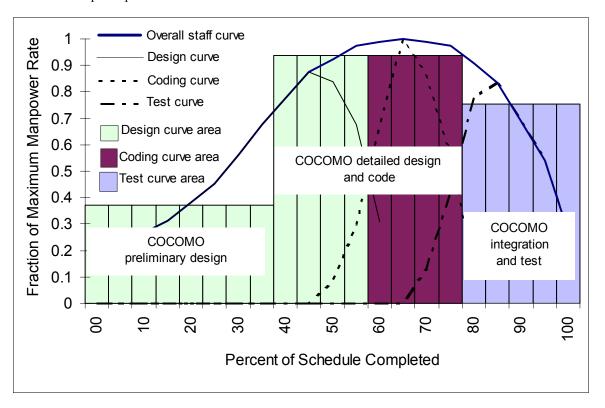


Figure 3.4-2: Correspondence Between Dynamic Model and COCOMO

When calibrating the model for other parameters, middle regions of published data trends were generally chosen as calibration points. Some parameters were set to Litton values when no other data was available. The default value for productivity is the same as in standard COCOMO for embedded mode projects. Error rates are chosen that approximate a large population of observed data including Litton data. The model default value of 50 defects/KSLOC for the overall error generation rate is a rounding of the

Litton value of 48 defects/KSLOC. Included in the demonstration cases in Chapter 5 are model calibrations for specific project instances.

Per the experience at Litton and accordant with other published data, inspection effort that includes preparation, meeting and rework generally consumes approximately 5-10% of total project effort. Guidelines for inspection rates are always stated as linear with the number of pages (or lines of code), and the inspection effort is set accordingly in the model. That is, inspection effort does not exhibit diseconomy of scale as total project effort does in COCOMO and most other cost models. The default inspection effort also corresponds to a rate of 250 LOC/hour during preparation and inspection with an average of four inspectors per meeting [Grady 92].

The rework effort per error found in inspection is set differently for design and code. Litton data shows that the average cost to rework an error during code is about 1.3 times that for design. The cost to fix errors from [Boehm 81] shows that the relative cost for code is twice that of design. The model is set at this 2:1 ratio since it is based on a larger set of data. The resulting values are also close to the reported ranges of published data from JPL [Kelly-Sherif 90]. The testing fixing effort per error is set at about 5 hours, which is well within the range of reported metrics. The inspection efficiency is nominally set at .6, representing the fraction of defects found through inspections. Reported rates vary from about 50% to 90% of defects found.

The utility of the model for a particular organization is dependent on calibrating it accordingly per local data. While model parameters are set with reasonable numbers to investigate inspections in general, the results using the defaults will not necessarily reflect all environments. Besides the efficiency and effort of inspections, differing project environments could have far different error rates, rework effort, testing effort or documentation sizes.

The model is completely original, though it can be compared to previous research. Using the system dynamics model in [Abdel-Hamid-Madnick 91] as a conceptual reference baseline, this inspection-based process model replaces the software production, quality assurance (QA) and system testing sectors. The model boundaries for this work are shown against a highly aggregated view of Abdel-Hamid's model in Figure 3.4-3. The boundary is drawn so that schedule pressure effects, personnel mix, and other coding

productivity determinants do not confound the inspection analysis.

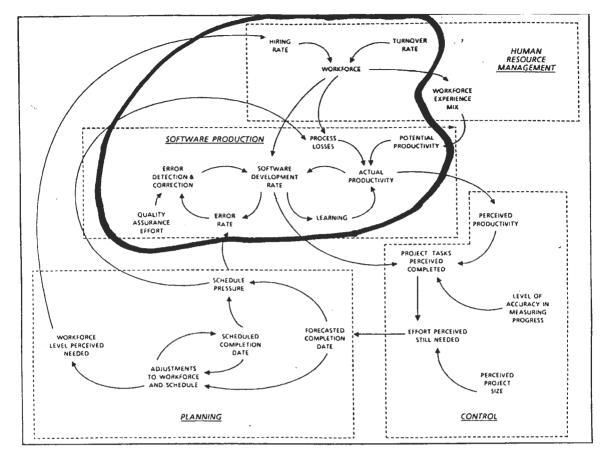


Figure 3.4-3: High Level Model Boundary

Major departures from the Abdel-Hamid model cover manpower allocation and disaggregation of development activities. In his implementation, only generic quality assurance activities are modeled for error detection on an aggregate of design and code. Instead of the Parkinsonian model in [Abdel-Hamid-Madnick 91] where QA completes its periodic reviews now matter how many tasks are in the queue, resources are allocated to inspections and rework as needed. This organizational behavior is thought to be one indication of a higher maturity level. Instead of suspending or accelerating reviews when under schedule pressure, error detection activities remain under process control.

The other major structural difference is the disaggregation of development phases. In [Abdel-Hamid-Madnick 91], a single rate/level element represents development that aggregates design and coding.

In this formulation, activities are delineated and decomposed corresponding to the phases defined in the COCOMO model. Design and coding are modeled independently.

See *Appendix A System Dynamics Model Supplement* for further descriptions of the model including source code, reference behavior charts and description, test case results, and summary results of the validation tests.

# **Chapter 4 Knowledge-Based Risk Assessment and Cost Estimation**

This chapter describes the development and usage of a method for providing knowledge-based assistance for software project risk management and cost estimation.

## 4.1 Background

The objective of software risk management is to identify, address and eliminate risk items before undesirable outcomes occur. Its practice can be improved by leveraging on existing knowledge and expertise. In particular, expert knowledge can be employed during cost estimation activities by using cost factors for risk identification and assessment to detect patterns of project risk.

During cost estimation, consistency constraints and cost model assumptions may be violated or an estimator may overlook project planning discrepancies and fail to realize risks. Approaches for identifying risks are usually separate from cost estimation, thus a technique that identifies risk in conjunction with cost estimation is an improvement.

COCOMO is a widely used cost model that incorporates the use of cost drivers to adjust effort calculations. As significant project factors, cost drivers can be used for risk assessment using sensitivity analysis or Monte-Carlo simulation, but this approach uses them to infer specific risk situations.

Mitre developed an Expert System Cost Model (ESCOMO) employing an expert system shell on a PC [Day 87]. It used 46 rules involving COCOMO cost drivers and other model inputs to focus on input anomalies and consistency checks with no quantitative risk assessment.

## 4.2 Method

Knowledge was acquired from written sources on cost estimation [Boehm 81, Boehm-Royce 89, Day 87], risk management [Boehm 89, Charette 89] and domain experts including Dr. Barry Boehm, Walker Royce and this author.

A matrix of COCOMO cost drivers was used as a starting point for identifying risk situations as a combination of multiple cost attributes, and the risks were formulated into a set of rules. As such, the risk

assessment scheme represents a heuristic decomposition of cost driver effects into constituent risk escalating situations.

A working prototype assistant called Expert COCOMO was developed that runs on a Macintosh using HyperCard. Earlier versions utilized an expert system shell, but the prototype was recoded to eliminate the need for a separate inference engine.

The Litton Software Engineering Process Group (SEPG) has also ported the rule base to a Windows environment, and has incorporated the risk assessment technique into standard planning and management practices. The tool, Litton COCOMO, encapsulates cost equations calibrated to historical Litton data and was written in Visual Basic as a set of macros within Microsoft Excel.

The tools evaluate user inputs for risk situations or inconsistencies and perform calculations for the intermediate versions of standard COCOMO [Boehm 81] and ADA COCOMO [Boehm-Royce 89, Royce 90]. They operate on project inputs, encoded knowledge about the cost drivers, associated project risks, cost model constraints and other information received from the user.

A typical risk situation can be described as a combination of extreme cost driver values indicating increased effort, whereas an input anomaly may be a violation of COCOMO consistency constraints such as an invalid development mode given size or certain cost driver ratings.

The screen snapshots in subsequent figures are from the prototype. The graphical user interface provides an interactive form for project input using radio buttons as seen in Figure 4.2-1, provides access to the knowledge base, and provides output in the form of dialog box warnings, risk summary tables and charts, calculated cost and schedule and graphs of effort phase distributions. It provides multiple windowing, hypertext help utilities and several operational modes.

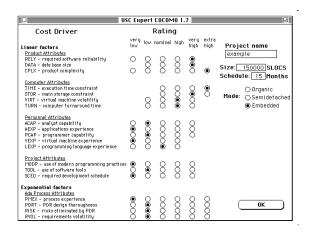


Figure 4.2-1: Sample Input Screen

#### 4.2.1 Risk assessment

Risk items are identified, quantified, prioritized and classified depending on the cost drivers involved and their ratings. A typical risk situation can be visualized in a 2-D plane, where each axis is defined by a cost driver rating range. An example is shown in Figure 4.2.1-1, where iso-risk contours are shown increasing in the direction of increasing product complexity (CPLX) and decreasing analyst capability (ACAP). As seen in the figure, this continuous representation is discretized into a table. A risk condition corresponds to an individual cell containing an identified risk level. The rules use cost driver ratings to index directly into these tables of risk levels. These tables constitute the knowledge base for risk situations defined as interactions of cost attributes. The tables are user-editable and can be dynamically changed for specific environments, resulting in different risk weights.

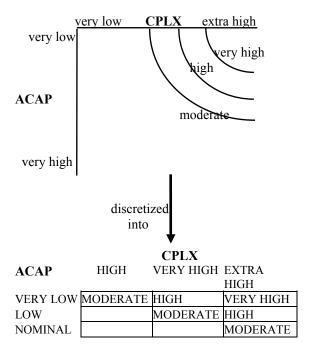


Figure 4.2.1-1: Assignment of Risk Levels

In order to categorize the risks, a risk taxonomy was developed by analyzing the proposed rule base with respect to existing COCOMO cost attribute categories and other attributes deemed important to risk assessment. The cost drivers in COCOMO are grouped into product, computer, personnel, and project categories. The project attributes were redesignated as process attributes, and ADA COCOMO process factors have also been included in the process category. The resulting project risk categories are schedule, product, personnel, process and computer. Input anomaly rules identify another type of risk where cost model constraints or consistency checks are violated; a cost estimation risk of a poorly done estimate.

After several iterations of the prototype, the experts were engaged again to help quantify the risks.

A quantitative risk weighting scheme was developed that accounts for the nonlinearity of the assigned risk levels and cost multiplier data to compute overall risks for each category and the entire project according to

project risk = 
$$\sum_{j=1}^{\text{\#categories \#category risks}} \sum_{i=1}^{\text{risk level}_{i,j} *}$$
 effort multiplier product $_{i,j}$ 

```
where risk level = 1 moderate

2 high

4 very high

effort multiplier product=

(driver #1 effort multiplier) *

(driver #2 effort multiplier) ... *

(driver #n effort multiplier).

If the risk involves a schedule constraint (SCED), then effort multiplier product=

(SCED effort multiplier)/(relative schedule)*

(driver #2 effort multiplier)...*

(driver #n effort multiplier)...*
```

The risk level corresponds to the probability of the risk occurring and the effort multiplier product represents the cost consequence of the risk. The product involves those effort multipliers involved in the risk situation. When the risk involves a schedule constraint, the product is divided by the relative schedule to obtain the change in the average personnel level (the near-term cost) since the staffing profile is compressed into a shorter project time. The risk assessment calculates general project risks, indicating a probability of not meeting cost, schedule or performance goals.

The risk levels need normalization to provide meaningful relative risk indications. Sensitivity analysis was performed to determine the sensitivity of the quantified risks with varying inputs, and extreme conditions were tested. An initial scale with benchmarks for low, medium and high overall project risk was developed as follows: 0-15 low risk, 15-50 medium risk, 50-350 high risk.

The individual risks are also ranked, and the different risk summaries are presented in a set of tables. An example risk output is seen in Figure 4.2.1-2, showing the overall project risk and risks for subcategories. This example is for an extremely risky project, where many cost drivers are rated at their costliest values. The interface supports embedded hypertext links, so the user can click on a risk item in a list to traverse to a screen containing the associated risk table and related information. Other outputs

include a prioritized list of risk situations as seen in Figure 4.2.1-3 and a list of advice to help manage the risks.

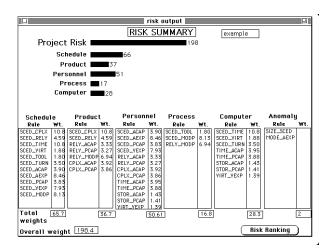


Figure 4.2.1-2: Sample Risk Outputs

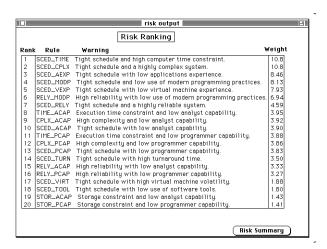


Figure 4.2.1-3: Prioritized Risks

### 4.2.2 Rule base

Currently, 77 rules have been identified of which 52 deal with project risk, 17 are input anomalies and 8 provide advice. There are over 320 risk conditions, or discrete combinations of input parameters that are covered by the rule base.

The knowledge is represented as a set of production rules for a forward chaining inference engine. The current rule base for project risks, anomalies and advice is shown in Tables 4.2.2-1. The four letter identifiers in the rulenames are the standard abbreviations for the COCOMO cost drivers.

Table 4.2.2-1: Rule Base

	RISK		ANOMALY	ADVICE
sced_cplx	rely_pcap	cplx_tool	mode_cplx	size_turn
sced_rely	rely_modp	time_tool	mode_rely	rely_data
sced_time	cplx_acap	cplx_acap_pcap	size_sced	data_turn
sced_virt	cplx_pcap	rely_acap_pcap	size_mode	time
sced_tool	time_acap	rely_data_sced	size_cplx	stor
sced_turn	time_pcap	rely_stor_sced	mode_virt	pcap_acap
sced_acap	stor_acap	cplx_time_sced	mode_time	data
sced_aexp	stor_pcap	cplx_stor_sced	mode_aexp	
sced_pcap	virt_vexp	time_stor_sced	mode_vexp	
sced_vexp			size_pcap	
sced_lexp	rvol_acap	acap_risk	size_acap	
sced_modp	rvol_aexp	increment_drivers	tool_modp	
rely_acap	rvol_sced	sced_vexp_pcap	tool_modp_turn	
modp_acap	rvol_cplx	virt_sced_pcap	pmex_pdrt_risk_rvol	
modp_pcap	rvol_stor	lexp_aexp_sced	increment_personnel	
tool_acap	rvol_time	ruse_aexp	modp_pcap	
tool_pcap	rvol_turn	ruse_lexp	sced	
tool_modp	size_pcap		acap_anomaly	

Figure 4.2.2-1 shows the rule taxonomy overlaid onto the risk taxonomy as previously described. For each risk category, the cost drivers involved for the particular risk type are shown in boldface. Note that most rules show up in more than one category. Figure 4.2.2-1 also shows the cost factors and rules for input anomalies and advice.

## 4.2.3 Summary and Conclusions

Further demonstration of the risk assessment and cost estimation is shown in Chapter 5. Also see section 5.5 for the results of testing the expert system against industrial data. It is shown that the results indicate a valid method for assessing risk.

This method is another example of cost drivers providing a powerful mechanism to identify risks. Explication of risky attribute interactions helps illuminate underlying reasons for risk escalation as embodied in cost drivers, thus providing insight into software development risk. Analysis has shown that risk is highly correlated with the total effort multiplier product, and the value of this approach is that it

identifies specific risk situations that need attention.

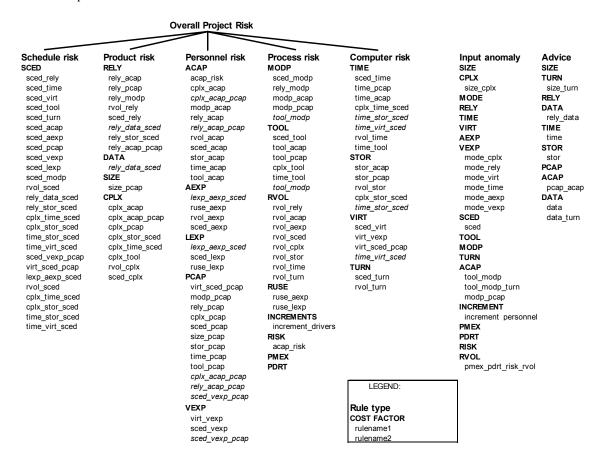


Figure 4.2.2-1 - Rule Taxonomy

At Litton, the knowledge base will continue to be extended for specific product lines and environments to assist in consistent estimation and risk assessment. It is being implemented in the risk management process, and has already been used as a basis for risk assessment of ongoing projects.

# **Chapter 5 Model Demonstration and Evaluation**

This chapter shows how the model is tested with various sets of test cases and industrial data, and demonstrates use of the model for several managerial purposes. Results of the simulation runs and risk assessments are evaluated from several perspectives and insights are provided by experimenting with the model.

