ABSTRACT

Title: INTEGRATING SOFTWARE BEHAVIOR INTO DYNAMIC PROBABILISTIC RISK ASSESSMENT

Dongfeng Zhu, Doctor of Philosophy 2005

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Software plays an increasingly important role in modern safety-critical systems. Although research has been done to integrate software into the classical Probability Risk Assessment (PRA) framework, current PRA practice overwhelmingly neglects the contribution of software to system risk. The objective of this research is to develop a methodology to integrate software contributions in the Dynamic Probabilistic Risk Assessment (DPRA) environment.

DPRA is considered to be the next generation of PRA techniques. It is a set of methods and techniques in which simulation models that represent the behavior of the elements of a system are exercised in order to identify risks and vulnerabilities of the system. DPRA allows consideration of dynamic interactions of system elements and physical variables. The fact remains, however, that modeling software for use in the DPRA framework is also quite complex and very little has been done to address the question directly and comprehensively.

This dissertation describes a framework and a set of techniques to extend the DPRA approach to allow consideration of the software contributions on system risk. The framework includes a software representation, an approach to incorporate the software representation into the DPRA environment SimPRA, and an experimental demonstration of the methodology.

This dissertation also proposes a framework to simulate the multi-level objects in the simulation based DPRA environment. This is a new methodology to address the state explosion problem. The results indicate that the DPRA simulation performance is improved using the new approach. The entire methodology is implemented in the SimPRA software. An easy to use tool is developed to help the analyst to develop the software model.

This study is the first systematic effort to integrate software risk contributions into the dynamic PRA environment.

INTEGRATING SOFTWARE BEHAVIOR INTO DYNAMIC PROBABILISTIC RISK ASSESSMENT

By

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Dedication

To my family.

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Glossary

AKB	Abstraction Knowledge Base
DPRA	Dynamic Probabilistic Risk Assessment
ESD	Event Sequence Diagram
ET	Event Tree
FSM	Finite State Machine
FIKB	Failure Injection Knowledge Base
IE	Initiating Event
PACS	Personnel Access Control System
PRA	Probabilistic Risk Assessment
SFSM	Simulation-based Finite State Machine
SimPRA	Simulation-based Probabilistic Risk Analysis
SKB	Simulation Knowledge Base
UML	Unified Modeling Language

Chapter 1: Introduction

1.1 Research Objective

The objective of this research is to extend current dynamic PRA methodology to integrate software behavior and risk contributions in the risk assessment process. Accordingly this research proposes a multi-level software representation and an approach to integrate such representation into the Simulation-based dynamic PRA (SimPRA) environment. The adaptive rules for adjusting multi-level components are designed in this research. It is shown that such adaptive rules increase the efficiency of the simulation, and mitigate the state explosion issue in Dynamic PRA environment. A case study is conducted demonstrate the usefulness of the framework and the methodology.

1.2 Research Statement

Modern safety critical systems usually are complex hybrid systems of hardware, software, and human operators. By taking over many of the hardware and human tasks, software is increasingly playing an important role in the systems. This naturally translates into an increase in the software's contribution to the system risk. A significant number of system failures can be attributed to software failures, such as the well known Northeast Blackout of 2003, Therac-25 radiation overdose accidents, NASA Mars Climate Orbiter, Mariner I Venus Probe, and Ariane 5 accidents.

Probabilistic Risk Assessment (PRA) is a methodology for identifying and assessing the probability of situations leading to undesired state of a system. It has been widely used to assess the likelihood of accident scenarios following an initiating failure or perturbation event. Classical PRA focuses on answering three basic questions: (i) What can go wrong? (ii) What is the consequence? (iii) What's the likelihood of such events? PRA is used to assess, predict, and reduce the risk of large technological systems. NASA, for example, requires PRA for all manned missions as well as for all missions with nuclear payloads or nuclear fuel. PRA has been proven to be a systematic, logical, and comprehensive methodology for risk assessment. In classical PRA method, the analysts need to construct separate models describing system vulnerabilities and risks. However the dynamic interactions among the components inside the system often make it infeasible to identify and predict all the possible scenarios. Enumeration of risk scenarios in case of highly complex and hybrid systems of hardware, software and human components is very difficult using the classical PRA method. The quality of a PRA is completely analyst dependent.

Some research has been conducted on the integration of software into the traditional PRA framework [1-3]. However the classical PRA framework is widely believed to be very limiting when it comes to identifying software and human contributions to system risk. Dynamic Probabilistic Risk Assessment (DPRA) is a set of methods and techniques in which executable models that represent the behavior of the elements of a system are exercised in order to identify risks and vulnerabilities of the system [4]. Using the DPRA method, the analyst no longer needs to identify and enumerate all the possible risk scenarios manually. The computer model explores the possible scenarios based on the system model. This observation has been one of the bases of the argument for the need for DPRA. The fact remains however that modeling software for use in the DPRA framework, is also quite complex and very little has been done to address the question directly and comprehensively. This research focuses on the software modeling for use in a simulation-based dynamic PRA environment.

1.3 Approach

A software representation methodology is proposed. The software model is integrated into the SimPRA dynamic PRA simulation environment. The software representation is a conceptual model of the software that allows consideration of software as an integral component of the system and contributor to risk, to the same level as humans or hardware. A multi-level software representation framework is established for the SimPRA environment. It includes both a *behavior model* and a simulation *guidance model*. The behavior model is an executable model. It is plugged into the system model to represent the software behavior. It is able to capture all phenomena that fall within the scope of the analysis. The software guidance model is used to guide the simulation to explore scenarios of interest instead of a wide-scale exploration. The software guidance model interacts with the high-level planner and scheduler to better estimate the total system risk.