Model validation in system dynamics extends quantitative validation with an extensive range and depth of qualitative criteria. The emphasis is on building confidence in the suitability of the model for its intended purposes and its consistency with observed reality [Richardson 91]. A summary of validation tests is shown in Table 5-1, which is adapted from [Richardson 81] and [Forrester-Senge 80]. For each test, the number, name and passing criteria are identified. The criteria for a valid model consist of the tests in this table and associated subtests. Each individual test is insufficient alone to validate a model, but taken together they provide a robust means of filtering out weak models.

The battery of tests in Table 5-1 considers the model's suitability for purpose, consistency with reality, and utility and effectiveness from both structural and behavioral perspectives. Specific modeling objectives to test against include the ability to predict design and code effort sans inspection, preparation and inspection meeting effort, rework effort, testing effort, schedule and error levels as a function of development phase. Simulation test case results are compared against collected data and other published data, existing theory and other prediction models. Testing includes examining the ability of the model to generate proper reference behavior, which consists of time histories for all model variables.

Table 5-1: Summary Table of System Dynamics Model Validation Tests

Testing criteria	Structure focus	Behavior focus
Suitability for purpose	SS1	SB1
	dimensional consistency	parameter (in)sensitivity
		-behavior characteristics
	variable dimensions agree with the	-policy conclusions
	computation, ensuring that the	
	model is properly balanced	model behavior sensitive to reasonable
		variations in parameters
		policy conclusions sensitive to
		reasonable variations in parameters
	SS2	SB2
	extreme conditions in equations	structural (in)sensitivity
		-behavior characteristics
	model equations make sense using extreme values	-policy conclusions
		model behavior sensitive to reasonable
		alternative structures
		policy conclusions sensitive to
		reasonable alternative structures
	SS3	
	boundary adequacy -important variables	
	-policy levers	
	model structure contains variables	
	and feedback effects for purpose of study	
	or study	

Table 5-1: Summary Table of System Dynamics Model Validation Tests (continued)

Testing criteria	Structure focus	Behavior focus
Consistency with reality	CS1	CB1
	face validity	replication of reference modes
	-rates and levels	(boundary adequacy for behavior)
	-information feedback	-problem behavior
	-delays	-past policies
		-anticipated behavior
	model structure resembles real	
	system to persons familiar with	model endogenously reproduces
	system	reference behavior modes that initially
		defined the study, including problematic
		behavior, observed responses to past
		policies and conceptually anticipated
	CCO	behavior
	CS2	CB2
	parameter values -conceptual fit	surprise behavior
	-numerical fit	model produces unexpected behavior
	-numerical int	under certain test conditions - 1) model
	parameters recognizable in real	identifies possible behavior, 2) model is
	system and values are consistent	incorrect and must be revised
	with best available information	meditect and must be revised
	about real system	
		CB3
		extreme condition simulations
		model behaves well under extreme
		conditions or policies, showing that
		formulation is sensible
		CB4
		statistical tests
		-time series analyses
		-correlation and regression
		model output behaves statistically with
		real system data; shows same
		characteristics

Table 5-1: Summary Table of System Dynamics Model Validation Tests (continued)

Testing criteria	Structure focus	Behavior focus
Utility and effectiveness	US1	UB1
of a suitable model	appropriateness of model	counter-intuitive behavior
	characteristics for audience	
	-size	model exhibits seemingly counter-
	-simplicity/complexity	intuitive behavior in response to some
	-aggregation/detail	policies, but is eventually seen as
		implication of real system structure
	model simplicity, complexity and	
	size is appropriate for audience	
		UB2
		generation of insights
		model is capable of generating new
		insights about system

The results of judging the model against these individual criteria are summarized in section A.3 and incorporate the following test cases described in section 5.1.

#### **5.1 Test Cases**

This section details specific test cases including variable and parameter settings. Results from running these test cases are discussed in section 5.2 and Appendix A. All model variables are italicized for identification.

#### 5.1.1 Reference Test Case

The reference test case number 1.1 demonstrates simulation of a generalized project for evaluating simulation output as valid reference behavior. Refer to section *A.1 Reference Behavior* for complete documentation of the simulation output for this test case and substantiation of the reference behavior.

A job size of 32 KSLOC is chosen within the intended range of middle to large size software projects (equivalent to 533.33 tasks at 60 SLOC/task). The project is also characterized as an embedded mode project. In this test case, 100% inspections are performed in both design and coding so both *design* inspection practice and code inspection practice are set to unity. As identified in Chapter 3, an overall error injection rate of 50 errors per KSLOC is simulated. Of those, 50% are introduced in design and 50% in coding with an error multiplication factor of one from design to code.

Certain other parameters in the model need to be calibrated for specific project situations, and the following subsection provides direction for doing so using this test case as an example.

#### 5.1.1.1 Calibration Procedure

Each modeled project should have productivity, error rates, rework effort parameters, test error fixing effort and inspection factors calibrated for the particular environment. Some hardwired model defaults include phase productivity proportions for design and coding, and schedule proportions for phase activities as illustrated in Figure 3.4-2 and further documented in section A.4 in the equations.

The *calibrated COCOMO constant* parameter represents an organizational productivity factor whose magnitude is determined through project data collection and analysis. It is the leading constant in the COCOMO effort equations. The default value of 3.6 for the embedded mode is used in this test case.

The error density of 50 errors/KSLOC is equivalent to 3 total errors per task distributed evenly between design and coding, so *design error density* is set at 1.5 and *code error density* is set at 1.5 in the model.

The parameters design rework effort per error and code rework effort per error are set at .055 and .11 person-days respectively (.44 and .88 person-hours), according to the parameter setting described in Chapter 3. The test error fixing effort is set at 4.6 person-hours with testing effort per error by appropriately setting the multiplier of the calibrated COCOMO constant. The inspection efficiency is nominally set at .6 as stated in Chapter 3. Both design inspection practice and code inspection practice are set to one, indicating 100% inspections are performed.

### 5.1.2 Additional Test Cases

Table 5.1.2-1 identifies sets of test cases, the factors investigated and model parameters that are varied for the simulation. Settings for the parameters in individual test cases are shown in the other sections of this chapter accompanied with the results of the specific simulation experiments. A complete list of test case results are shown in section A.2.

Table 5.1.2-1: Test Cases

Test case numbers	Factors investigated	Model parameters varied				
1.1 through 4.3	use of inspections, job size, productivity	design inspection practice, code inspection practice, job size, calibrated COCOMO constant				
8.1 through 8.18	error generation rates	design error generation rate, code error generation rate, design inspection practice, code inspection practice				
9.1 through 9.6 and 14.1 through 16.12	error multiplication	average design error amplification				
10.1, 10.2	staffing profiles	design staffing curve, coding staffing curve, test staffing curve				
11.1 through 11.4	schedule compression	SCED schedule constraint				
14.1 through 16.12	ROI of inspection strategies, use of inspections per phase, testing effort	design inspection practice, code inspection practice, testing effort per error, average design error amplification				

#### **5.2 Process Assessment**

This section shows the model being used in various facets of software process planning and analysis. The effects of performing inspections, error generation rates, defect amplification between phases, various staffing policies, schedule compression, and personnel experience are investigated with the system dynamics model.

## 5.2.1 Example 1: Effects of Performing Inspections

Test cases 1.1 through 4.3 are designed to evaluate the system dynamics model for job size scalability, ability to be calibrated for specific environments, and to reproduce the effects of inspections. Factors varied are use of inspections, job size and productivity.

Cumulative test case results are shown in Table 5.2.1-1 consisting of cost, schedule and error levels. The test case previously described in section 5.1.1 for evaluating reference behavior is test case number 1.1. The inspection and rework effort are sums for design and coding. More detailed results from these test cases are shown in Table A.2-1 in Appendix A.

Predictions from the Basic COCOMO model using the embedded mode are provided as a basis of comparison for effort and schedule in the table. It is not expected that the model output will match

COCOMO for the testing and integration phase, as COCOMO does not explicitly account for the effects of different error rates on testing effort and schedule. One of the salient features of the system dynamics model is the incorporation of an error model, so comparison with the COCOMO estimate provides an indication of the sensitivity of testing effort to error rates. It is seen that the simulation results and COCOMO differ considerably for the testing and integration phase as the process incorporates inspections.

It is not meaningful to compare schedule times for the different phases between COCOMO and the dynamic model. As shown in Figure 3.4-2, the non-overlapping rectangular profiles of COCOMO will always be shorter than the overlapping staffing curves of the dynamic model.

The remaining errors is zero in each test case since ample resources were provided to fix all the errors in testing. If insufficient testing manpower or decreased productivity is modeled, then some errors remain latent and the resultant product is of lower quality.

Table 5.2.1-1: Test Results Summary - Effects of Inspections

											Schedule			
	Test Case	Description			Effort (person-days)				(days)	Errors				
												reworked		
	COCOMO		inspection	estimation					Test +			from	corrected	l I
#	constant	job size	practice	method	Design	Coding	Inspection	Rework	Integration	Total		inspection	during test	remaining
1.1	3.6	32 KSLOC	1	simulation	2092	1224	203	100	575	4194	260	1152	448	0
1.2			0.5	simulation	2092	1224	101	58	895	4370	272	648	952	0
1.3			0	simulation	2092	1224	0	0	1188	4504			1600	0
			-	СОСОМО	2028	1290	-	-	1290	4608	280	-	-	-
2.1	3.6	64 KSLOC	1	simulation	4807	2812	406	200	1380	9605	341	2304	896	0
2.2			0.5	simulation	4807	2812	202	116		9993				
2.3				simulation	4807	2812	0	0	2729	10348			3200	0
			-	COCOMO	4658	2964	-	-	2964	10586	365	-	-	-
3.1	7.2	32 KSLOC		simulation	4184	2448	203	100		8086			448	
3.2			0.5	simulation	4184	2448	101	58		8559				
3.3				simulation	4184	2448	0	0	2376	9008			1600	0
			-	COCOMO	4055	2580	-	-	2580	9215	350	-	-	-
4.1	7.2	64 KSLOC		simulation	9614	5625	406	200		18606			896	
4.2			0.5	simulation	9614	5625	202	116		19634		1296		
4.3			0	simulation	9614	5625	0	0	5459	20698			3200	0
			-	COCOMO	9316	5929	-	-	5929	21174	456	-	-	-

Figure 5.2.1-1 represents a major result by showing a dynamic comparison of manpower utilization for test cases 1.1 and 1.3 (with and without inspections). Curve #1 in the figure is with inspections. These curves demonstrate the extra effort during design and coding, less test effort and reduced overall schedule much like the effect on project effort previously shown in Figure 3.1-1. The small irregularity at the top is due to the time interval delay of inspections compounded with the end of design and maximum coding manpower rate.

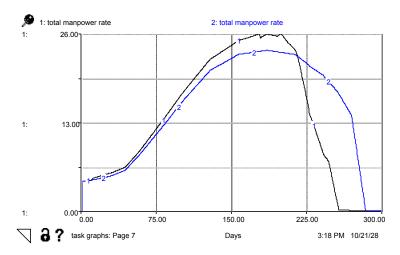


Figure 5.2.1-1: Manpower Rates With and Without Inspections (1: with inspections, 2: without inspections)

Many effects can be gleaned from the results such as the basic return-on-investment of performing inspections, relative proportions of inspection effort, schedule performance, defect profiles, and others. It is seen that inspections add approximately 10% effort in the design and coding phases for these representative test cases, and reduce testing and integration effort by about 50%. The schedule for testing can also be brought in substantially to reduce the overall project schedule. These results are corroborated by numerous projects in the literature and verified by experts interviewed during this research. Further experiments into the effect of inspections follow that investigate the relative returns for design and code inspections, the defect amplification from design to code, and testing effort per error.

## Analysis of Inspection Policies

The data in Table 5.2.1-1 corresponds to equal inspection practices in design and code, though an alternate policy is to vary the amount. The model can be used to investigate the relative cost effectiveness of different strategies. For example, literature suggests that design inspections are more cost effective than code inspections. The model accounts for several factors that impact a quantitative analysis such as the filtering out of errors in design inspections before they get to code, the defect amplification from design to code, code inspection efficiency, and the cost of fixing errors in test. These effects are investigated in the sections below, and lead to a comprehensive analysis of cost effectiveness.

## **Error Generation Rates**

The effects of varying error generation rates are shown in Figure 5.2.1-2 from the results of test cases 8.1 through 8.18 and including 1.1 and 1.3. The overall defects per KSLOC are split evenly between design and code for the data points in the figure.

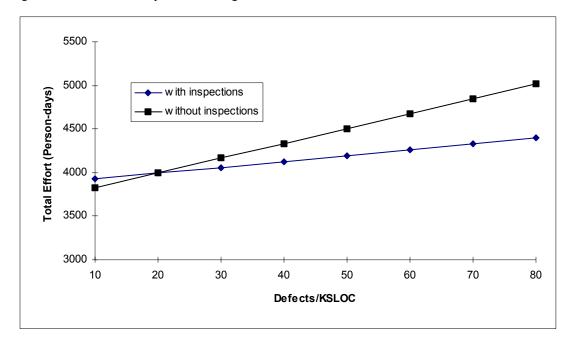


Figure 5.2.1-2: Error Generation Rate Effects

The figure shows that there are diminishing returns of inspections for low error rates. The breakeven point lies at about 20 defects/KSLOC for the default values of inspection effort, rework and error fixing. While inspection and preparation effort stay fairly constant, the rework and test error fixing effort vary with the defect rates. If there is a low defect density of inspected artifacts, then inspections take more effort per detected error and there are diminishing returns. For this reason, a project may choose not to perform inspections if error rates are already very low. Likewise it may not always be cost effective to inspect code if the design was inspected well as seen in sections below.

A specific instance when inspections are not warranted would be during the cleanroom development process. As described in Chapter 2, cleanroom techniques produce code with zero or very low defect rates. As such, inspections would not be cost effective since the process would generate code at the extreme low end of the defect density scale.

Some error detection activities become overloaded with high error rates such as traditional walkthroughs. Since inspections are highly structured meetings with strict protocols and time limits, experience and the model both indicate that no upper bound of defect rates exists for the utility of inspections. However, other types of error detection may be more cost effective for certain types of errors. It is also possible that the inspection process may breakdown with extremely high error rates. In particular if there are interacting errors, then the assigning of defect causes and the rework of those errors may become complex.

Though not explicitly modeled, there is a feedback effect of inspections that would tend to reduce the error generation rate. As work is reviewed by peers and inspection metrics are publicized, an author becomes more careful before subjecting work to inspection.

## Error Multiplication

Defect amplification rates vary tremendously with the development process. For example, processes that tend to leverage off of high-level design tools such as automatic generation of code via graphic drawing tools would amplify errors more than using preliminary design language (PDL) that is mapped 1:1 with code.

As the model aggregates high-level design and detailed design, the default multiplication factor of one assumes that a highly detailed design is the final task state before coding. If more levels of design or requirements were modeled, amplification rates would increase towards the initial requirements state. The average ratio of code to design errors is varied from 1:1 up to 10:1 in this analysis.

Figure 5.2.1-3 shows the effect of design error multiplication rate for performing inspections versus not. It is seen that as the multiplication factor increases, the value of inspections increases dramatically.

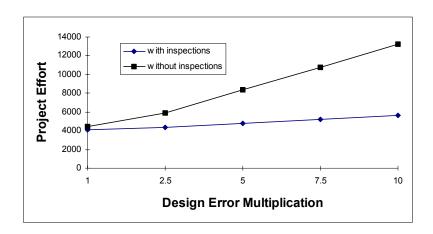


Figure 5.2.1-3: Error Multiplication Rate Effects

The effects of error multiplication must be traded off against effects of error injection rates for different inspected documents. If error multiplication is very high from design to code, then design inspections become relatively more advantageous through multiplication leverage (and code inspections are very important if design inspections are not well-performed). Conversely if error multiplication is low, then inspection of design documents is not as cost effective compared to high multiplication rates.

This analysis also varies the cost of fixing errors. One insight provided by the model is that inspections are only worthwhile if the average cost of fixing errors is more expensive than the inspection effort, where the threshold is determined by multiple parameters. The following section on net return from inspections provides a multivariate analysis involving the error multiplication rate, error injection rate and test error fixing costs.

## Net Return of Inspections

Figure 5.2.1-4 shows the results of performing inspections for design only, code only, or both design and code inspections. The formulation used for net return (NR) from inspections in terms of effort saved is

NR = effort saved - inspection effort.

Since effort is saved downstream in the process,

NR <sub>design</sub> = (code effort saved+test effort saved) - design inspection effort

NR code = test effort saved - code inspection effort

 $NR_{design+code} = (code\ effort\ saved\ + test\ effort\ saved)\ -\ (design\ inspection\ effort+code\ inspection\ effort).$ 

These can be calculated from the test results as

 $NR_{design} = (code inspection effort_{0,0} - code inspection effort_{1,0}) + (test effort_{0,0} - test effort_{1,0})$ 

- design inspection effort<sub>10</sub>

 $NR_{code} = (test \ effort_{0,0} - test \ effort_{0,1}) - code \ inspection \ effort_{0,1}$ 

 $NR_{design+code} = (test\ effort_{0,0} - test\ effort_{1,1}) - (design\ inspection\ effort_{1,1} + code\ inspection\ effort_{1,1})$ 

where the numeric subscripts refer to design inspection practice and code inspection practice.