The software behavior model is a combination of a deterministic model and stochastic model. The deterministic model is used to simulate the behavior of the software, as well as the interaction between the software and other parts of the system. The stochastic model is superimposed onto the deterministic model to represent the uncertain behavior of the software, e.g., software failures. Finite State Machine (FSM) is chosen to build the deterministic behavior model. Finite state machine has been defined as: “a computational model consisting of a finite number of states and transitions between these states, possibly with accompanying actions” [5, 6]. Simulation-based Finite State Machine (SFSM) is defined by adding simulation-related components to traditional FSM. Multiple controllable variables are defined in the behavior model including simulation level of detail, software failure injection, failure level of detail. The values of the variables are controlled by the guidance model.

The guidance model adjusts the behavior model based on the requirements from the high-level scheduler and planner. Meanwhile, the software guidance model also provides information to update the planner. An adaptive guidance rule is designed in the high-level planner, scheduler and the software guidance model to adjust the software simulation level of detail to the appropriate level for different scenarios based on simulation result and prior knowledge. It is demonstrated that this increases the simulation efficiency and mitigates the state explosion problem in dynamic PRA.

A complete procedure to build the software representation and integrate the software representation into SimPRA environment is provided. Figure 1 presents an overview of the software modeling in the SimPRA environment.

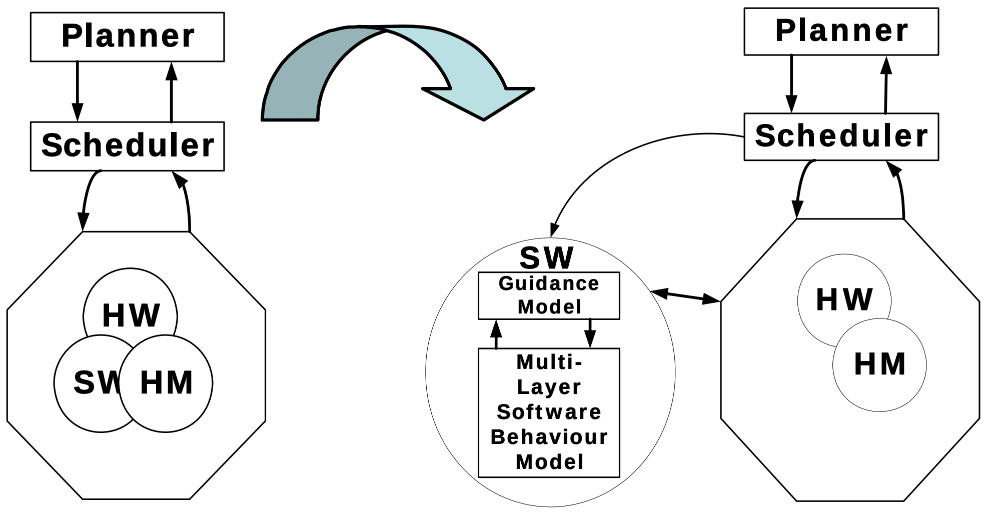

Figure 1 Overview of the software representation in SimPRA environment

1.4 Content

Chapter 2 presents an overview of the related work and motivation for this research. Software modeling in classical PRA and dynamic PRA are also introduced. The difference in modeling methodologies between traditional PRA environment and Dynamic PRA environment is described. The SimPRA environment is reviewed.

Chapter 3 summarizes the software modeling requirements in dynamic PRA environment. The requirements are discussed in terms of general modeling requirements, simulation requirements, interaction requirements, and non-functional requirements.

Chapter 4 presents the proposed software representation methodology, based on the software modeling requirements. The software behavior model and guidance model are also established.

The integration of the software representation into the SimPRA environment is described in Chapter 5. This includes a detailed description of the adaptive scheduling in SimPRA environment. The state explosion problem in dynamic PRA environment is described and possible approaches to mitigate it are discussed. A new multi-level simulation based approach is proposed. The necessary modification to the SimPRA environment is summarized. The detailed integration procedure is presented at the end of the chapter.

Chapter 6 describes the implementation of the software representation on a parallel system. The methodology has been applied to the benchmark problem proposed for an invited session on advanced PRA methods in PSAM 2006. The benchmark problem is a Propulsion System Mission and Design Problem proposed by NASA headquarters.

Chapter 7 presents an application of the methodology for a Personnel Access Control System (PACS). PACS is a relatively complex system with human, software and hardware involved. A complete system model is developed. The integration process is discussed. A 3-level software abstraction is defined. The model is then used in the modified SimPRA software to generate risk scenarios and corresponding probabilities. At the end of the chapter, a comparison between using the classical PRA methodology and dynamic PRA methodology are summarized using this example.

Chapter 8 develops a procedure to establish a consistently quantified software model when code is available and objective test data can be obtained.

Chapter 9 concludes this dissertation by highlighting the contribution and also the limitation of the approach. Possible future research topics are also discussed.