These are calculated for different values of error multiplication and cost of fixing errors in test, as seen in the curve families in Figure 5.2.1-4 using results from test cases 14.1 through 16.12.

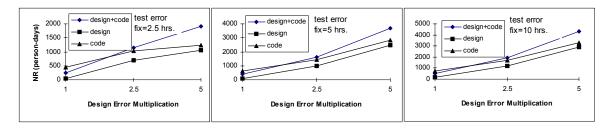


Figure 5.2.1-4: Net Return for Different Inspection Policies

The depictions in Figure 5.2.1-1 are for equal error rates in design and code though many organizations report that more errors are introduced in design (see Figure 3.1-2). Thus the return for design is understated in this case. In the figure, code inspections appear to have more benefit because they are detecting equal proportions of escaped design errors as original code errors. It is seen however that design return approaches code return as the error multiplication rate increases. This analysis can be repeated for any design and code generation rates. When more design errors are generated then code errors such as in test cases # 8.3 and # 8.4, then design inspections are more cost effective than code inspections.

### 5.2.2 Example 2: Staffing Policies

Different staffing curves are easily incorporated into the model. Test cases are shown for "idealized" and rectangular staffing curves. The idealized staffing curve is a modified Rayleigh-like curve according to [Boehm 81] used in the test cases 1.1 - 4.3, and is shown in section *A.1 Reference Behavior* 

and some subsequent figures in this chapter. Further details on the Rayleigh curve and its applicability to software projects can be found in [Putnam 80].

A rectangular staffing profile is often the constraint of organizations with a relatively fixed staff and no appropriations for additional hiring when projects come in. In the case demonstrated here, the maximum manpower allocation is utilized 100% for the project duration, and represents a smaller staff than the average number of personnel and much less than the peak of an idealized staffing curve.

Using a constant staff size of 12 people, the onset of coding is simulated with a simple ramp for the proportion of people devoted to code with an analogous decline in design manpower (likewise for coding to testing). The ramps shown are steep, and the transition slope could be at a lower rate if one desires a more gradual phase transition. The phase durations are adjusted to match total estimated effort with the actual number of staff personnel. The relative phase durations don't match the idealized case because of the constant staff size. The staffing profiles are shown in Figure 5.2.2-1, with results of the simulation in Figure 5.2.2-2. Line #5 in the figure for the actual completion time is a cycle-time utility. Since it measures the time in-process of tasks from requirements generation through testing, it remains at zero until tasks start to complete testing. It then jumps to the current simulation time and stays even with current time until all tasks are tested.

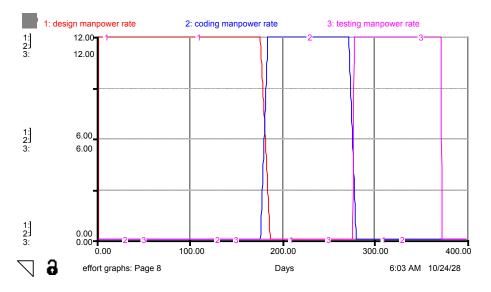


Figure 5.2.2-1: Rectangular Staffing Profile Input

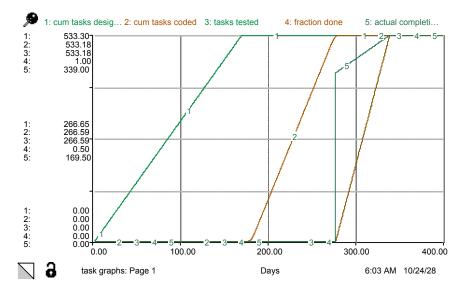


Figure 5.2.2-2: Rectangular Staffing Simulation Results

In this example, the fixed size staff of 12 entails a longer project schedule by about 30%. The overhead of having too many people in the early design phases is not modeled.

## 5.2.3 Example 3: Schedule Compression

The effects of schedule compression are demonstrated by varying the relative schedule (desired/nominal). Per COCOMO and other cost models, overall effort increases with compressed schedule time. The relative schedule is varied from 1 to .7 by changing the parameter *SCED schedule constraint* accordingly. The results are shown in Figure 5.2.3-1 with the total manpower rate curve for the four cases, and Figure 5.2.3-2 shows the cumulative effort and actual schedule time against the relative schedule.

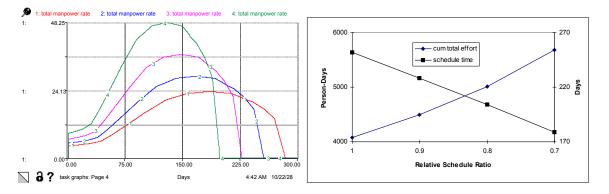


Figure 5.2.3-1: Total Manpower Rate Curves for Relative Schedule

Figure 5.2.3-2: Cumulative Effort and Actual Schedule Time vs. Relative Schedule

(1: relative schedule=1, 2: relative schedule=.9, 3: relative schedule=.8, 4: relative schedule=.7)

## 5.2.4 Example 4: Monte-Carlo Simulation

A deterministic point estimate from a simulation exercise represents one of many possibilities.

The prudent estimator looks at the range of possibilities and ascertains the most likely ones. Monte-Carlo simulation supports this type of risk analysis by selecting random samples from an input distribution for each simulation run, and providing a probability distribution as output.

Many parameters can be chosen for probabilistic representation over multiple simulation runs. In this example, inspection efficiency as the fraction of defects found during inspections is represented using a normal distribution with a mean of .6 and a standard deviation of .2 to gauge the impact on cost, schedule and quality. The results of 50 simulations for total manpower are shown in Figure 5.2.4-1, and in Table 5.2.4-1 for overall project effort, schedule and errors fixed in test.

Note that the Monte-Carlo technique identifies the relative leverage of the varied parameter on different simulation outputs. For example, the standard deviations of effort and schedule are a very small percentage of their means, while errors fixed in test has a standard deviation of about 50% of its mean.

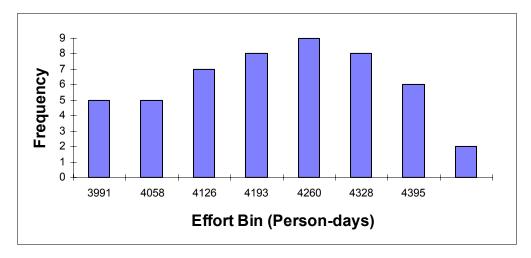


Figure 5.2.4-1: Probability Distribution for Project Effort

Table 5.2.4-1: Monte-Carlo Statistical Summary

Simulation Output	Mean	Standard Deviation
Total project effort (person-days)	4190	130

Completion time (days)	260	6
Errors fixed in test	340	251

## 5.2.5 Example 5: Experience Learning Curve

In this example, a learning curve is implemented to simulate increasing productivity as a project progresses. A COCOMO cost driver is used to set the curve, demonstrating further commonality with factors in Expert COCOMO. Whereas COCOMO uses discretized experience factors, the dynamic model incorporates a continuous learning curve to better approximate the gradual increase in personnel capability.

The applications experience cost driver AEXP is simulated for design activities with the curve in Figure 5.2.5-1. The values used during the time span would approximate the effect of experience from a low rating increasing towards nominal over the course of approximately one year. Figures 5.2.5-2 and 5.2.5-3 show the effect of learning on the design productivity in tasks/person-day and the cumulative tasks designed, where curve #1 does not account for learning while curve #2 does.

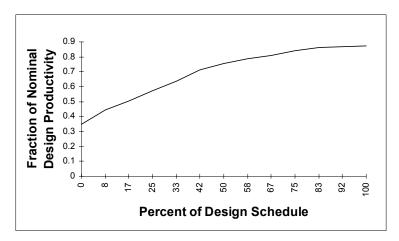
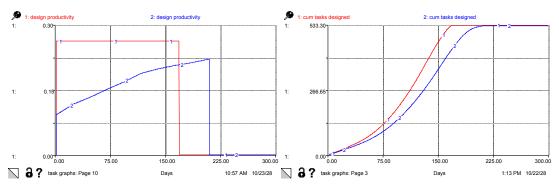


Figure 5.2.5-1: Design Learning Curve

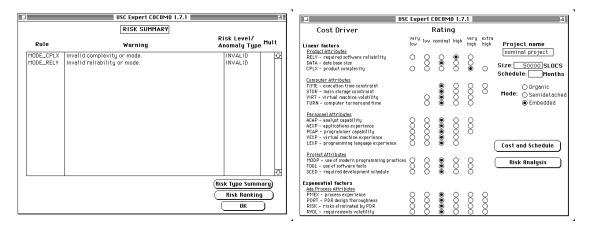


When accounting for learning effects, the design phase takes longer to complete and consumes more personnel resources. A model that uses a realistic learning curve will better support time-phased task planning compared to static models.

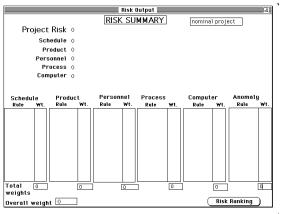
#### 5.3 Integrated Risk Assessment and Simulation

Integration of the knowledge-based risk assessment / cost estimation method and system dynamics model is further demonstrated in this example. The relationship between the taxonomic risk assessment and simulation output, as well as initialization of the dynamic model with the phase estimations from Expert COCOMO are shown. The COCOMO cost estimate, as refined through interactive use of the expert system to be anomaly free and analyzed for risk, provides an initial project estimate to the simulation model.

The test cases are for a nominal and relatively risky project to gauge the sensitivity of the techniques to project conditions. As an example for a nominal project, an embedded mode project is specified with a size of 50 KSLOC and all cost drivers set to nominal. The Expert COCOMO tool informs the user of input anomalies, allowing modification before committing to analysis. The anomaly output for the aforementioned inputs is shown in Figure 5.3-1. The warnings refer to the ratings for reliability and complexity violating the COCOMO definition for an embedded mode project. To eliminate this anomaly, reliability and complexity are reset to high and very high respectively. The revised inputs for this project are shown in Figure 5.3-2, and no anomalies are detected by the rulebase.



The taxonomic risk analysis and cost/schedule outputs for the nominal project are shown in Figure 5.3-3. It is seen that no particularly risky situations are detected by the rulebase. Even though product reliability and complexity are high, other factors such as personnel or schedule are nominal so no cost driver interactions exceed the risk threshold in the rulebase.



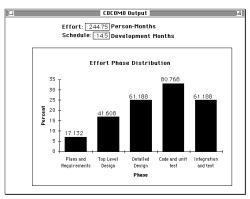


Figure 5.3-3: Expert COCOMO Output for Nominal Project

Inputs for the riskier project are shown in Figure 5.3-4 where the size is kept the same but a number of other cost drivers are set off nominal. The personnel factors are rated relatively low, the computer platform is new and volatile, and there is a schedule constraint.

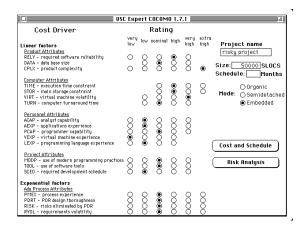
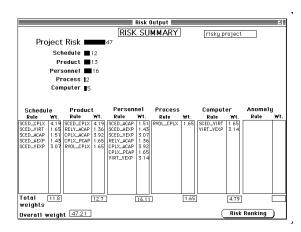


Figure 5.3-4: Inputs for Risky Project

The outputs corresponding to this higher risk example are shown in Figure 5.3-5. It is seen that Expert COCOMO is highly sensitive to these changed project conditions. According to the risk scale in Chapter 4, the value of 47 places this project near the border of medium and high risk projects.



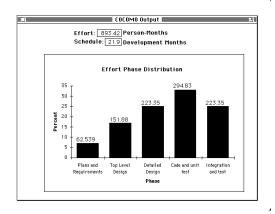


Figure 5.3-5: Expert COCOMO Output for Risky Project

Results of simulation runs for these cases are shown next. Translating the phase effort outputs of Expert COCOMO into the dynamic model requires the *calibrated COCOMO constant* to be set differently for these two projects. The product of effort multipliers sans the relative schedule factor must be incorporated into the constant, since the dynamic model does not explicitly contain the cost driver effects except for the schedule constraint. Thus increased risk indicates a higher value for the COCOMO constant used in the dynamic model in lieu of effort multipliers, and both the *calibrated COCOMO constant* and the relative schedule constraint must be properly set for these cases. The resulting staffing profiles are shown in Figure 5.3-6 overlayed onto each other.

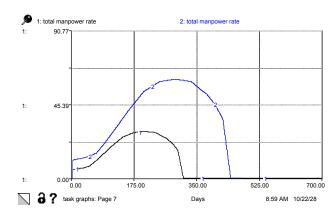


Figure 5.3-6: Resulting Staffing Profiles (1: nominal project, 2: risky project)

The effort and schedule compare favorably with the Expert COCOMO calculations. It is seen that the project with the high risk profile costs more and has a longer schedule time (despite the schedule constraint) than the nominal project. The user can refine the project description, and iterate the sequence

of risk and simulation analysis. This type of information is valuable for several aspects of project planning to analyze project profiles and propose changes during concept studies, proposal activities, and detailed project planning.

In an enhanced dynamic model that contains more cost drivers, personnel factors for example would directly impact the error generation rates. Instead of modifying the COCOMO constant, changes to overall effort and schedule would be a result of cost driver ratings directly affecting dynamic project behavior.

#### 5.4 Derivation of a Detailed COCOMO Cost Driver

In this example, effort multipliers for a proposed cost driver *Use of Inspections* are derived using the default calibrations in test cases 1.1 through 4.3. In detailed COCOMO, effort multipliers are phase sensitive. The model parameters *design inspection practice* and *code inspection practice* are mapped into nominal, high and very high cost driver ratings according to Table 5.4-1. As identified in section 3.4, the dynamic model is calibrated to zero inspection practice being equivalent to standard COCOMO effort and schedule.

Table 5.4-1: Rating Guidelines for Cost Driver Use of Inspections

Simulation Parameters		COCOMO Rating for
design inspection practice	code inspection practice	Use of Inspections
0	0	Nominal
.5	.5	High
1	1	Very High

Figure 5.4-1 shows the model derived effort multipliers by COCOMO phase. This depiction is a composite of test cases 1.1 through 4.3, and there is actually a family of curves for different error generation and multiplication rates, inspection efficiencies, and costs of fixing defects in test. The effort multiplier for high in the integration and test phase is not necessarily exactly halfway between the other points because there is a fixed amount of testing overhead while half of the error fixing effort is saved.

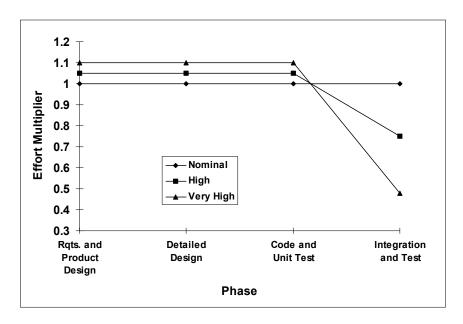


Figure 5.4-1 Effort Multipliers by Phase for Use of Inspections

This result is unique because no other detailed COCOMO effort multipliers cross the nominal line. This is the first instance of a cost driver increasing effort in some phases while reducing it in others.

#### 5.5 Validation Against Industrial Data

Insights provided by the model regarding inspection effectiveness factors were demonstrated in previous sections, as well as replication of different phenomena. In this section, results of comparing model output against industrial data are reported on. Comparison with project data is problematic because no reported data sets contain all the parameters incorporated in the system dynamics model. No project data was found to be complete enough for a global comparison of total effort, schedule and inspection parameters. For instance, published data does not include project size, productivity constants or error multiplication rates and usually does not include phase effort and schedule. The results of performing inspections are normally aggregated for all activities or reported in limited fashion (e.g. "defect rates decreased by 50% during formal test" without providing the specific defect rates). Due to these limitations, the model output can only be validated in certain regards as shown in the following comparisons.

The first comparison is for return on investment (ROI) during testing. As identified in section 3.2, the default error generation rate of 50 errors/KSLOC is based on Litton data and the productivity constant is calibrated to a wide variety of industrial data per COCOMO (the productivity constant for the Litton project is company private and cannot be published). The ROI for performing inspections is calculated as ROI = net return / inspection effort.

Calculating the net return during testing necessitates comparison with a similar project that does not use inspections. This is done for Litton Project A compared to the previous project in the same product line with identical environmental factors (except for no inspections), and test case 1.1 against test case 1.3 using default model values. The results are shown in Table 5.5-1 below. The Litton data is from [Madachy 94b].

Table 5.5-1: Inspection ROI Comparison

Project/Test Case	Net Return	Inspection Effort	ROI
Litton Project A	20206 person-hours saved in	8716 person-hours	2.32
	test using the average cost to		
	fix an error during test		
Test case 1.1	613 person-days saved in test	303 person-days	2.02
	compared to test case 1.3		

This result shows that the model is fairly well-balanced to the experience at Litton, and the 13% difference is acceptable given the wide variability of reported inspection metrics.