1.5 Summary of Research Contributions

The significant contributions of this dissertation are as follows:

1. Development of a software representation for dynamic PRA environment: This research is the first effort to develop a methodology to systematically identify software contributions to the system risk in a dynamic PRA environment. Since the methodology is built on current PRA techniques and since a tool is provided, it is expected that PRA practitioners should find it easy to use and understand.
2. Development of a methodology for simulating multi-level objects in the dynamic PRA environment: This is a new methodology to address the state explosion problem in simulation-based dynamic PRA methodologies. Our results indicate that the use of the proposed approach improves the DPRA simulation performance.
3. Enhancement of the simulation based dynamic PRA (SimPRA) environment. SimPRA is more complete PRA modeling environment with the addition of the software model. An easy to use tool is developed for the end user. The methods development and tool enhancements achieved in this research are significant steps forward in improving capabilities for conducting risk analysis of complex systems, particularly those offered by dynamic PRA methodologies. The modeling procedures and tools proposed here also help in developing procedures to enhance the system design and development activities.

Chapter 2: Background

2.1 Software modeling in classical PRA

PRA has been applied to large complex systems for over 30 years. It is required as part of the risk management process in the US Nuclear Regulatory Commission (NRC) and National Aeronautical and Space Administration (NASA).

The first full scale application of PRA methods was the Reactor Safety Study WASH-1400 [7]. Since its completion in 1975, NRC has been exploring ways of systematically applying PRA to nuclear plants. A "PRA procedure guide" was developed by NRC in 1983 in the background of increasing application of PRA methods within the nuclear industry and the regulatory process. This guide describes the principal methods used in PRA and provides general guidance for performing PRAs for nuclear power plants [8].

NASA instituted a number of programs for PRA analysis after the Challenger accident in 1986 [9]. After the extensive review of NASA safety policy, NASA managers decided to use PRA as one of the bases for the support of decisions regarding improvements in Space Shuttle safety. Office of Safety and Mission Assurance at NASA headquarters published several handbooks to enhance the PRA expertise at NASA [10]. Software tools such as QRAS have been designed to automate the PRA analysis procedure [11].

However, current PRA practice effectively neglects the contributions of software. The consequence is that one of the major potential causes of safety-critical system failures is not included in the analysis.

Some related research has been conducted in recent years. But the focus has been mostly on the software risk assessment itself rather than as an integral part of the PRA super-structure [12-14]. A literature review for the recent work is found in [15]. We briefly summarize it below.

Dugan [13] used fault trees for software reliability analysis. Lutz [14] investigated the use of fault trees to study the root causes of safety-related software errors in safety-critical embedded systems. The research results are used to identify methods by which requirements errors can be prevented.

A risk index factor has been developed by Lee to quantify the risk associated with individual software components in programs developed for space flight applications [16]. The risk index attempts to quantify the risk, utilizing the results from software complexity analysis, the evaluation of test coverage, and a failure modes and effects analysis.

Schneidewind's model [17] was used to quantify the reliability of the shuttle's on-board system software. Ammarrt [12] presented a methodology of risk assessment of functional-requirement specifications for complex real-time software systems using a heuristic risk assessment technique based on CPN (colored Petri-net) models. Yacoub [18] presents a methodology for risk assessment at the architectural level by developing heuristic risk factors for architectural elements using complexity factors and severity. These studies stay at the software component level without consideration of the PRA super-structure.

Li's study is the first step towards a systematic approach to integrating software into a traditional PRA framework [1-3]. This framework of integrating software into the traditional PRA environment follows the standard PRA procedure.

The so-called test-based approach has been designed to integrate software contributions into PRA analysis [3]. Using this approach, software related failures need to be identified first. A software-related failure modes taxonomy has been established and validated by Li [2]. Once the software-related failure modes have been identified, the system- and software-related functions need to be identified in the system failure scenarios. The input tree and output tree need to be defined per function and per scenario. The basic procedure of Li's approach is:

1. Identify events/components controlled/supported by software in MLD, accident scenarios, fault trees;
2. Specify the functions involved;
3. Model software function in Event Sequence Diagram (ESD), or Event Tree (ET), and fault trees;
4. Identify (i.e., estimate probability of) the input tree;
5. Quantify the input tree;
6. Develop and perform software safety tests;
7. Build and quantify the output tree.

The test-based approach has several limitations.

First, the methodology is test based; therefore it assumes the availability of source code. Also it precludes risk analysis during other software life-cycle phases. An analytical approach needs to be developed to handle the risk analysis prior to the source-code stage.

Second, the testing is performed at the software-component level, implying that the risk scenarios should also model the software at that level. That may not produce sufficient detail in some risk analyses. Modifications are required to study the software at a lower level.

The third limitation is that the analyst is still responsible for identifying the risk scenarios, as well as the input and output tree. The quality of the risk assessment depends greatly on the analyst. Meanwhile, if the software needs to be studied at a lower level, software-failure propagation will become a major obstacle for the analyst in exploring all the possible risk scenarios.

The final limitation is the quality of the software operational profile. A profile is defined as a set of disjoint (only one can occur at a time) alternatives with the probability that each will occur [19]. The detailed software operational profile is essential to the final risk assessment quality in the traditional PRA framework. In the test-based approach, the functional profile needs to be defined for each function in each scenario. In a complex hybrid system, obtaining a detailed functional profile is usually very time-consuming and costly. The analyst needs to strike a balance between the degree of profile detail and the final cost, which also limits the final risk-assessment quality.