Testing effort and schedule performance for the inspection-based project at Litton is also compared against the model. Note that the project is currently in the testing phase and is approximately 85% done with testing activities at this time. The reported reductions are the current estimates-to-complete based on comprehensive project metrics, and the percentages are already adjusted for a 22% difference in project size. Comparisons are shown in Table 5.5-2.

Table 5.5-2: Testing Effort and Schedule Comparison

Project/Test Case	Test Effort Reduction	Test Schedule Reduction
Litton Project A compared to previous project	50%	25%
Test case 1.1 with Litton productivity constant and job size compared to test case 1.3 with Litton parameters	48%	19%
Test case 1.1 compared to test case 1.3	48%	21%

Using both default model parameters and Litton-specific parameters, the model again matches actual project data well.

Another comparison afforded by available data is the ratio of rework effort to preparation and meeting inspection effort. This is done for Litton and JPL data as shown in Table 5.5-3, with JPL data from [Kelly-Sherif 90]. The Litton data is for 320 inspections, and the JPL data covers 203 inspections. No other published data separates out the rework effort.

Table 5.5-3: Rework Effort Ratio Comparison

Project/Test Case	Rework Effort	Preparation and Meeting Effort	Ratio
Litton Project A	2789 person-hours	5927 person-hours	.47
JPL (several projects)	.5 person-hours per defect	1.1 person-hours per defect	.45
Test case 1.1	100 person-days	203 person-days	.49

This demonstrates that the model accurately predicts the relative amount of rework effort to overall inspection effort for these organizations within 9%.

The model outputs can also be compared against the Softcost cost model that accounts for inspection practices by incorporating a cost driver for peer review practice [Softcost 93]. Though the mapping between the cost driver ratings and model results are subject to interpretation, Table 5.5-4 shows the static effort multipliers against the derived multipliers from test cases 1.1 through 1.3. The Softcost multipliers are based on a data set of more than 100 projects.

The multipliers for the dynamic model are calculated by dividing the cumulative project effort by the effort for the nominal case of no inspections, where the case of 100% inspections is mapped to the Softcost *very high* rating and 50% inspections to *high*. The case of no inspections maps well to the *nominal* Softcost rating since formal inspections are not performed. It is seen that the multipliers are

relatively close to each other, demonstrating that the dynamic model replicates the aggregated results of the Softcost database given the caveats of this comparison.

Table 5.5-4: Softcost Effort Multiplier Comparison

Softcost rating for use of peer reviews	Softcost effort multiplier	Model derived effort multiplier
Nominal - design and codewalkthroughs	1.0	1.0
High - design and code inspections	.95	.97
Very high - peer management reviews, design and code inspections	.84	.93

Though the intent of this research is to examine inspection practices, it should also be noted that the system dynamics model will approximate the prediction accuracy of COCOMO for projects not using inspections since the case of zero inspections is calibrated to COCOMO effort and schedule. Specifically, Basic COCOMO predicts effort within 20% of actuals 25% of the time, and schedule within 20% of actuals 58% of the time against the original COCOMO database. This improves considerably as effort multipliers are incorporated, increasing to 20% of effort actuals 68% of the time. The model has effectively incorporated an effort multiplier for schedule constraint and mimicked the multiplier effect for a subset of modern programming practices, and should slightly improve upon Basic COCOMO predictions.

Testing and evaluation of the expert system has been done against the COCOMO project database and other industrial data. In one test, correlation is performed between the quantified risks versus actual cost and schedule project performance. Using an initial subset of the rules corresponding to standard COCOMO cost drivers on the COCOMO database shows a correlation coefficient of .74 between the calculated risk and actual realized cost in labor-months/KDSI, as shown in Figure 5.5-1. Figure 5.5-2 shows risk by project number and grouped by project type for the COCOMO database. This depiction also appears reasonable and provides confidence in the method. For example, a control application is on average riskier than a business or support application.

Industrial data from Litton and other affiliates of the USC Center for Software Engineering is being used for evaluation, where the calculated risks are compared to actual cost and schedule variances from estimates. Data is still being collected, and correlation will be performed against the actual cost and

schedule variance from past projects. In another test, the risk taxonomy is being used as a basis for postmortem assessments of completed projects.

Software engineering practitioners have been evaluating the system and providing feedback and additional project data. At Litton, nine evaluators consisting of the SEPG and other software managers have unanimously evaluated the risk output of the tool as reasonable for a given set of test cases, including past projects and sensitivity tests.

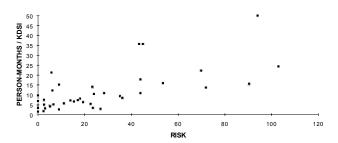


Figure 5.5-1 - Correlation Against Actual Cost

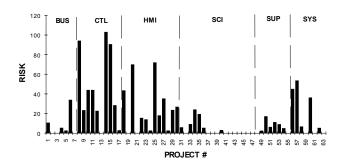


Figure 5.5-2 - Risk by COCOMO Project Number

#### **5.6 Evaluation Summary**

A detailed validation summary is provided in Appendix A. All variables in the reference behavior in section A.1 seem reasonable. For each validation test in section A.3 based on the criteria in Table 5-1, an assessment is made as to how well the model performed, and plans are provided for future enhancement where applicable. No outright failures are identified. Experts that were interviewed have also evaluated the reasonableness of the time history output, the quantitative effects of inspections, and found no major deficiencies.

The model is shown to be suitable for its expressed purpose of demonstrating the effects of inspections from both structural and behavioral perspectives. Policy conclusions are sensitive to reasonable parameter variations of error generation and inspection efficiency. The model is also shown to be consistent with reality by comparison with project data, idealized inspection trends and expert experience. It is useful and effective as a suitable model because it is appropriate for an audience of software practitioners and provides new insights into the development process.

The model has met its goals of demonstrating the behavior of a project using an inspection-based process and is able to predict the relative change in effort, schedule and quality using inspections. When properly calibrated for specific environments, the model is expected to show high fidelity. The results of the experiments support the original hypothesis that a system dynamics model can be developed of various aspects of an inspection-based process.

# **Chapter 6 Conclusions**

This chapter provides a summary of research results. After a summary of previous chapters in Section 6.1, specific research contributions are presented in Section 6.2. Following that, directions for future research are provided in Section 6.3.

#### **6.1 Research Summary**

In Chapter 1, an introduction to the research problem was presented. There is a knowledge gap for interdependent software project phenomena. Without models that integrate various aspects of the software process, practitioners will continue to encounter problems in project planning, development, and process improvement.

Chapter 2 provided a comprehensive background of literature and research in the relevant areas of software engineering, simulation and software project dynamics. The areas of process technology, cost estimation, risk management and knowledge-based software engineering have much to bear on each other. A challenge of research is to integrate the various perspectives and techniques for the purposes of project management and process improvement.

Chapters 3 and 4 highlighted original modeling done for an inspection-based process and taxonomic risk assessment. Inspections are a method to reduce software defects, and the model was developed to investigate the incorporation of inspections in the development process. The knowledge-based risk assessment scheme was developed to support risk management, and leverages on information from cost estimation.

Chapter 5 showed that the system dynamics model has successfully demonstrated several phenomena of software projects, including the effects of inspections and management decision policies. It was also shown that the model is scalable for project size and calibratable for productivity, error generation and error detection.

The model demonstrates that performing inspections slightly increases development effort and decreases effort and schedule in testing and integration, with the effect relatively linear as more inspections are performed. It shows that the cost effectiveness of inspections depends on phase error injection rates, error amplification, testing error fixing effort and inspection efficiency.

The user can specify nominal error rates as well as the efficiencies of error detection during inspection. With increased errors, the model demonstrates that more effort is required in rework and testing activities to fix the errors. Increased inspection efficiency results in increased rework effort from inspections and less effort in testing and integration.

The model accounts for the effects of relative schedule (desired/nominal) which is related to the COCOMO cost driver *SCED*. With a reduced schedule, the average personnel level increases and the overall cost goes up. Different staffing curves can also be easily incorporated into the model. Test cases are shown for rectangular and idealized staffing curves with corresponding project results.

Complementary features of dynamic and static models for the software process were also shown. Intersection of the dynamic model with the static COCOMO was demonstrated in several regards. Phase effort and schedule from COCOMO was used to nominally calibrate the dynamic model, and the dynamic model furthers COCOMO by accounting for dynamic error generation. Common factors for schedule constraint and experience factors were used, with the dynamic model improving on static assumptions. Integration of Expert COCOMO and the dynamic model was also demonstrated, as well as derivation of a COCOMO cost driver from the simulation results.

#### **6.2 Contributions**

This research has demonstrated the dynamic effects of performing inspections and contributed to the body of knowledge regarding the interrelated factors of inspection effectiveness. The model successfully demonstrates the behavior of a project using an inspection-based process and is able to predict the relative change in effort, schedule and quality when using inspections. It will support ongoing research since updated model parameters can be easily incorporated. This work has also corroborated that system dynamics is a suitable modeling paradigm for software processes in general and shown that such modeling can be augmented with expert heuristics to support process management. The combined dynamic model and knowledge-based project assessment also supports risk management in several regards.

This research has also examined complementary features of dynamic and static models of the software development process. It was shown how a static model can be used to nominally calibrate a

dynamic model, and the dynamic model then incorporating more realistic assumptions of time-varying phenomena. The dynamic model was also used to derive effort multipliers for a static model.

This is a step towards developing a unified model incorporating additional lifecycle process variations. Such a model would support behavioral understanding, prediction and evaluation of process improvement, project planning and system acquisition across a range of alternative processes. Some of the modeling constructs can be used for other lifecycle process models, such as an evolutionary risk-driven process since inspections are akin to inserting risk management activities into the lifecycle.

Several facets of this research have been published and presented at conferences or are forthcoming: [Madachy 94] presented the knowledge-based method for risk assessment and cost estimation, [Madachy 94a] documents the knowledge-based method being adopted in industrial practice, [Madachy et al. 93a] discusses analysis of inspection data which supported inspection model parameter development, and [Madachy 94b] enhances the previous analysis of inspection data and elevates it to an organizational level. Other aspects of this research, particularly the inspection-based process model, are being readied for submission to an appropriate refereed journal.

## **6.3 Directions for Future Research**

There are many interesting problems and challenging opportunities for extensions of this research.

An outline of directions for future research are provided in the paragraphs below.

Different error models can be incorporated into the model. There are a variety of alternative formulations to account for error generation and detection, including multiplication of errors through the phases. Additionally, accounting for the severity and type of errors would enhance the model and further support defect prevention and causal analysis efforts. The effects of extremely high error rates should also be investigated, as the model currently shows no degradation of the inspection process under such conditions.

The current model does not account for other defect finding activities such as walkthroughs, cleanroom reviews, etc. Though many organization opt for only inspections, there are various other peer reviews and new methods of development that warrant examination in a dynamic model.

As previously identified, this model examines software production, testing and personnel policies independent of other factors included in Abdel-Hamid's model. This model can be integrated with his model by replacing some portions and adding to others. In particular, the software production sector would be augmented. Bellcore has translated Abdel-Hamid's model into ITHINK [Glickman 94] which could provide a foundation for modification.

The system dynamics model can be enhanced for usability by adding "authoring" capabilities. To support policy analysis and experimentation, user friendly slide controls for varying model parameters can be employed with additional software.

An experiment is proposed to compare the discrete-event STATEMATE approach being developed at the SEI with system dynamics modeling. Raffo is using Kellner's modeling technique to evaluate the effects of inspections on the process [Raffo 93]. Both approaches can model the effect of inspections using a common test case, and the discrete and continuous staffing outputs and quality profiles will be compared. This experiment will help identify the relative merits of both approaches for the research community.

Numerous variations on the staffing and scheduling policies can be tested. Some implicit policy assumptions were used in this model regarding the personnel availability and error rates in the delivered product. Many other possibilities exist besides those investigated here, such as organizations choosing to deliver a product before all known errors are eliminated. Another possibility is modeling Brooks' Law with mentoring costs, assimilation time, and disaggregation of personnel into experience levels.

The system dynamics model can be refined for finer granularity in the phases. Initially, high level and detailed design can be separated out and requirements activities can eventually be incorporated. Data exists for calibrating the defect rates of requirements artifacts as documented in [Madachy et al. 93a] and [Madachy 94b]. The testing and integration phase can also be further disaggregated.

The model could be enhanced to "drill down" further into the inspection process for the purpose of optimization, and look into the dynamics of inspection efficiency, rates, etc. The factors leading to overall inspection effectiveness include learning and training effects of authors and inspectors, the number of inspectors, preparation time, inspection time, inspection rate and the type of document inspected.

The dynamic model can be enhanced for additional COCOMO cost drivers, and investigation of their dynamic effects can be undertaken. Conversely, one can also derive effort multipliers per section 5.4 for different COCOMO drivers by constructing unique models for investigation. For instance, the model can be used as a platform for varying levels of experience to assist in deriving multiplier weights.

More validation against project data is also desired. The model should be re-tested when more complete project datasets are available. Any cases where the model does not perform well should be investigated, and a determination made as to why not. This will likely point to aspects of the model that need improvement.

Other lifecycle process models can be incorporated such as those identified in Section 2.1.1.1 towards a unified system dynamics model for multiple alternative lifecycle processes. Constructs in this model may be modified for an evolutionary risk-driven process, the cleanroom process, personal software process and others.

A variety of enhancements and further research can be undertaken for the knowledge-based aspect. More refined calibrations are still needed for meaningful risk scales. Consistency with other risk taxonomies and assessment schemes is also desired, such as the SEI risk assessment method [Carr et al. 93] and the Software Technology Risk Advisor method of calculating the disparities between functional needs and capabilities [Toth 94].

Additional data from industrial projects can be collected and analyzed, and the risk taxonomy can serve as a data collection guide. Other features can be incorporated into the tool such as incremental development support, additional and refined rules, cost risk analysis using Monte Carlo simulation to assess the effects of uncertainty in the COCOMO inputs, and automatic sensitivity analysis to vary cost drivers for risk minimization. Additional rules can be identified and incorporated to handle more cost driver interactions, cost model constraints, incremental development inheritance rules, rating of consistency violations and advice. Substantial additions are expected for process related factors and advice to control the risks.

The currently evolving COCOMO 2.0 model has updated cost and scale drivers relative to the original COCOMO upon which the risk assessment heuristics in Chapter 4 are based. The risk and

anomaly rulebases should be updated to correspond with the new set of cost factors and model definitions.

A working hypothesis for COCOMO 2.0 is that risk assessment should be a feature of the cost model

[Boehm et al. 94a]. The risk assessment scheme can also be incorporated into the WinWin spiral model prototype [Boehm et al. 93] to support COCOMO negotiation parameters.

One drawback of the integrated model is that it isn't implemented as a single, cohesive tool. The software packages used for the taxonomic risk assessment and system dynamics model are not amenable to integration. A challenge is to overcome this current limitation and integrate them into a unified application.

# **Bibliography**

[Abdel-Hamid 89] Abdel-Hamid T, The dynamics of software project staffing: A system

dynamics based simulation approach, IEEE Transactions on Software

Engineering, February 1989

[Abdel-Hamid 89a] Abdel-Hamid T, Lessons learned from modeling the dynamics of

software development, Communications of the ACM, December 1989

[Abdel-Hamid 90] Abdel-Hamid T, Investigating the cost/schedule trade-off in software

development, IEEE Software, January 1990

[Abdel-Hamid-Madnick 91] Abdel-Hamid T, Madnick S, Software Project Dynamics. Englewood

Cliffs, NJ, Prentice-Hall, 1991

[Abdel-Hamid 93] Abdel-Hamid T, Adapting, correcting, and perfecting software

estimates: a maintenance metaphor, IEEE Computer, March 1993

[Abdel-Hamid 93a] Abdel-Hamid T, Modeling the dynamics of software reuse: an

integrating system dynamics perspective, Presented at the Sixth Annual

Workshop on Software Reuse, Owego, NY, November 1993

[Ackerman et al. 84] Ackerman AF, Fowler P, Ebenau R, Software inspections and the

*industrial production of software*, in "Software Validation, Inspections-Testing-Verification-Alternatives" (H. Hausen, ed.), New York, NY,

Elsevier Science Publishers, 1984, pp. 13-40

[Agresti 86] Agresti W (ed.), New Paradigms for Software Development, IEEE

Computer Society, Washington, D.C., 1986

[Balzer et al. 83] Balzer R, Cheatham T, Green C, Software technology in the 1990's:

using a new paradigm, Computer, Nov. 1983, pp. 39-45

[Baumert-McWhinney 92] Baumert J, McWhinney M, Software Measures and the Capability

Maturity Model. CMU/SEI-92-TR-25, Software Engineering Institute,

Pittsburgh, PA, 1992

[Biggerstaff 89] Biggerstaff T, Perlis, eds., Software Reusability. Addison-Wesley,

1989

[Boehm 76] Boehm BW, Software engineering, IEEE Transactions on Computers,

vol. C-25, no. 12, December 1976, pp. 1226-1241

[Boehm 81] Boehm BW, Software Engineering Economics. Englewood Cliffs, NJ,

Prentice-Hall, 1981

[Boehm 88] Boehm BW, A spiral model of software development and enhancement,

IEEE Software, May 1988

[Boehm 89] Boehm BW, Software Risk Management. Washington, D. C., IEEE-

CS Press, 1989

[Boehm 92] Boehm BW, Knowledge-based process assistance for large software projects, white paper in response to Rome Laboratories PRDS #92-08-PKRD, USC, November, 1992 [Boehm 94] Boehm BW, COCOMO 2.0 program preliminary prospectus. Proceedings of the USC Center for Software Engineering Annual Research Review, USC, February 1994 Boehm BW, Belz F, Applying process programming to the spiral [Boehm-Belz 88] model, Proceedings, Fourth International Software Process Workshop, ACM, May 1988 [Boehm-Papaccio 88] Boehm BW, Papaccio PN, Understanding and controlling software costs, IEEE Transactions on Software Engineering, October 1988 [Boehm-Royce 89] Boehm BW, Royce WE, Ada COCOMO and the Ada process model, Proceedings, Fifth COCOMO Users' Group Meeting, SEI, October 1989 [Boehm et al. 93] Boehm BW, Bose P, Horowitz E, Scacchi W, and others, Next generation process models and their environment support, Proceedings of the USC Center for Software Engineering Convocation, USC, June 1993 [Boehm et al. 94] Boehm BW, Horowitz E, Bose P, Balzer R, White paper: draft options for integrated software product/process technology in satellite ground station and operations control center domains, working paper to be submitted to DARPA, USC, January 1994 [Boehm et al. 94a] Boehm BW, and others, COCOMO 2.0 program preliminary prospectus, USC Center for Software Engineering, USC, May 1994 [Boehm-Scherlis 92] Boehm BW, Scherlis WL, Megaprogamming, DARPA, 1992 [Brooks 75] Brooks FP, *The Mythical Man-Month*, Reading, MA, Addison Wesley, 1975 [Buck-Dobbins 84] Buck R, Dobbins J, Application of software inspection methodology in design and code, in "Software Validation, Inspections-Testing-Verification-Alternatives" (H. Hausen, ed.), New York, NY, Elsevier Science Publishers, 1984, pp. 41-56 [Carr et al. 93] Carr M, Konda S, Monarch I, Ulrich F, Walker C, Taxonomy-Based Risk Identification, Technical Report CMU/SEI-93-TR-06, Software Engineering Institute, 1993 [Charette 89] Charette RN, Software Engineering Risk Analysis and Management, McGraw-Hill, 1989 [Cohen 91] Cohen S, *Process and products for software reuse and domain* analysis, Software Engineering Institute, Pittsburgh, PA, 1991

[Conte et al. 86] Conte S, Dunsmore H, Shen V: Software Engineering Metrics and Models. Menlo Park, CA, Benjamin/Cummings Publishing Co., Inc. 1986 [Curtis et al. 92] Curtis B, Kellner M, Over J, *Process modeling*, Communications of the ACM, September 1992 [Danner 91] Danner B, Integrating Reuse into a lifecycle process, STARS '91 Proceedings, STARS Technology Center, Arlington, VA, December 1991 [Davis 88] Davis A, Bersoff E, Comer E, A strategy for comparing alternative software development life cycle models, IEEE Transactions on Software Engineering, October 1988 [Day 87] Day V, Expert System Cost Model (ESCOMO) Prototype, Proceedings, Third Annual COCOMO Users' Group Meeting, SEI, November 1987 [Demarco 91] Demarco T, Lister T: Controlling Software Projects: Management, Measurement and Estimation, The Atlantic Systems Guild, New York, 1991 Fagan ME, Design and code inspections to reduce errors in program [Fagan 76] development, IBM Systems Journal, V. 15, no. 3, 1976, pp. 182-210 [Fagan 86] Fagan ME, Advances in software inspections, IEEE Transactions on Software Engineering, V. SE-12, no. 7, July 1986, pp. 744-751 [Feiler-Humphrey 93] Feiler P, Humphrey W, Software process development and enactment: concepts and definitions. Proceedings of the Second International Conference on the Software Process, IEEE Computer Society, Washington D.C., 1993 [Fenton 91] Fenton N, Software Metrics - A Rigorous Approach, Chapman and Hall, Great Britain, 1991 [Fishwick-Luker 91] Fishwick P, Luker P (eds.), Qualitative Simulation Modeling and Analysis, Springer-Verlag, New York, NY, 1991 [Fishwick-Modjeski 91] Fishwick P, Modjeski R (eds.), Knowledge-Based Simulation, Springer-Verlag, New York, NY, 1991 [Forrester 61] Forrester JW, *Industrial Dynamics*. Cambridge, MA: MIT Press, 1961 [Forrester 68] Forrester JW, Principles of Systems. Cambridge, MA: MIT Press, 1968 [Forrester -Senge 80] Forrester JW, Senge P, Tests for building confidence in system dynamics models, in A. Legasto et al. (eds.), TIMS Studies in the Management Sciences (System Dynamics), North-Holland, The Netherlands, 1980, pp. 209-228

[Freedman-Weinberg 82] Freedman D, Weinberg G, Handbook of Walkthroughs, Inspections, and Technical Reviews: Evaluating Program, Projects and Products, Little Brown, 1982 [Gilb 88] Gilb T, Principles of Software Engineering Management. Addison-Wesley, Wokingham, England, 1988 [Glickman 94] Glickman S, The Bellcore-CSELT collaborative project, Proceedings of the Ninth International Forum on COCOMO and Software Cost Modeling, USC, Los Angeles, CA, 1994 [Goethert et al. 92] Goethert W, Bailey E, Busby M, Software Effort and Schedule Measurement: A Framework for Counting Staff Hours and Reporting Schedule Information. CMU/SEI-92-TR-21, Software Engineering Institute, Pittsburgh, PA, 1992 [Grady 87] Grady R, Caswell D, Software Metrics: Establishing a Company-Wide Program. Prentice-Hall, Englewood Cliffs, NJ, 1987 [Grady 92] Grady R, Caswell D, Practical Software Metrics for Project Management and Process Improvement Prentice-Hall, Englewood Cliffs, NJ, 1992 [Green et al. 87] Green C, Luckham D, Balzer R, Cheatham T, Rich C, Report on a Knowledge-Based Software Assistant, Kestrel Institute, RADC#TR83-195, Rome Air Development Center, NY, 1983 [Huff-Lessor 89] Huff K, Lessor V, A plan-based intelligent assistant that supports the software development process, Proceedings of the Third Software Engineering Symposium on Practical Software Development Environments, Software Engineering Notes, vol. 13, no. 5, 1989 [Humphrey 89] Humphrey W, Managing the Software Process. Addison-Wesley, 1989 [Humphrey-Sweet 87] Humphrey W, Sweet W, A Method for Assessing the Software Engineering Capability of Contractors . CMU/SEI-87-TR-23, Software Engineering Institute, Pittsburgh, PA, 1987 [Jensen 79] Jensen R, Tonies C: Software Engineering. Englewood Cliffs, NJ, Prentice-Hall, 1979 [Kellner 90] Kellner M, Software process modeling example. Proceedings of the 5th International Software Process Workshop, IEEE, 1990 [Kellner 91] Kellner M, Software process modeling and support for management planning and control. Proceedings of the First International

Kellner M, *Overview of software process modeling*, Proceedings of STARS '92, STARS Technology Center, Arlington, VA, 1992

Conference on the Software Process, IEEE Computer Society,

Washington D.C., 1991, pp. 8-28

[Kellner 92]

[Kelly-Sherif 90] Kelly J, Sherif J, An analysis of defect densities found during software inspections, Proceedings of the Fifteenth Annual Software Engineering Workshop, Goddard Space Flight Center, 1990 [Khoshnevis 92] Khoshnevis B, Systems Simulation - Implementations in EZSIM. McGraw-Hill, New York, NY, 1992 [Lai 93] Lai R, The move to mature processes, IEEE Software, July 1993, pp. 14-17 [Law-Kelton 91] Law M, Kelton W, Simulation Modeling and Analysis. McGraw-Hill, New York, NY, 1991 [Legasto et al. 80] Legasto A, Forrester J, Lyneis J, (eds), TIMS Studies in the Management Sciences (System Dynamics), North-Holland, The Netherlands, 1980 [Lin-Levary 89] Lin C, Levary R: Computer-aided software development process design, IEEE Transactions on Software Engineering, September 1989 [Lin et al. 92] Lin C, Abdel-Hamid T, Sherif J: Software-engineering process simulation model. TDA Progress Report 42-108, Jet Propulsion Laboratories, February 1992 [Lowry-McCartney 91] Lowry M, McCartney R (eds.), Automating Software Design, AAAI Press, Menlo Park, CA, 1992 [Madachy 90] Madachy R, CASE and hypertext integration issues. The Third Annual Teamworkers International User Group Conference. San Diego, CA. March, 1990 [Madachy 90a] Madachy R, Directed research final report, class report, ISE 590, University of Southern California, May 1990 [Madachy 93] Madachy R, Knowledge-Based Assistance for Software Cost Estimation and Project Risk Assessment, Proceedings of the Eighth International Forum on COCOMO and Software Cost Modeling, SEI, Pittsburgh, PA, 1993 [Madachy et al. 93a] Madachy R, Little L, Fan S, Analysis of a successful inspection program, Proceedings of the Eighteenth Annual Software Engineering Workshop, NASA/SEL, Goddard Space Flight Center, Greenbelt, MD, 1993 [Madachy 94] Madachy R, Knowledge-based risk assessment and cost estimation, Proceedings of the Ninth Knowledge-Based Software Engineering Conference, Monterey, CA, IEEE Computer Society Press, September 1994 [Madachy 94a] Madachy R, Development of a cost estimation process, Proceedings of the Ninth International Forum on COCOMO and Software Cost

Modeling, USC, Los Angeles, CA, 1994

[Madachy 94b] Madachy R, Process improvement analysis of a corporate inspection program, Submitted to the Seventh Software Engineering Process Group Conference, October 1994 [McCracken-Jackson 83] McCracken D, Jackson M, Life-cycle concept considered harmful, ACM Software Engineering Notes, April 1982, pp. 29-32 [Mi-Scacchi 91] Mi P, Scacchi W, Modeling articulation work in software engineering processes. Proceedings of the First International Conference on the Software Process, IEEE Computer Society, Washington D.C., 1991, pp. 188-201 [Mi-Scacchi 92] Mi P, Scacchi W, Process integration for CASE environments. IEEE Software, March, 1992, pp. 45-53 [Mills 87] Mills H, Dyer M, Linger R, Cleanroom engineering, IEEE Software, September 1987 [Mitre 88] Mitre Corporation, Software Management Metrics. ESD-TR-88-001 [NASA 90] NASA, Managers Handbook for Software Development. SEL-84-101, November 1990 [Naur 69] Naur P, Randell B (eds.), Software Engineering: A Report on a Conference sponsored by the NATO Science Committee, NATO Scientific Affairs Division, Brussels, Belgium, 1969. [Osterweil 87] Osterweil L, Software processes are software too, Proceedings ICSE 9, IEEE Catalog No. 87CH2432-3, Mar. 1987, pp. 2-13 [Parsaye-Chignell 88] Parsaye K, Chignell M: Expert systems for experts. John Wiley and Sons, New York, 1988. [Parsaye et al. 89] Parsaye K, Chignell M, Khoshafian, Wong: *Intelligent databases*: Object-oriented, deductive hypermedia technologies. John Wiley and Sons, New York, 1989. [Paulk et al. 91] Paulk M, Curtis B, Chrissis M, and others, Capability Maturity Model for Software. CMU/SEI-91-TR-24, Software Engineering Institute, Pittsburgh, PA, 1991 [Pressman 87] Pressman R, Software Engineering - A Practitioners Approach. McGraw-Hill, NY, 1987 [Prieto-Diaz 91] Prieto-Diaz R, Arango G, Domain Analysis and Software Systems Modeling, IEEE Computer Society Press, Los Alamitos, CA, 1991 [Prieto-Diaz 91a] Prieto-Diaz R, Domain analysis process model, STARS '91 Proceedings, STARS Technology Center, Arlington, VA, December 1991 [Putnam 80] Putnam L (ed.), Software Cost Estimating and Lifecycle Control: Getting the Software Numbers, IEEE Computer Society, New York, NY, 1980

[Radice-Phillips 88] Radice RA, Phillips RW, Software Engineering - An Industrial Approach, Englewood Cliffs, NJ, Prentice-Hall, 1988, pp. 242-261 [Raffo 93] Raffo D, Evaluating the impact of process improvements quantitatively using process modeling, working paper, Dept. of Industrial Administration, Carnegie Mellon University, 1993 [Rechtin 91] Rechtin E, Systems Architecting, Englewood Cliffs, NJ, Prentice-Hall, 1991 [Reddy et al. 86] Reddy Y, Fox M, Husain N, McRoberts M, The knowledge-based simulation system, IEEE Software, March 1986 [Remus 84] Remus H, Integrated software validation in the view of inspections /reviews, in "Software Validation, Inspections-Testing-Verification-Alternatives" (H. Hausen, ed.), New York, NY, Elsevier Science Publishers, 1984, pp. 57-64 [Richardson-Pugh 81] Richardson GP, Pugh A, Introduction to System Dynamics Modeling with DYNAMO, MIT Press, Cambridge, MA, 1981 [Richardson 91] Richardson GP, System dynamics: simulation for policy analysis from a feedback perspective, Qualitative Simulation Modeling and Analysis (Ch. 7), Fishwich and Luker, eds., Springer-Verlag, 1991 [Richmond et al. 90] Richmond B, and others, ITHINK User's Guide and Technical Documentation, High Performance Systems Inc., Hanover, NH, 1990 [Rodriguez 91] Rodriguez S, SESD inspection results, April 1991 [Rook 93] Rook P, Cost estimation and risk management tutorial, Proceedings of the Eighth International Forum on COCOMO and Software Cost Modeling, SEI, Pittsburgh, PA, 1993 [Royce 70] Royce W, Managing the development of large software systems, Proceedings IEEE Wescon, 1970 [Royce 90] Royce WE, TRW's Ada process model for incremental development of large software systems, TRW-TS-90-01, TRW, Redondo Beach, CA, January 1990 [Softcost 93] Softcost-Ada Reference Manual, Resource Calculations Inc., Denver, CO, 1993 [Suzuki-Katayama 91] Suzuki M, Katayama T, Metaoperations in the process model HFSP for the dynamics and flexibility of software processes, Proceedings of the First International Conference on the Software Process, IEEE Computer Society, Washington, D.C., 1991, pp. 202-217 [Sabo 93] Sabo J, Process model advisor, CSCI 577A class project, University

of Southern California, 1993

[Scacchi-Mi 93] Scacchi W, Mi P, Modeling, enacting and integrating software engineering processes, Presented at the 3rd Irvine Software Symposium, Costa Mesa, CA, April, 1993 [Scott-Decot 85] Scott B, Decot D, Inspections at DSD - automating data input and data analysis, HP Software Productivity Conference Proceedings, 1985, pp. 1-79 - 1-80 [Selby 88] Selby RW, Empirically analyzing software reuse in a production environment, in W. Tracz (ed), Software Reuse: Emerging Technology, IEEE Computer Society Press, 1988, pp. 176-189 [SPC 91] Software Productivity Consortium, Software Measurement Guidebook., SPC-91060-MC, June 1991 [Thayer 79] Thayer RH, Modeling a Software Engineering Project Management System, unpublished Ph.D. dissertation, University of California, Santa Barbara, CA, 1979 [Toth 94] Toth G, Knowledge-based advisory system: expert assistance for software risk management, Proceedings of the Third Software Risk Conference, SEI/CMU, Pittsburgh, PA, April 1994 Verner J, Tate G, Estimating size and effrot in fourth generation [Verner-Tate 88] development, IEEE Software, July 1988, pp. 15 - 22 [Waterman 86] Waterman D, A Guide to Expert Systems, Addison-Wesley, Reading, MA, 1986 [Weller 93] Weller E, Three years worth of inspection data, IEEE Software, September 1993, pp. 38 - 45

Wolstenholme E, System Enquiry: A System Dynamics Approach,

Wiley and Sons, West Sussex, England, 1990

[Wolstenholme 90]

# Appendix A System Dynamics Model Supplement

This appendix provides additional detail of the system dynamics model and its validation including reference behavior, test case results, a validation summary and its equations.

## A.1 Reference Behavior

Each time trend from test case number 1.1 is discussed below, providing rationale for the observed trend. Figures A.1-1 through A.1-3 show the graphs for task, error and effort variables respectively.