2.2 Dynamic PRA environment

Dynamic PRA refers to an approach to identification and quantification of risk scenarios of complex systems. The essence of this approach is the probabilistic simulation of the dynamic behavior of the system using the models of the system elements and rules of their internal and external interactions. Due to the fact that risk scenario generation in DPRA is more detailed, and context-rich, it is generally believed that software can be more realistically modeled in such framework. A literature review for different DPRA methodologies is found in [4, 20]. We briefly summarize it below.

Amendola proposed an approach to incorporate process dynamics with stochastic transitions in 1981 [21]. After that, different approaches have been attempted to solve the DPRA problems.

Some research proposes extensions to include the dynamic feathers in the traditional ET/FT methods [22, 23]. Others introduced graphic tools to capture the dynamic feathers, such as Petri-Net [24-26], Dynamic Flowgraph [27], Go-Flow [28], and Dynamic Event Sequence Diagram [29-31]. The mathematic framework was proposed for probabilistic dynamics by several researchers [32, 33]. The close form analytical solution is hard to find for large systems using DPRA methodologies. The simulation-based methods present great potential to solve DPRA problems.

The simulation-based DPRA methodology provides a framework for explicitly capturing the influence of time and process dynamics on risk scenarios. Using the DPRA approach, a formal representation of the system behavior needs to be constructed for the hardware, software, and human components. A set of rules needs to be prescribed to systematically decompose the system. The executable model is then used to simulate the behavior of the system and the physical processes taking place in the system, as a function of time. The event sequences are generated automatically by controlling the stochastic events in the model, such as hardware, software, and human failures. Each sequence represents a unique combination of timing and occurrence of the stochastic events. The system vulnerabilities, defined as the elements inside the system that could bring the system to an undesirable state, are identified, using the sequence simulation results. This significantly reduces the need for specialized risk models developed by the analyst, thus closing the gap between the design and risk assessment process.

Current DPRA frameworks largely rely on two strategies, which are referred to as systematic exploration (Discrete Dynamic Event Tree Simulation) and random exploration (Continuous Event Tree Simulation). The Discrete Dynamic Event Tree (DDET) methods systematically explore a large number of scenarios by introducing, at set points in time, branch points whose branches represent distinct courses of events, thus leading to distinct sequences of events. All possible branches of the system evolution are simulated systematically [34, 35]. Continuous Event Tree (CET) simulation does not involve the discretization of the event sequence space. The event sequences are randomly generated by randomly deciding on the occurrence and timing of events. Biasing techniques are typically applied in the DPRA approaches based on CET simulation [36, 37].

DPRA is considered to be the next generation of PRA techniques. The technique is not currently in use because of the state explosion problem, which needs resolution, and because some components, such as software and human behavior, are currently not systematically modeled. The recent progress in computational methods and in state explosion solutions makes DPRA a more practical PRA technique. However, the software model still needs to be systematically studied, and new solutions are still needed to mitigate the state explosion problem.

There is no generally accepted software presentation methodology in DPRA environment. Most DPRA methodologies either neglect the software contribution to the system risk in comparison to hardware component contributions, or treat the software component in the same way as hardware components. Software failures however are in general the result of faults or flaws possibly introduced in the logic of the software design, or in the code-implementation of that logic. These may or may not produce an actual functional failure, depending on whether or not they are found by an execution path activated according to the specific inputs to the software that drive the execution at a specific time [10].

Thus, software contribution to the system risk is highly input condition depended. The relationship between software failures and different input conditions should be modeled inside the DPRA environment.

2.3 SimPRA environment

2.3.1 Introduction

An adaptive-scheduling simulation-based DPRA environment has been developed at the University of Maryland [38, 39]. Entropy-based biasing techniques are used to adaptively guide the simulation towards events and end-states of interest. The prior knowledge of the systems and knowledge gained during simulation are used to dynamically adjust the exploration rules in the DPRA environment. That approach has been demonstrated in a computer code implementation known as SimPRA (Simulation-based PRA). See [38].

In SimPRA, a high-level simulation scheduler is constructed to control the simulation process, generally by controlling the occurrence of the random events inside the system model. To stimulate the desired types of scenarios, the input to the simulation model is also controlled, using scheduling algorithms. Rather than using a generic wide-scale exploration, the scheduler is able to pick up the important scenarios, which are essential to the final system risk, thus increasing the simulation efficiency. To do that, a high-level simulation planner is constructed to guide the scheduler to simulate the scenarios of interest. Figure 2 is an overview structure of the adaptive-scheduling simulation-based DPRA environment.

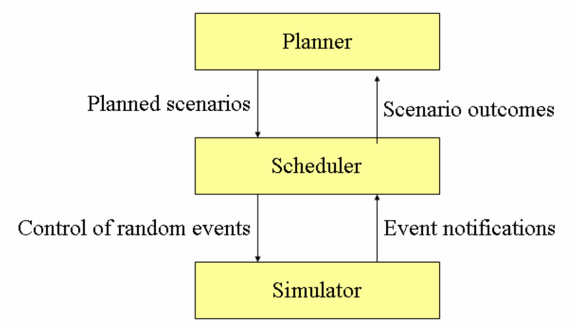

Figure 2: Structure of the adaptive scheduling DPRA environment [38]

2.3.2 Software Representation in DPRA

Software modeling in the DPRA environment differs from the traditional PRA environment. The analyst no longer needs to study the fault propagation and enumerate all the possible accident sequences. That task is replaced by that of building an executable software model and identifying possible software-related initiating events. The simulation environment will explore the scenario space, based on the system model, which includes model of the hardware, human and software elements. In this approach an executable software model first needs to be constructed to simulate the software behaviors. The software-related failure modes need to be identified similarly, as in the traditional PRA framework. The selected failure modes will be superimposed on the executable behavior model as stochastic events. The software-related failures are controlled by the simulation guidance model during simulation, based on the predefined rules for exploring the risk-scenarios space, following the selected initiating events.