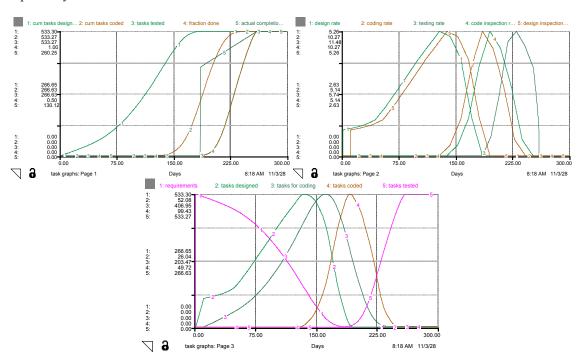


Figure A.1-1: Task Graphs

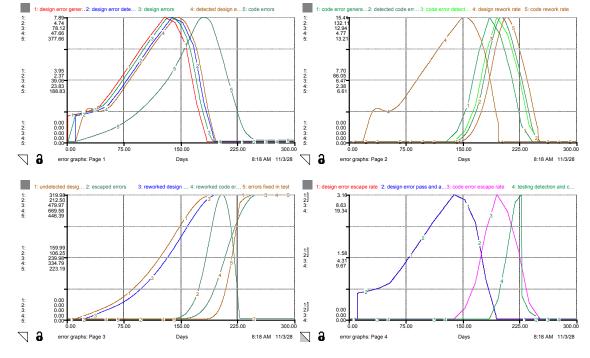


Figure A.1-2: Error Graphs

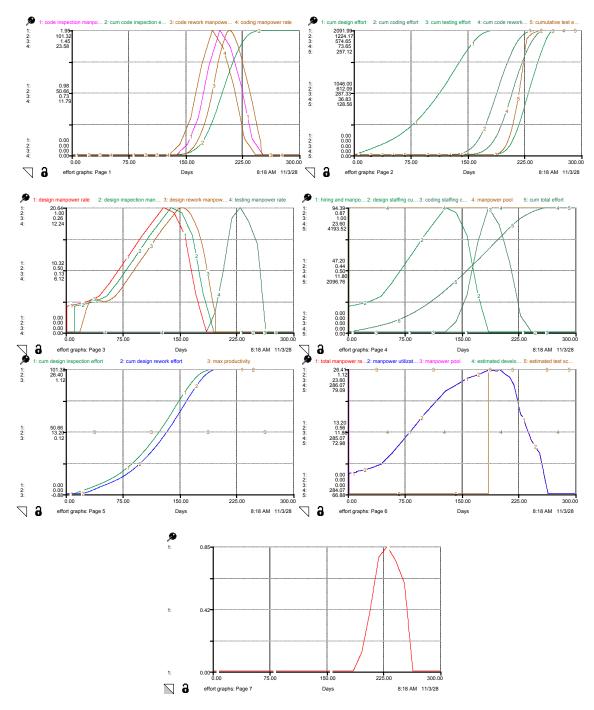


Figure A.1-3: Effort Graphs

#### task graphs: Page 1

This graph presents a high level overview of project progress, including cumulative depictions of task progress for the main activities of design, code and test; fraction done; and completion time.

#### 1: cum tasks designed

The cumulative tasks designed is monotonically increasing while design is taking place and levels off as design completes. Since the design rate builds up and decreases, it exhibits an s-shaped behavior. This shape is consistent with progress tracking charts from projects that have similar staffing patterns. With a constant design rate, it would be a perfect ramp.

#### 2: cum tasks coded

The cumulative tasks coded is monotonically increasing while coding is taking place and levels off as coding completes. It also exhibits an s-shaped behavior due to the escalation and declination in the rate of coding.

## 3: cum tasks tested

The cumulative tasks tested is monotonically increasing while testing is taking place and levels off as testing completes. It also exhibits an s-shaped behavior due to the escalation and declination in the rate of testing.

#### 4: fraction done

The fraction done is the ratio of tasks tested to job size, indicating project completion percentage and is monotonically increasing. Scaled independently, it properly matches the curve for cumulative tasks tested and is coincident.

#### 4: actual completion time

The actual completion time is a cycle time utility that instruments the maximum time of tasks in-process that are time-stamped at requirements generation rate and complete testing. It's final value indicates the project's actual schedule time. It is a ramp once testing commences since it measuring the maximum time in process of all tasks that have completed testing up to that point.

## task graphs: Page 2

These curves show the rates of various lifecycle activities in terms of tasks/day.

## 1: design rate

The design rate is influenced by the amount of personnel devoted to it and the fluctuation in productivity. It follows the staffing profile policy input which is a Rayleigh-like curve. Productivity remains constant in this test case for ease of analysis.

#### 2: coding rate

The coding rate is influenced primarily by the amount of personnel devoted to it, and secondarily by the fluctuation in productivity. It follows the staffing profile policy input which is a Rayleigh-like curve.

#### 3: testing rate'

It follows the test staffing Rayleigh-like curve. Productivity remains constant in this test case for ease of analysis.

#### 4: code inspection rate

As seen in the curve, code inspection is set with a delay of 10 days after coding. It also has the same magnitude of coding in tasks/day since this test case simulates 100% inspections performed and inspection tasks do not fall behind.

## 5: design inspection rate

Similar to the code inspection rate, design inspection is set with a delay of 10 days after design and also has the same magnitude as the design curve.

## task graphs: Page 3

This graph shows the levels of tasks as they progress through phases in the development process.

## 1: requirements

The level of requirements is initiated with a pulse of magnitude job size at time zero. It then declines in a manner converse to the cumulative tasks designed, and reaches zero when all tasks have been designed.

## 2: tasks designed

The tasks designed increases as design starts, and the rate of increase slows as design gives way to coding. Tasks transition to the state of tasks in coding after they are inspected. The sharp angle at the beginning is due to inspections starting to take place, thus the outgoing rate starts to increase and tasks enter the "tasks for coding" state.

## 3: tasks in coding

Tasks in coding represents the intermediate state between design and tasks coded. It builds up as tasks finish design, and decreases when more tasks are being coded than designed.

#### 4: tasks coded

The tasks in coding increases as coding starts, and the rate of increase slows as coding gives way to testing.

Tasks transition to tasks ready for test after they are inspected.

## 5: tasks tested

Same as tasks tested on page 1 of the task graphs.

#### error graphs: Page 1

This graph depicts design error levels, design error rates and code errors.

## 1: design error generation rate

The design error generation rate is slaved to the design rate, since it is a co-flow. It is seen that its magnitude is properly 1.5 times the design rate shown in the task graphs.

## 2: design error detection rate

The design error detection rate is slaved to the level of design errors shown in curve 3, and its magnitude is determined by the efficiency of inspections. It is seen that its magnitude is 60% of the level of design errors, as expected since the detection efficiency is .6.

#### 3: design errors

Since design errors are generated simultaneously as a co-flow of design, its curve shape matches the level of design tasks. Its magnitude is determined by the rate of design error generation. As design inspections are performed, they transition to the detected or undetected state.

#### 4: detected design errors

The detected design errors rise as design inspections are performed, and decrease as they are reworked.

The early hump is a start-up artifact of the delay for inspections (ingoing rate) compounded with the fixed delay for rework (outgoing rate), and causes humps in downstream related variables such as rework effort.

## 5: code errors

The level of code errors represents errors in code before inspection. It is fed by a co-flow of coding as well as the passing and amplification of undetected design errors. As code inspections are performed, they transition to the detected or undetected state.

#### error graphs: Page 2

This graph shows the rates and levels of code errors in various states, as well as the design rework rate.

## 1: code error generation rate

The code error generation rate is linearly related to the coding rate, since error production is a co-flow of coding. It properly matches the shape of the coding rate curve, and the magnitude is seen to be correct at 1.5\* coding rate.

## 2: detected code errors

The detected code errors rise as code inspections are performed, and decrease as they are reworked since this represents code errors detected during inspection before rework occurs.

#### 3: code error detection rate

The code error detection rate is slaved to the level of code errors, and its magnitude is determined by the efficiency of inspections. It is seen that its magnitude is 60% of the level of code errors, as expected since the detection efficiency is .6.

#### 4: design rework rate

Design error rework follows inspection by 10 days, and thus the rate follows the level of detected design errors with the proper delay.

#### 5: code rework rate

Code error rework follows inspection by 10 days, and thus the rate follows the level of detected code errors with the proper delay.

#### error graphs: Page 3

This graph shows cumulative levels of errors, except for non- cumulative escaped errors.

1: undetected design errors

The level of undetected design errors rises with the generated design errors. This cumulative depiction

instruments the total number of design errors undetected during inspection which are passed and amplified

to the coding phase. Its final magnitude is correct as the total number of design errors multiplied by (1-

inspection efficiency).

2: escaped errors

The level of escaped errors rises as code inspections complete, but then starts falling as testing activities

detect and fix them. The level reaches zero as testing completes.

3: reworked design errors

The level of design errors reworked due to inspection is monotonically increasing from design inception

until design completes.

4: reworked code errors

The level of code errors reworked due to inspection is monotonically increasing from coding inception

until coding completes.

5: errors fixed in test

The level of errors detected and fixed during testing is cumulative as testing takes place.

error graphs: Page 4

This graph shows various rates of error escape, passage through phases and detection.

1: design error escape rate

100

The rate of design errors escaping to coding follows the level of design errors, as multiplied by (1-inspection efficiency).

# 2: design error pass and amplification rate

The pass and amplification rate of design errors to code errors is linearly related to the design error escape rate, as multiplied by the average design error amplification. It peaks and drops since error generation occurs simultaneously as tasks are designed, which is a similar curve as seen in the task graphs.

## 3: code error escape rate

The rate of code errors escaping to test follows the level of code errors, as multiplied by (1- inspection efficiency).

## 4: testing detection and correction rate

The testing detection and correction rate is implemented as a delay from escaped errors equivalent to the estimated duration for testing.

# effort graphs: Page 1

The graph shows some coding manpower rates and cumulative code inspection effort.

# 1: code inspection manpower rate

The code inspection manpower rate equals the rate of code inspection multiplied by the inspection effort per task, and is seen to match the curve of code inspection rate and scaled accordingly by the effort per task.

## 2: cum code inspection effort

The cumulative code inspection effort continues to increase monotonically as code inspection are performed.

3:	code	rework	manpower	rate
----	------	--------	----------	------

The code rework manpower rate rises as code errors are detected, and falls as they are reworked.

# 4: coding manpower rate

The coding manpower rate follows the coding staffing profile curve seen in page 4 of the effort graphs, with the magnitude determined by the manpower pool.

# effort graphs: Page 2

All the curves on this chart are cumulative effort.

# 1: cum design effort

The cumulative design effort is monotonically increasing while design takes place.

# 2: cum coding effort

The cumulative code effort is monotonically increasing while coding takes place.

# 3: cum testing effort

The cumulative testing effort is monotonically increasing while testing takes place.

## 4: cum code rework effort

The cumulative code rework effort is monotonically increasing while code errors are reworked.

# effort graphs: Page 3

This graph shows more manpower rates for various development activities.

# 1: design manpower rate

The design manpower rate follows the design staffing profile curve seen in page 4 of the effort graphs, with the magnitude determined by the manpower pool.

# 2: design inspection manpower rate

The design inspection manpower rate equals the rate of design inspection multiplied by the inspection effort per task, and is seen to match the curve of design inspection rate and scaled accordingly by the effort per task.

## 3: design rework manpower rate

The design rework manpower rate rises as design errors are detected, and falls as they are reworked.

# 4: testing manpower rate

The testing manpower rate has two components: the fixed portions for test planning and execution, and the variable component of error detection and correction. It is proportional to the test staffing curve, and multiplied by the manpower allocation.

## effort graphs: Page 4

This effort graph shows manpower allocation policies and cumulative total effort.

# 1: hiring and manpower allocation

The hiring and manpower allocation is a pulse as determined by project size, schedule and staff productivity. It occurs at time zero only. Since the DT time increment is equal to .25 for the simulation, the pulse magnitude is four times the allocated staff size.

## 2: design staffing curve

The design staffing curve is a Rayleigh-like curve that peaks and subsides during the initial part of development, expressed as a fraction of the available personnel.

3: coding staffing curve

The coding staffing curve is a Rayleigh-like curve that peaks and subsides, starting after design with the

proper phase delay and expressed as a fraction of the available personnel.

4: manpower pool

The manpower pool represents the level of available personnel that were pulsed in by the hiring and

manpower allocation rate at time zero. It stays constant with the zero attrition.

5: cum total effort

The cumulative total effort of all activities is monotonically increasing from design inception until the last

task is tested.

effort graphs: Page 5

This graph shows some cumulative effort curves. Some variables for debugging purposes only are not

discussed.

1: cum design inspection effort

The cumulative design inspection effort is monotonically increasing from design inception until the end of

design. It exhibits s-shaped behavior due to the peaked curve of design manpower rate.

2: cum design rework effort

The cumulative design rework effort follows the shape of cumulative design inspection effort since they

are directly correlated with each other with a short delay.

effort graphs: Page 6

This graph shows the project-wide effort curve and manpower utilization.

104

# 1: total manpower rate

The total manpower rate is a sum of all the other manpower rates. It approximates the intended Rayleighlike staffing curve, and is seen to be the correct sum of all activities.

# 2: manpower utilization

The manpower utilization is a ratio of the total manpower rate to the manpower pool, and the shape is necessarily coincident with the total manpower rate. It is slightly greater than one because the inspection manpower is not allotted in the initial staffing curves (calibrated to zero inspections).

# effort graphs: Page 7

This graph shows the project-wide effort curve and manpower utilization.

# 1: test staffing curve

The test staffing curve is a Rayleigh-like curve that peaks and subsides, starting after coding with the proper phase delay and expressed as a fraction of the available personnel. It is scaled for the error density.

# **A.2 Test Case Results**

Parameter settings and cumulative results from the simulation test cases are shown in Table A.2-1. Values are in simulation units: job size is in tasks, effort is in person-days and schedule is in days. To convert to other units use 60 SLOCS/task for size, 20 person-days per person-month for effort and 20 days per calendar month.

			calibrated	calibrated design code		design			testing		1	cum	uno	cum code	cum code	uno			undetected
test case	ob size	relative	COCOMO	inspection	ction	error	code error	design error amplification	effort per	design	coding c	ion	design	inspection rework effort effort		testing	cum total	completion	design
-	533.3	1.0	33	-	-	1.5		1		2092	1224	101							
1.2	533.3			0.5	0.5		1.5	1	0.58		1224	51	13	51	45				560
1.3	533.3		3	0	0	1.5		+	0.58		1224	0	0			1188		280	
2.1	1066.7	1.0		•	-	1.5			0.58		2813	203	53	203				341	
2.2	1066.7				0.5	מ			0.58		2813	5	2					333	]
2.3	1066.7			0	0	3.	1.5		0.58	44807	2813	0	2 80		0 2	2729	10349		
2.5	523.3			-	- 4	ט ע			1 15		2449	2 2	13	2 4					560
3.2	5333	-			200	2 4			1 15		2448	0							
2 4	1066.7					15			1.15		5625	203	53				L	L	
4.2	1066.7			0	0.5	1.5		-	1.15		5625	101	26			4077	19635		,
4.3	1066.7				0	1.5		1	1.15	9614	5625	0	O			"	20698		٦
8.1	533.3				-	2.4		1	0.58	2002	1224	101	42	101		715	4394		
8.2	533.3			*-	-	1.2	1.2	-	0.58		1224	101	21						
8.3	533.3				-	1.8			0.58		1224	101	63						
8.4	533.3					2.1		-	0.58		1224	5	74						
8.5	533.3					9.0		-	0.58		1224	101	÷	F					
8.6	533.3			0	0	2.4	2.4		0.58		1224	0		0		1697			1280
8.7	533.3				0	1.2		-	0.58		1224	0	0						
89.89	533.3	Ì			0	1.8			0.58		1224	0							ľ
8.0	533.3	Ì			0	2.1			0.58		1224	0							1120
8.10	533.3				0	9.0	9.0		0.58		1224	0							
8.11	533.3			-	-	0.3		-	0.58		1224	101	2						64
8.12	533.3				0	0.3	0.3		0.58		1224		0 1	0		510	3826		
8.13	533.3				-	2.1	2.1		0.58		1224	יסר	3/						ľ
8.14	533.3			0		7.7			800		477	2	٥١٤						
0.10	533.3					Σ α			200		4224	בויי	30						
0.10	533.3			3	5	0 0	0 0	-	0 0		4271	2	0 0	707			1		
2 0	0000			-	- 0	0.00			000	2002	1224	2							
- 1 -	533.3			5	5	8.0	8.0		0.58		\$77.	0 7	2 2				4165		480
9 (1.1)	223.3			-	-	ני ע		3 6		1	P221	2 5	2						
9.7	533.3				-	5 4		-			1224	5	200						320
0.0	533 3	0.0		-	-	5 4		7.5	0.58		1224	101	53	100	211				
95	533.3				-	1.5					1224	101	53				5667		
9.6 (1.3)	533.3				0	1.5	-		0.58		1224	0	0					L	
16	533.3				0	1.5		2.5	0.58		1224	0	0	0	0				800
98	533.3			0	0	1.5	1.5		0.58	2092	1224	0	0			5044	8360		
9.9	533.3				0	1.5		_	0.58		1224	0	0						
9.10	533.3			0	0	1.5	-	10	0.58		1224	0	0			٦			800
11.1 (1.1)	533 3				-	1.5		-	0.58		1224	101	53	101					
11.2	533.3	0	3.6	-	-	1.5		-	0.58		1359	101	53			į			
11.3	533.3	0.8	3.6		-	1.5		-	0.58		1530	101	53	101		537			
11.4	533.3		3.6	-	-	1.5		-	0.58		1751	101	53					179	
141	533.3		3.6			1.5	-	-	0.31		1224	101	53		74			252	320
14.2	533.3		3.6		0	1.5		-	0.31		1224	101	53	0	0				
14.3	533.3		3.6		0	1.5	1.5	-	0.31		1224	0	0						
14.5	533.3		3.6		-	1.5	1.5	2.5	0.31		1224	101	53	<u></u>	106	764			320
146	533.3		3.6	-	0	15	6.	25	0.31	2082	1224	101	53	0			4899	288	

# Table A.2:1 Test Case Results (continued)

_		calibrated design	design	code	design		average	testing				cum	cum code	cum code cum code cum	En L		actual	undetected
2	relative	COCOMO inspection inspection error	inspection	inspection	error	code error	design error	effort per	design	coding	design	design	inspection rework	rework	testing	cum total	completion design	design
Ñ	schedule	constant	practice	practice	density	density	amplification error	error	effort	effort	inspection rework	rework	effort	effort	effort	effort	time	errors
_	1.0	3.6	0	0		-				1224	0	)		0 0	2281	5598		
533.3	1.0	3.6	0	,	1.5	-	2.5	0.31	2092	1224			101		196			800
533.3	1.0	3.6	-	-	1.5	1.5				1224	101	λ		158		4808	268	
533.3	1.0	3.6		0		-					101	່ວ່າ	3			5650	300	
533.3	1.0	3.6	0	0		1.5	5				0			0		6715		
533.3	1.0	3.6	0	-	1.5	-	5	0.31		1224	0			1 317	1750	5485		
533.3	1.0	3.6	-	•	1.5	1.5	+	0.63		1224	101		101	1 74		4060	252	
6	1.0	3.6	-	0		1.5	-	0.63								4370		
533.3	1.0	3.6	0	0	1.5	1.5	1	0.63	2002	1224	0	0		0	1157	4474	272	800
9	1.0	3.6	-		1.5	1.5	2.5						101			4330		
3	1.0	3.6	1	0		1.5												
533.3	1.0	3.6	0	0		1.5	2.5						0			5965		
6	1.0	3.6	0	•	1.5	1.5				1224								
3	1.0	3.6	-	-	1.5					1224							267	
533.3	1.0	3.6	-	0													312	
3	1.0	3.6	0	0		1.5	5			1224				0		8451	345	
3	1.0	3.6	0	-	1.5	1.5												
6	1.0	3.6	-	1	1.5		-	1.25										
က	1.0	3.6	-	0			1	1.25		1224			3 0	0 0	1	4327		
533.3	1.0	3.6	0	0														
533.3	1.0	3.6	-	-	1.5									·				
ε,	1.0	3.6		0									3 0			5016		
533.3	1.0	3.6	٥				2.5			1224				0 0		6194		
533.3	1.0	3.6	٥		1.5	1.5						_	101	·				
533.3	1.0	3.6	-	-	1.5							5.						
533.3	1,0	3.6	-	0							1	5						
533.3	1.0	3.6	0	0				1.25		1224	0	)				9906		
533.3	1.0	3.6	0	-	1.5	1.5	S					)	101	1 317		5753		800
533.3	1.0	3.6	-	0		-	-	0.58			101	7	0 0	0 0				
533.3	1.0	3.6	0	0		-	-	0.58			0							
533.3	1.0	3.6	0	-	2	-	-	0.58				)				4196		
533.3	1.0	3.6	-	-	2	-	2.5		2092	Ì	101	7.	101	105			258	427
533.3	1.0	3.6	-	0			2.5	0.58			101	70		0				
6	-	3.6	0	0		-	2.5				0	٥						ľ
533.3	0.1	36	0	1	2	1	2.5			1224	0	J	101	1 211				1067

## A.3 Validation Summary

A summary of model validation follows in the sections below, drawing upon the test cases demonstrated in Chapter 5 and the reference behavior results in section A.1 to judge the model against the suite of validation tests shown in Table 5-1.

## Test SS1 - dimensional consistency

The dimensions of the variables in each equation agree with the computation. Simulation time units are days, the units for job size are tasks and effort is in person-days. Appropriate conversions between months and days are documented in the source code (see section A.4). The defect density is measured in defects/task converted from defects/KSLOC, with conversions also documented in the source code.

# SS2 - extreme conditions in equations

Extreme conditions in equations have been tested by varying job size, productivity, error generation rates, defect density, error multiplication and process delays. Job size has varied from very small (2 KSLOC) to the high end of the middle-large project size region (128 KSLOC). The simulation has remained stable under these conditions, with some fluctuating behavior seen with extreme process delays.

## Test SS3 - boundary adequacy

Refer to Figure 3.4-3 for the model boundary definition. The structural boundary does contain the variables and feedback loops to investigate the aforementioned aspects of the inspection process, and eliminates effects that would confound the inspection analysis. Policy levers include various process parameters, where managerial decision policies control their settings. These include appropriating the amount of effort put into inspections, whether or not manpower constraints are employed, and dictating schedule constraints. It is seen that varying the amount of effort on inspections has important effects on product quality and project cost.

# Test CS1 - face validity

The model structure matches the real system in terms of tasks, error flow and manpower utilization. Face validity of constructs is checked against experts, other software practitioners, written sources and personal experience. Face validity has been verified by international experts in relevant areas including system dynamics, cost estimation, process technology and inspections. The overall effect of inspections corroborates a good deal of published data, and inspection delays are consistent with experience. The effect of inspections matches Fagan's generalized curve fairly well. His testing peak is greater than that in the COCOMO model, and is not literally meant to be an effort estimation curve.

## Test CS2 - parameter values

Default assignment of parameters are documented in the source code shown in section A.4. All available data on inspections was used to assign parameter values.

## <u>Test US1 - appropriateness of model characteristics for audience</u>

Refer to the initial goals of the modeling experiment. The model is appropriate for examining defect finding rates from inspections, the resulting escaped and reworked errors and the associated efforts. Effort for specific activities available from the simulation is also consistent with the stated goals of the research identified in Chapter 3. A managerial audience wants to see the impact of using inspections or not, and the relative process efficiency of varying the inspection effort in different phases.

# Test SB1 - parameter (in)sensitivity

In this test, the sensitivity of behavior characteristics to parameter changes is examined as well as policy conclusions. The following parameters are used to evaluate model sensitivity: job size, workforce available, defect density, staffing curves, error multiplication, and others. The results of these tests are detailed in Chapter 5. The resulting project cost, duration and/or error levels varied as expected when varying these parameters. Policy insight is afforded based on the sensitivity tests.

# Test SB2 - structural (in)sensitivity

Sensitivity of behavior characteristics to structural formulations was gauged during model development. Overall, the model behavior is stable with minor perturbations in the structure. For example, certain delays were also represented as dependent on successor levels instead of the rates going into those levels. The major instance of this was for defining the inspection rate as a delay from the level of designed/coded tasks versus a fixed delay from the design/coding rates. The resultant behavior was less smooth, or "non-ideal" because of minor fluctuations, but cumulative results stayed the same. It is arguable whether such structures are more realistic since they better approximate true state transitions, but the chosen structure is easier to assess simulation behavior because it is a smoothed version of the fluctuating behavior and provides equivalent cumulative results. Policy conclusions should not change drastically with minor changes in structure.

# <u>Test CB1 - replication of reference modes (boundary adequacy for behavior)</u>

See the section A.1 on reference behavior. The model endogenously reproduces behavior modes initially defined in the study in terms of past policies and anticipated behavior.

# Test CB2 - surprise behavior

Little surprise behavior has been noted. See the discussion for test SB2 above on fluctuating trends. These trends were initially a surprise, but investigation showed them to be realistic. For example, personnel often save up certain tasks until a threshold is reached, and then spend time on the saved up tasks. For instance, the average developer does not spend some time each day on programming and inspection preparation.

Instead, he prepares for inspection when it is time to do so, and then spends nearly full-time on that until it's finished. Other surprise results was that inspections were not cost effective for certain organizations where the cost of fixing defects during test was less than the cost of inspections. This is one insight of the model; that under certain conditions inspections are not worthwhile.

## Test CB3 - extreme condition simulations

Extreme condition simulations were performed, as identified in the SS2 validation tests. The model formulation is sensible, since the model behaved well under extreme conditions.

# Test CB4 - statistical tests

As demonstrated in Chapter 5, various statistical tests were performed. The model output statistically matched real system data in terms of inspection and rework effort, error rates, schedule performance, overall effort and inspection return on investment. See section 5.5 for validation of the model against industrial data.

## Test UB1 - counter-intuitive behavior

Counter-intuitive behavior demonstrated was the diminishing returns of inspections, as noted in the CB2 test above.

## Test UB2 - generation of insights

The model has provide several insights into the dynamic effects of inspections on the development process. One insight is that inspections are worthwhile under certain project conditions. Besides when inspection efficiency is reduced, inspections are not necessarily cost-effective if the organization can find and fix defects cheaply during the testing phase. Also, depending on the error multiplication rate, design inspections are more cost effective than code inspections.

# A.4 Equations

Table A.4-1 lists the underlying equations for the model diagram shown in Figure 3.4-1 supplemented with documentary comments for each equation. Comments describe the variables, provide units and identify assumptions used in the formulations.

```
code errors(t) = code_errors(t - dt) + (code_error_generation_rate +
    design_error_pass_and_amplification_rate - code_error_detection_rate - code_error_escape_rate)
 INIT code errors = 0
    DOCUMENT: errors in code before inspection
    INFLOWS:
      ⇒ code error generation rate = code error density*coding rate
          DOCUMENT: error production as a co-flow of coding

★ design_error_pass_and_amplification_rate = 
          design error escape_rate*average_design_error_amplification
          DOCUMENT: amplification of design errors to code errors
    OUTFLOWS:
       🖈 code error_detection_rate =
          (code_error_density + design_error_density_in_code) *code_inspection_rate *inspection_effi
          iency
          DOCUMENT: rate of detecting code errors during inspection (errors/day)
          slaved to inspection rate
       🕏 code_error_escape_rate =
          (code error density + design error density in code) *(code inspection rate*(1-inspection
          fficiency) + code non inspection rate)
          DOCUMENT: rate of code errors escaping to test (errors/day)
          co-flow of inspections and non-inspection rate
cumulative_test_error_fix_effort(t) = cumulative_test_error_fix_effort(t - dt) +
    (test error fix manpower rate) * dt
    INIT cumulative test error fix effort = 0
    DOCUMENT: effort for fixing errors during test
    INFLOWS:
       ★ test error fix manpower rate =
           testing detection and correction rate*testing effort per error
           DOCUMENT: manpower rate for test error fixing (person-days/day)
cum code inspection effort(t) = cum code inspection effort(t - dt) +
    (code_inspection_manpower_rate) * dt
    INIT cum code inspection effort = 0
    DOCUMENT: cumulative code inspection effort (person-days)
    INFLOWS:
       ♂ code_inspection_manpower_rate = code_inspection_rate*inspection_effort_per_task
```

## Table A.4-1: System Dynamics Model Equations (continued)

```
DUCUIVIENT: manpower rate (person-days per day) = rate of code inspection ^ effort per
   cum code rework effort(t) = cum_code_rework_effort(t - dt) + (code_rework manpower rate)
    * dt
    INIT cum code rework effort = 0
    DOCUMENT: cumulative code rework effort (person-days)
    INFLOWS:
      ☆ code rework manpower rate = code rework rate*code rework effort per error
          DOCUMENT: person-days / day
cum coding effort(t) = cum coding effort(t - dt) + (coding manpower rate) * dt
    INIT cum coding effort = 0
    DOCUMENT: cumulative code effort (person-days)
    INFLOWS:
       🕏 coding manpower rate = manpower pool*coding staffing curve
          DOCUMENT: available people * planned staffing utilization * resource leveling constraint
          (person-days / day)
cum design effort(t) = cum design effort(t - dt) + (design manpower rate) * dt
    INIT cum design effort = 0
    DOCUMENT: cumulative design effort (person-days)
    INFLOWS:
       ☆ design manpower rate = manpower pool*design staffing curve
          DOCUMENT: available people * planned staffing utilization * resource leveling constraint
          (person-days / day)
cum design inspection effort(t) = cum design inspection effort(t - dt) +
    (design inspection manpower rate) * dt
    INIT cum design inspection effort = 0
    DOCUMENT: cumulative design inspection effort (person-days)
    INFLOWS:
       ☆ design inspection manpower rate = design inspection rate*inspection effort per task
           DOCUMENT: person-days / day
cum_design_rework_effort(t) = cum_design_rework_effort(t - dt) +
    (design rework manpower rate) * dt
    INIT cum design rework effort = 0
    DOCUMENT: cumulative design rework effort (person-days)
```

```
rack design rework manpower rate = design rework rate*design rework effort per error
           DOCUMENT: person-days / day
cum testing effort(t) = cum testing effort(t - dt) + (testing manpower_rate) * dt
    INIT cum testing effort = 0
    DOCUMENT: cumulative testing effort (person-days)
    INFLOWS:

★ testing manpower rate = 
           manpower pool*test staff curve*test manpower_level adjustment
           DOCUMENT: testing, integration, test planning effort + error detection and correction
           adjusted for error levels
           magnitude adjusted for schedule scaling
cum total effort(t) = cum total effort(t - dt) + (total manpower rate) * dt
    INIT cum total effort = 0
    DOCUMENT: cumulative total effort of all activities (person-days)
    INFLOWS:
       ★ total manpower rate =
           design manpower rate + design inspection manpower rate + design rework manpower_r
           te + coding manpower rate + code inspection manpower rate + code rework manpower r
           te+testing manpower rate
           DOCUMENT: total manpower rate sum (person-days / day)
 design errors(t) = design errors(t - dt) + (design error generation rate -
    design error escape rate - design error detection rate) * dt
    INIT design_errors = 0
    DOCUMENT: errors generated during design
     INFLOWS:
       ☆ design error generation rate = design error density*design rate
           DOCUMENT: error generation as a co-flow of design
           error density * design rate
           1.5*design rate = 25 design errors / KSLOC
           2*design rate = 33 design errors / KSLOC
     OUTFLOWS:
       ಈ design_error_escape_rate =
           design error density *(design inspection rate*(1-inspection efficiency) + design non insp
           ction rate)
           DOCUMENT: rate of errors escaping to coding (errors/day)
           co-flow with inspections and non-inspection rate
```

```
design error density*design inspection rate*inspection efficiency
           DOCUMENT: rate of detecting design errors during inspection (errors/day)
           slaved to inspection rate
detected code errors(t) = detected code errors(t - dt) + (code error detection rate -
    code rework rate) * dt
    INIT detected code errors = 0
    DOCUMENT: code errors detected during inspection before rework occurs
    INFLOWS:
       🕏 code error detection rate =
           (code error density + design error density in code) *code inspection rate *inspection effi
           DOCUMENT: rate of detecting code errors during inspection (errors/day)
           slaved to inspection rate
    OUTFLOWS:
       ☆ code rework rate = DELAY(detected code errors/10,7)
           DOCUMENT: rework follows inspection and completes in about 1.5 weeks
detected design errors(t) = detected_design_errors(t - dt) + (design_error_detection_rate -
    design rework rate) * dt
    INIT detected design errors = 0
    INFLOWS:

⇒ design error detection rate = 
           design error density*design inspection rate*inspection efficiency
           DOCUMENT: rate of detecting design errors during inspection (errors/day)
           slaved to inspection rate
    OUTFLOWS:
       design_rework_rate = delay(detected design errors/10,7)
           DOCUMENT: rework follows inspection and completes in about 1.5 weeks
errors_fixed_in_test(t) = errors_fixed_in_test(t - dt) + (testing_detection_and_correction_rate) *
    INIT errors fixed in test = 0
    DOCUMENT: errors detected and fixed during testing
     INFLOWS:

★ testing detection and correction rate =
           testing rate * defect density/test effort adjustment
           DOCUMENT: error detecting and correcting rate a function of defect density, and
           adjusted same as test effort for different productivity as function of defect levels
escaped_errors(t) = escaped_errors(t - dt) + (code_error_escape rate -
    testing detection and correction rate) * dt
    INIT escaped_errors = 0
```

```
INFLOWS:

☆ code error escape rate =
          (code error density + design_error_density_in_code) *(code inspection_rate *(1-inspection_
          fficiency) + code non inspection rate)
          DOCUMENT: rate of code errors escaping to test (errors/day)
          co-flow of inspections and non-inspection rate
    OUTFLOWS:

    ★ testing detection_and_correction_rate =
          testing rate'*defect density/test effort adjustment
          DOCUMENT: error detecting and correcting rate a function of defect density, and
          adjusted same as test effort for different productivity as function of defect levels
\Box level(t) = level(t - dt) + (rate) * dt
    INIT level = 0
    DOCUMENT: for legend only
    INFLOWS:
       🕏 rate = auxiliary_variable
           DOCUMENT: for legend only
manpower_pool(t) = manpower_pool(t - dt) + (hiring_and_manpower_allocation - attrition_rate)
    INIT manpower pool = 0
    DOCUMENT: available personnel
    INFLOWS:
       🕏 hiring and manpower allocation =
           SCED schedule constraint^2*1.46*pulse((20*calibrated COCOMO constant*(.06*job si
           e) ^1.2)/(20*2.5*(calibrated COCOMO constant*(.06*job size) ^1.2) ^.32),0,99999)
           DOCUMENT: resource policy for allocating development personnel according to
           COCOMO estimated manpower levels with appropriate conversions for job size (SLOCS
           to tasks) and time (months to days). Square of SCED multiplier due to: 1) it indicates
           extra fraction of personnel required (effort in numerator) and 2) for relative schedules <
           1, reciprocal approximates relative schedule shortening (schedule in denominator).
    OUTFLOWS:

★ attrition rate = if (resource leveling > 0)then

           pulse(manpower_pool*(1-resource_leveling),999,999) else 0
           DOCUMENT: manpower level is adjusted by resource leveling, otherwise use simplifying
           assumption of zero attrition that keeps available personnel constant
reworked code errors(t) = reworked code errors(t - dt) + (code rework rate) * dt
    INIT reworked code errors = 0
    DOCUMENT: code errors reworked due to inspection
```

```
중 code rework_rate = DELAY(detected_code_errors/10,7)
           DOCUMENT: rework follows inspection and completes in about 1.5 weeks
reworked design errors(t) = reworked design errors(t - dt) + (design rework rate) * dt
    INIT reworked design errors = 0
    DOCUMENT: design errors reworked due to inspection
    INFLOWS:
       ☆ design rework rate = delay(detected design errors/10,7)
           DOCUMENT: rework follows inspection and completes in about 1.5 weeks
sampled defect density(t) = sampled defect density(t - dt) + (sampler) * dt
    INIT sampled defect density = 0
    DOCUMENT: takes pulse of running defect density
    INFLOWS:
       🕏 sampler = pulse(running_defect_density,(.65*estimated_development_schedule-dt),9999)
           DOCUMENT: samples running defect density
tasks tested(t) = tasks tested(t - dt) + (testing rate) * dt
    INIT tasks tested = 0
    DOCUMENT: cumulative tasks tested, indicating completion status
    INFLOWS:

★ testing rate = testing rate'

           DOCUMENT: roll-up of testing rate'
undetected design errors(t) = undetected design errors(t - dt) + (design error escape rate) *
    INIT undetected design errors = 0
    DOCUMENT: design errors not detected during design inspection
    INFLOWS:

★ design error escape rate =
           design error density *(design_inspection_rate*(1-inspection_efficiency) + design_non_insp
           ction rate)
           DOCUMENT: rate of errors escaping to coding (errors/day)
           co-flow with inspections and non-inspection rate
actual completion time = CTMAX(testing rate)
    DOCUMENT: actual final schedule derived from cycle-time utility that instruments maximum
    in-process time of tasks that are time stamped at requirements generation
    alias_of a variable = 0
```