Based on the above description, the software representation in the adaptive-scheduling DPRA environment should include both a behavior model and a software guidance model. The behavior model is an executable model. It will be plugged into the system environment to simulate the software behavior. It should be able to capture all phenomena that fall within the scope of the analysis. The software guidance model guides the simulation to explore scenarios of interest instead of a wide-scale exploration. The software guidance model should also interact with the high-level planner and scheduler to better estimate the total system risk. See Figure 1

The software representation is established based on the information available. The following assumptions and limitations are implied in this dissertation:

- Basic information about the software is obtainable.
- The software model can only be built based on information available. It can not go beyond the level of information available.

- The software model is not guaranteed to be correct once the information is limited. But the software model can be refined once the analyst gets more information.

2.4 Teamwork

The research of SimPRA environment is a teamwork result. All team members contribute their individual efforts to make this research come true. The whole team includes Professor Ali Mosleh, Dr. Frank Greon, Dr. Yunwei Hu, Hamed Nejad, Thiago Tinoco Pires, and me. My contribution to this research includes designing the software model, implementing the software representation in SimPRA, developing a methodology to simulate multi-level objects, and enhancing current SimPRA environment to simulate multi-level objects. Figure 3 presents a teamwork chart to identify the contributions from each individual team member.

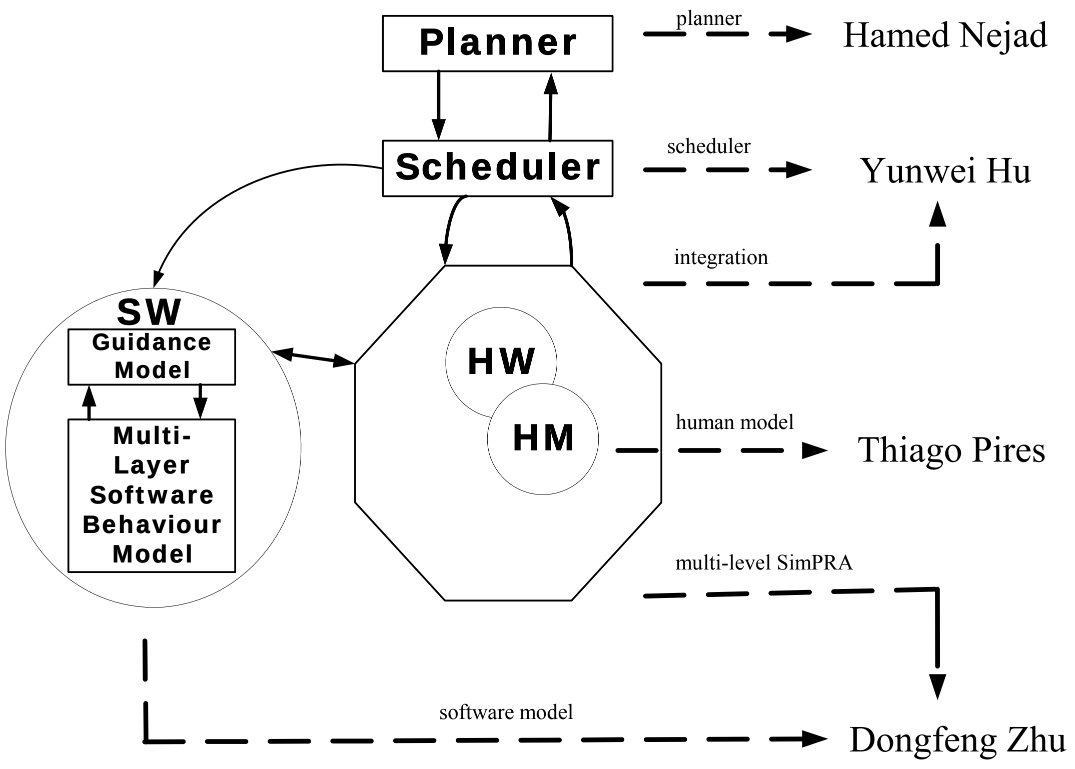

Figure 3. Teamwork chart for SimPRA

2.5 Glossary of terms

The following terms are used in this dissertation:

1. Model: an abstraction of the real-life system. Models are used to obtain predictions of the behavior of real system, especially how one or more changes in various aspects of the modeled system would affect the other aspects of the system. [38, 40]
2. Event: following the convention of discrete event simulation, an event is

defined as an instantaneous occurrence that changes the system configuration. [41]

   a. Random Events are the events whose occurrences are depicted by a stochastic model and can be controlled by the simulation environment.
   b. Deterministic Events are induced by the deterministic rules.

3. Scheduling: the process of controlling the generation of event sequences. It is done by deciding on the occurrence and timing of the random events in the model.
4. Branch Point: a point in the simulation of the system at which the occurrence of a random event is considered by the algorithm controlling the simulation. Each branch point will have two or more branches, corresponding to occurrence of possible events.
5. End State: a classification of the condition of the system at the end of an event sequence.
6. Scenario: One simulation realization as a sequence of events from the Initiating Event (IE) to one End State (ES).
7. One round of simulation: One round of simulation is defined as a specific number of scenarios generated before updating the plan. In other words, it is the number of event sequences of one updating interval
8. Plan updating interval: The planner is part of SimPRA. It serves as a map for exploration. The scenarios of interest are highlighted in the planner. The map will be updated after each round of simulation.

Chapter 3: Software Modeling Requirements in DPRA

This chapter describes the basic requirements that a successful integration of software behavior models in DPRA must meet.

3.1 General Modeling Requirement

From a general modeling perspective, the software model should be:

- Simple in methodology
- Easy to learn. The basic modeling concept should be easy to understand
- Easy to use, with acceptable modeling costs
- Quickly and seamlessly developed
- Accompanied with a tool to help end users build the model
- Easily and economically maintained and modified
- Reusable

3.2 Simulation Requirements

From the simulation perspective, there are different requirements for the behavior model and the guidance model. The software behavior model should have the following characteristics:

- *Complete*. Since the model needs to capture all phenomena that fall within the scope of the analysis, the software model should be able to represent most (ideally, all) of the software systems and software characteristics as they relate to risk assessment.

- *Executable and linkable.* The behavior model should be executable and linkable with other elements, such as humans and hardware, inside the DPRA framework. This is a basic requirement of the simulation environment.
- *Hierarchical.* First the model should have a hierarchical structure from the lines of code to the coarser-grained software model. Meanwhile, different levels of abstraction should also be defined to simulate the software behavior at each level. Secondly one needs to model the software at different stages of the software development life-cycle: requirement, design and code. The modeling method should be usable at various stages and should also be updatable as the analysts get more information about the real software.
- *Flexible.* The level of the abstraction should be flexible and controlled by the simulation scheduler. As was specified in the hierarchical requirements, different levels of abstraction should be constructed, and the scheduler should be able to flexibly control the simulation level of detail, based on the different simulation requirements.
- *Controllable Stochastic Events.* The behavior model is a combination of deterministic model and stochastic model. Stochastic events represent possible software failures inside the behavior model. The latter should be controllable by the software scheduler and the high-level system scheduler. During simulation, the stochastic events will be triggered to study the impact

of possible software faults.

- *Explorable.* The simulation scheduler should be able to perform a systematic exploration of the software model behavior.

The software guidance model is designed to guide the simulation to explore scenarios of interest. It also interacts with the high-level simulation scheduler to automatically adjust the software level of detail used in the simulation, based on prior knowledge and previous simulation results. To fit into the DRPA simulation environment, the guidance model should:

- Capture common software vulnerabilities
- Include a software scheduler to control the stochastic events inside the behavior model
- Adjust the software simulation rules, based on prior simulation results
- Adjust the software simulation rules, upon requests from the high-level system simulation scheduler

3.3 Interaction Requirements

Modern safety-critical systems are usually X-ware systems [42]. The systems consist of interacting X-ware components of hardware, software, and human operators. Software components thus interact with hardware, and human components within the simulation environment. Therefore, we should also establish the software model requirements from an interaction perspective.

Interaction in X-ware systems is defined as mutual or reciprocal action or influence in relation to certain functions. It results in the exchange of matter, energy, force, and/or information [42]. The system functions are achieved via the interactions of components. As there are three types of components in X-ware systems (hardware, software, and human), the interactions between any two components need to be studied separately.

Software-Software interactions

Interaction between two software takes place via information exchange. The information can be categorized into value-related information and time-related information [43].

- Value-related information
  - Amount: the total number or quantity of input or output
  - Value: The value taken by the input or output
  - Range: the limits of input/output's quantities.
  - Type: a set of data with values having defined characteristics
- Time-related information
  - Time: the point at which the i^{th} input/output element is available or feeds into/out of the software
  - Rate: the frequency at which the input is sent or the output is received
  - Duration: the time period during which the input or the output lasts
  - Load: the quantity that can be carried at one time by a specified input or output medium

Software interactions need to be modeled in the software representation. The representation should also have the capability to model all value-related failure modes as well as time-related failure modes.

Software-Hardware interactions

Software interaction with hardware can be simplified as an information exchange. Software obtains hardware-state information and then sends command signals to the hardware. From this perspective, this interaction is similar to a software-software interaction. Both value-related failure modes and time-related failure modes need to be considered.

The hardware can also act as a support medium for software, such as memory, CPU, etc. In that sense, support failure modes should also be modeled inside the software representation.

Software-Human interactions

For complex, critical, and reliability-demanding operating environments, the software/human interaction is equally important. Information related to human detection can be divided into the following categories: visual detection, auditory detection, olfactory detection, and tactual detection. Tactual detection and olfactory detection usually invoke human/hardware interactions. When considering human/software interaction, we usually need to consider the following characteristics:

- Auditory interaction

  Spectrum; Frequency; Amplitude; Relative intensity

- Visual interaction

Overall layout; Position; Distance; Size; Color; Contrast; Brightness; Flash rate

These characteristics need to be added to the software output to human as additional factors. Different value of these factors can influence human detection capability to software output. These factors can be represented using value-related information and time-related information. For instance, the relationship between distance and human movement time can be modeled using Fitts' Law [44]. The movement time can be future used in the human model to predict the performance of operators using complex system. Fitts' law is stated as follows:

$$MT = a + b \log2(2A/W) \tag{3.1}$$

where

- MT = movement time
- a,b = regression coefficients
- A = distance of movement from start to target center
- W = width of the target

3.4 Non-Functional Requirements

A non-functional requirement is defined as a software requirement that describes not what the software will do, but how the software will do it, as in for example, software performance requirements, software external interface requirements, software design constraints, and software quality attributes. [43] Nonfunctional requirements are difficult to test; therefore, they are usually evaluated subjectively.