DOCUMENT: for legend only

중 code rework rate = DELAY(detected code errors/10,7)

```
DOCUMENT: rework follows inspection and completes in about 1.5 weeks
reworked design errors(t) = reworked design errors(t - dt) + (design rework rate) * dt
    INIT reworked design errors = 0
    DOCUMENT: design errors reworked due to inspection
    INFLOWS:
       ⇒ design rework rate = delay(detected design errors/10,7)
           DOCUMENT: rework follows inspection and completes in about 1.5 weeks
sampled defect density(t) = sampled defect density(t - dt) + (sampler) * dt
    INIT sampled defect density = 0
    DOCUMENT: takes pulse of running defect density
    INFLOWS:
       🕏 sampler = pulse(running defect density,(.65*estimated development schedule-dt),9999)
           DOCUMENT: samples running defect density
tasks_tested(t) = tasks_tested(t - dt) + (testing_rate) * dt
    INIT tasks tested = 0
    DOCUMENT: cumulative tasks tested, indicating completion status
    INFLOWS:
       ★ testing_rate = testing_rate
           DOCUMENT: roll-up of testing rate'
undetected design errors(t) = undetected design errors(t - dt) + (design error escape rate) *
    INIT undetected design errors = 0
    DOCUMENT: design errors not detected during design inspection
    INFLOWS:

☆ design error escape rate = 
           design error density*(design inspection rate*(1-inspection efficiency)+design non insp
           ction rate)
           DOCUMENT: rate of errors escaping to coding (errors/day)
           co-flow with inspections and non-inspection rate
actual_completion time = CTMAX(testing rate)
    DOCUMENT: actual final schedule derived from cycle-time utility that instruments maximum
    in-process time of tasks that are time stamped at requirements generation
    alias of a variable = 0
```

DOCUMENT: for legend only

Ō	auxiliary_variable = 0 DOCUMENT: for legend only
Ō	average_design_error_amplification = 1  DOCUMENT: multiplication factor for design error to code errors
Ō	calibrated_COCOMO_constant = 3.6 DOCUMENT: linear organizational "productivity" constant in COCOMO effort equation 3.6 = default for Basic COCOMO, embedded mode
Ō	code_error_density = 1.5 DOCUMENT: equivalent to 25 errors/KSLOC in code
Ō	code_rework_effort_per_error = .11 DOCUMENT: default value of just under one hour (twice the effort for design)
Ō	current_productivity = max_productivity*learning/100/SCED_schedule_constraint DOCUMENT: tasks/person-day modified by learning effect and schedule constraint
Ō	defect_density = sampled_defect_density  DOCUMENT: defect density used to adust test effort and schedule
Ō	design_error_density = 1.5 DOCUMENT: equivalent to 25 errors/KSLOC in design
Ō	<pre>design_error_density_in_code = undetected_design_errors*average_design_error_amplification/cum_tasks_designed DOCUMENT: calculated to conserve flows out of code errors</pre>
0	design_rework_effort_per_error = .055 DOCUMENT: 1/3 of total inspection effort (Litton, JPL)
Ō	.23 days = 1.84 hours/error from Litton data estimated_development_schedule = 20*2.5/SCED_schedule_constraint*(calibrated_COCOMO_constant*(.06*job_size)^1.2)^.32 DOCUMENT: initial schedule estimate from COCOMO, converted to days
Ō	estimated_test_schedule = .35*20*2.5/SCED_schedule_constraint*(test_effort_adjustment*calibrated_COCOMO_constant*(06*job_size)^1.2)^.32 DOCUMENT: calculate test schedule for apparent defect density
Ō	use 35% of total project effort that is multiplied by test effort adjustment final_defect_density = if (tasks_tested > 1)then errors_fixed_in_test/tasks_tested else 0 DOCUMENT: final defect density at project completion

fraction done = tasks tested/job\_size DOCUMENT: fraction of total job completed through testing inspection efficiency = .6 DOCUMENT: fraction of defects found during inspections to total defects (.5 - .9 per [Radice-Phillips 88], [Fagan 86] and others) inspection effort per task = .19 DOCUMENT: xx man-days per task (2% of deleted Litton rate). Total inspection effort = 3%, preparation and meeting is 2/3 and rework is 1/3. .19 represents middle ground on percentage basis  $\bigcirc$  job size = 533.3 DOCUMENT: number of tasks to be developed at 60 SLOCS/task 33.3 tasks = 2 KSLOC, 533.3 tasks = 32 KSLOC, 1066.6 tasks = 64 KSLOC manpower utilization = if (manpower pool > 0)then total manpower rate/manpower pool else 0 DOCUMENT: fraction of manpower pool used max productivity = job size/(20\*calibrated COCOMO constant\*(.06\*job size)^1.2) DOCUMENT: tasks/person-day (.0262 = 1.62 SLOC/person-day)(.133 = 8 SLOC/person-day).4138 = basic cocomo for 1.8 KSLOC resource leveling = 0 DOCUMENT: fraction of personnel to cut running defect density = if (tasks ready for test > 1) then escaped\_errors/tasks\_ready\_for\_test else 0 DOCUMENT: running defect density before testing SCED schedule constraint = 1.0 DOCUMENT: relative schedule constraint effort multiplier from COCOMO testing\_effort\_per\_error = .16\*calibrated\_COCOMO\_constant DOCUMENT: testing effort related to overall productivity default set to .16 \* COCOMO constant for 4.6 hours (Litton rate deleted from source code comment) test\_effort\_adjustment = (.0803\*(20\*calibrated\_COCOMO\_constant\*(.06\*job\_size)^1.2)+job\_size\*sampled\_defect\_densi y\*testing effort\_per\_error)/(.0803\*(20\*calibrated\_COCOMO\_constant\*(.06\*job\_size)^1.2)+job\_ ize \*3 \*testing effort per error) DOCUMENT: ratio adjustment to test effort for defect density. Uses defect density of nominal case, and adjusts for current defect density due to inspections with value of testing effort per error.

test manpower level adjustment = test effort adjustment/test schedule adjustment DOCUMENT: scale height of staffing curve to reflect time scale compression with no corresponding vertical scaling test schedule adjustment = estimated\_test\_schedule/(.35\*estimated\_development\_schedule) DOCUMENT: adjust duration of testing for different error levels coding staffing curve = GRAPH(time/(.85\*estimated development schedule)) (0.00, 0.00), (0.0588, 0.00), (0.118, 0.00), (0.176, 0.00), (0.235, 0.00), (0.294, 0.00),(0.353, 0.00), (0.412, 0.00), (0.471, 0.00), (0.529, 0.00), (0.588, 0.0847), (0.647, 0.297),(0.706, 0.72), (0.765, 1.00), (0.824, 0.86), (0.882, 0.551), (0.941, 0.127), (1.00, 0.00)DOCUMENT: dev time =  $.74*(2.5*(3.6*(KSLOC^1.2)^.32)$ from Basic COCOMO [Boehm 81], p. 90 for medium embedded design staffing curve = GRAPH(time/(.85\*estimated development schedule)) (0.00, 0.18), (0.0588, 0.195), (0.118, 0.215), (0.176, 0.25), (0.235, 0.345), (0.294, 0.453),(0.353, 0.563), (0.412, 0.676), (0.471, 0.775), (0.529, 0.875), (0.588, 0.839), (0.647, 0.775)0.678), (0.706, 0.267), (0.765, 0.00), (0.824, 0.00), (0.882, 0.00), (0.941, 0.00), (1.00, 0.00 DOCUMENT: dev time =  $.74*(2.5*(3.6*(KSLOC^1.2)^.32)$ from Basic COCOMO [Boehm 81], p. 90 for medium embedded learning = GRAPH(fraction\_done) (0.00, 100), (0.0833, 100), (0.167, 100), (0.25, 100), (0.333, 100), (0.417, 100), (0.5, 100),(0.583, 100), (0.667, 100), (0.75, 100), (0.833, 100), (0.917, 100), (1.00, 100) DOCUMENT: learning curve - fraction of maximum productivity as function of job completion test staff curve = GRAPH((time-.65\*estimated development schedule)/estimated test schedule) (0.00, 0.00), (0.143, 0.127), (0.286, 0.424), (0.429, 0.781), (0.571, 0.85), (0.714, 0.75),development\_process = tasks\_ready\_for\_test + tasks\_coded + tasks\_for coding + tasks designed + requirements DOCUMENT: submodel for development activities INFLOWS: 중 requirements\_generation\_rate = PULSE(job\_size,0,9999) DOCUMENT: pulse in job size at time = 0 **OUTFLOWS:** ☆ testing rate = testing rate' DOCUMENT: roll-up of testing rate' cum\_code\_tasks\_inspected(t) = cum\_code\_tasks\_inspected(t - dt) + (code inspection rate') \* dt INIT cum\_code\_tasks inspected = 0

DOCUMENT: cumulative code tasks inspected

```
INFLOWS:
      ☆ code inspection rate' = code_inspection_rate
          DOCUMENT: code tasks per day
cum design tasks inspected(t) = cum design tasks inspected(t - dt) +
    (design inspection rate') * dt
    INIT cum design tasks inspected = 0
    DOCUMENT: cumulative design tasks inspected
    INFLOWS:
      충 design_inspection_rate' = design_inspection_rate
cum tasks coded(t) = cum tasks coded(t - dt) + (coding rate') * dt
    INIT cum tasks coded = 0
    INFLOWS:
      ☆ coding rate' = coding rate
          DOCUMENT: tasks coded per day
cum_tasks_designed(t) = cum_tasks_designed(t - dt) + (design_rate') * dt
    INIT cum tasks designed = 0
     INFLOWS:
       🕏 design_rate' = design_rate
          DOCUMENT: tasks designed per day
   requirements(t) = requirements(t - dt) + (requirements_generation rate' - design rate) * dt
    INIT requirements = 0
     INFLOWS:
       requirements generation rate' = requirements generation rate
          DOCUMENT: roll down of requirements generation rate
     OUTFLOWS:

☆ design_rate = design_manpower_rate*current_productivity/.454

          DOCUMENT: tasks designed per day
          manpower rate (person-days/day) * overall productivity (tasks/day) / fraction of effort
          for design
 tasks_coded(t) = tasks_coded(t - dt) + (coding_rate - code_inspection_rate -
    code non inspection rate) * dt
    INIT tasks coded = 0
     INFLOWS:

☆ coding rate = coding manpower rate*current productivity/.2657

           DOCUMENT: tasks coded per day
           manpower rate (person-days/day) * overall productivity (tasks/day) / fraction of effort
          for coding
     OUTFLOWS:

    code_inspection_rate = delay(code_inspection_practice*coding_rate,10,0).
```

DOCUMENT: code inspections take place 10 days after coding completion

```
☆ code non inspection rate = (1-code_inspection_practice)*coding_rate
        DOCUMENT: non-inspected tasks pass through immediately
] tasks designed(t) = tasks_designed(t - dt) + (design_rate - design_inspection_rate -
  design non inspection rate) * dt
  INIT tasks designed = 0
  DOCUMENT: design tasks developed and ready for inspection
   INFLOWS:

    ⇔ design rate = design manpower rate*current productivity/.454
         DOCUMENT: tasks designed per day
         manpower rate (person-days/day) * overall productivity (tasks/day) / fraction of effort
         for design
   OUTFLOWS:
    ☆ design inspection rate = delay(design inspection practice*design rate,10,0)
         DOCUMENT: design inspections take place 10 days after design completion
    design_non_inspection_rate = (1-design_inspection_practice)*design_rate
         DOCUMENT: non-inspected tasks pass through immediately
  tasks for coding(t) = tasks for coding(t - dt) + (design inspection rate +
  design non inspection rate - coding rate) * dt
  INIT tasks for coding = 0
  DOCUMENT: design tasks inspected
   INFLOWS:
     design inspection_rate = delay(design_inspection_practice*design rate,10,0)
         DOCUMENT: design inspections take place 10 days after design completion
     ☆ design non inspection rate = (1-design inspection practice)*design rate
         DOCUMENT: non-inspected tasks pass through immediately
   OUTFLOWS:
     충 coding rate = coding manpower rate*current productivity/.2657
         DOCUMENT: tasks coded per day
         manpower rate (person-days/day) * overall productivity (tasks/day) / fraction of effort
         for coding
  tasks_ready_for_test(t) = tasks_ready_for_test(t - dt) + (code inspection_rate +
  code non inspection rate - testing rate') * dt
  INIT tasks ready for test = 0
  DOCUMENT: tasks coded and not yet tested
```

# Table A.4-1: System Dynamics Model Equations (continued)

### INFLOWS:

- ♂
   code\_inspection\_rate = delay(code\_inspection\_practice\*coding\_rate,10,0)

   DOCUMENT: code inspections take place 10 days after coding completion
- code\_non\_inspection\_rate = (1-code\_inspection\_practice)\*coding\_rate
   DOCUMENT: non-inspected tasks pass through immediately

## **OUTFLOWS:**

- testing\_rate' =
  testing\_manpower\_rate\*current\_productivity/.255/test\_effort\_adjustment
  DOCUMENT: tasks tested per day. Manpower rate(person-days/day)\*
  productivity/fraction of effort for test adjusted for error rate (magnitude and schedule duration)
- ocode\_inspection\_practice = 1.0

  DOCUMENT: fraction of code tasks that are inspected
- design\_inspection\_practice = 1.0
  DOCUMENT: fraction of design tasks that are inspected