To model the software completely, the software representation should also be able to capture the related non-functional requirements, which can be summarized in the following categories:

- Design constraints:
  - cost and delivery date
  - development process to be used
  - platform
  - accuracy requirements
  - interface requirement: describe how the system is to interface with its environment, users, and other systems. (e.g., user interfaces) and their qualities (e.g., user-friendliness)
  - response time: the time that elapses from when a user issues a command to when the system provides enough results for the user to continue to work
  - throughput: computations or transactions per minute
  - technology to be used
  - resource usage
- Lifecycle requirements
  - flexibility: the ability to handle requirement changes
  - installability: ease of system installation
  - operability: ease of everyday operation
  - allowance for maintainability and enhancement
  - allowance for reusability: describes the percentage of the system, measured in lines of code, that must be designed generically, so that it can be reused
  - usability and availability: a quality that measures the amount of time that a

    system is running and able to provide services to its users

    - robustness, recovery from failure
    - reliability: an important quality of software that measures the frequency of failures, as encountered by testers and end-users
    - security requirements
    - portability: the capacity to be moved to different platforms or operating systems

- Other requirements
    - economic requirements
    - organization requirements
    - political requirements

Among all these requirements, we need to consider the requirements related to software behavior and system risk. From that perspective, we mainly consider design constraints, including the following:

- platform;
- accuracy requirements;
- interface requirements;
- response time;
- throughput; resource usage

The non-functional requirements should be captured inside the behavior model. The simulation environment should have the capability to simulate different overload situations to check for software vulnerability.

3.5 Discussion

In this chapter, the software modeling-requirements in the DPRA environment are summarized from different perspectives.

The simulation requirements are basic requirements imposed by the simulation environment. The software representation developed in this dissertation meets the simulation requirements. The software methodology should be able to model all time-related information and value-related information in order to model the interaction requirements and the non-functional requirements. The methodology developed in the following chapter ensures the integration of value-related information and time-related information. It is the author's belief that general modeling requirements are met. A modeling tool is developed for software representation that is easy to learn, easy to use, and easily maintained. The methodology is designed to be reusable.

Chapter 4: Software Representation Framework for simulation

4.1 Overview

Among the available methodologies for modeling software behavior are: finite-state charts [6], UML [45], Petri-Net[46], and pattern concepts [47]. Those methods, and others, fall into one of two broad categories: 1) those based on software data flow, representing the software through decomposition of the system into dataflow diagrams that capture the successive transformations of system input into system output, and 2) those that model the procedural stages of the software, represented in the form of states and transitions between those states, leading to a finite-state chart. Because of its ability to model reactive systems, the latter seems appropriate for our purpose.

Table 1 compares some existing software representations with respect to the modeling requirements:

	Executable	**Hierarchical**	**Flexible**	**Explorable**	**Complete**	**Easy to learn**	**Easy to use**	**Reusable**	**Tool Support**
Pattern	No	No	NA	No	No	Good	TBD	Yes	NA
UML	Engine required	No	NA	No	TBD	Fair	TBD	Partially	Available
FSM	Partially	Yes	Yes	Yes	TBD	Very Good	TBD	Partially	Available
Petri-Net	Partially	Yes	No	Yes	TBD	Good	TBD	Partially	Available

Table 1. Comparison of the software representation methodologies

Table 1 shows that two of the criteria can not be assessed since completeness can never be fully proven. No experimental evidence exists which would allow us to conclude on the respective ease of use of the modeling approaches considered. Thus we conclude based on the remaining factors that FSM best fits our purpose.

FSM has been defined as: A computational model consisting of a finite number of states and transitions between these states, possibly with accompanying actions [5]. FSM accepts input events (or stimuli) that cause an output (or action) and possibly a change in state. Both the output actions and the next state of the machine are pure functions of input event and current state. Transitions can be separated into two parts: conditions and transitions. Transitions are triggered when the conditions are true.

There are two concepts of states. 1) A condition or mode of existence that a system, component, or simulation may be in; and 2) the values assumed at a given instant by the variables that define the characteristics of a system, component, or simulation.

The concept of simulation-based Finite State Machine (SFSM) is defined in the following sections. The model is based on FSM but integrates all the simulation-required components.

4.2 Key Concept

The following concepts will to be used in the sections that follow.

1) Multi-Layer Software Representation

   The software representation is defined during different stages of the software development life-cycle. In this sense, it is a multi-layer software representation starting with the requirement specification and continuing through the design specification and coding stages. The software representation is refined after more information becomes available. At any given time point in the software-development life cycle, the software representation also has a multi-level structure. (See next definition, below.)

2) Multi-Level Software Representation

The multi-level abstractions may be viewed as a hierarchical structure of software representations from the lines of code to the coarser-grained software model. The level of detail used in simulation is dynamically adjusted, based on the different simulation requirements.

The relationship between the Multi-Layer and Multi-Level structure is illustrated in Figure 4.

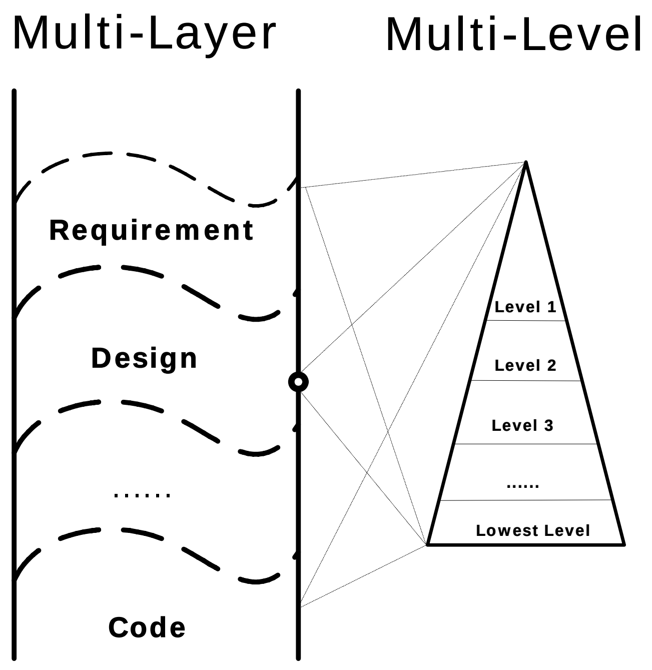

Figure 4. Relationship between the Multi-Layer structure and the Multi-Level structure

3) Failure Modes

Failure modes f_m are defined as the observable typically functional ways in which a system, a component, an operator, a piece of software, or a process can fail. All the failure modes considered in this dissertation belong to the pre-defined failure modes set.

$$f_m \in F_{ms} \tag{4.1}$$

4) Failure Sets

Failure-mode Sets F_{ms} is simply a set of failure modes. A pre-defined failure-mode set is defined in the following sections.

$$F_{ms} = \{f_{m1}, f_{m2}, \cdots, f_{mn}\} \tag{4.2}$$

5) Stochastic Failures

Stochastic failures are the real failures injected at random, and according to a stochastic model, in the software behavior model. Each stochastic failure is a realization of a selected failure mode. Each failure has the following attributes:

- Failure location
- Failure mode
- Stochastic properties (e.g., occurrence probabilities)

6) Abstraction

Abstraction techniques are defined as techniques that derive simpler representations while maintaining the validity of the simulation results with respect to the questions being addressed by the simulation. [48] Abstraction techniques can be categorized into three broad techniques: *model boundary modification*, *model behavior modification* and *model form modification* [48] [49]. Model boundary modification refers to the modification of the input variable space. Model behavior modification involves modification of behaviors within a model rather than the inputs to a model. Model form modification refers to modification of model form, characterized by a simplication of the input-output transformation within a model or model component.

In this research, *functional abstraction* and *continuous abstraction* are defined for software abstraction based on the nature of software. Functional abstraction is an abstraction of the discrete structure of the software. Functional abstraction can be defined for all high-level functions. However, the lowest level function can not be abstracted in this way. Functional abstraction is a mixed modification of model boundary modification and model behavior modification.

Continuous abstraction is a mathematical abstraction of the continuous behavior of basic functions. For instance, a complex equation using physical quantities, such as temperature and pressure, i.e. continuous variables, can be abstracted using a look-up table. Continuous abstraction focuses on model form modification.

7) Functional Abstraction vs. Functional Decomposition

Functional decomposition is a methodology used to break down complex systems into low-level tasks or functions. A hierarchical function tree can be constructed using the functional decomposition methodology. Functional abstraction is an abstract description of high-level functions in the function tree. Use of functional abstraction disables all sub-functions under high-level function.

4.3 Behavior Model

4.3.1 Overview

The behavior model is designed to capture all possible software behavior within the scope of analysis. The real software is used directly in the previously mentioned test-based methodology proposed for the classical PRA framework. Clearly, the software itself could also be used as the behavior model in the DPRA environment. But using the software directly in the simulation environment may be unacceptable for any of the following reasons:

1) The software code is not available.
2) Software development is still in the requirement stage or the design stage.
3) The execution of the real software is time-consuming, which makes it unacceptable for the purpose of simulation.

Software failures include requirement and implementation failures. Both types are naturally included if the real software is used directly as the behavior model. There are no controllable variables, so the software representation is merely a software-behavior model. The software model gets inputs from the simulation environment and provides outputs to hardware and human models.

In most cases the software-behavior model needs to be constructed separately by the analyst. The behavior model can be constructed from the information available and then refined after the analyst receives more information about the software. The analyst may start with the information available from the software requirement document, the design document, or the real source code. The closer to the real software, the less uncertainty there will be in the final risk estimation, since the representation is a more accurate description of reality.

When the real software is not available, abstraction needs to be made to construct the behavior model based on the information available. As stated earlier, abstraction could be done at different levels, making the software representation a multi-level software representation. Considering the following functional decomposition of the software (Figure 5), an abstraction (the shaded blocks) could be done at function level F1 or function level F11. The abstraction will lead to omission of details related to sub-functions. For instance, if the abstraction of function F1 is activated, all the sub-functions F11, F12, etc are disabled automatically.

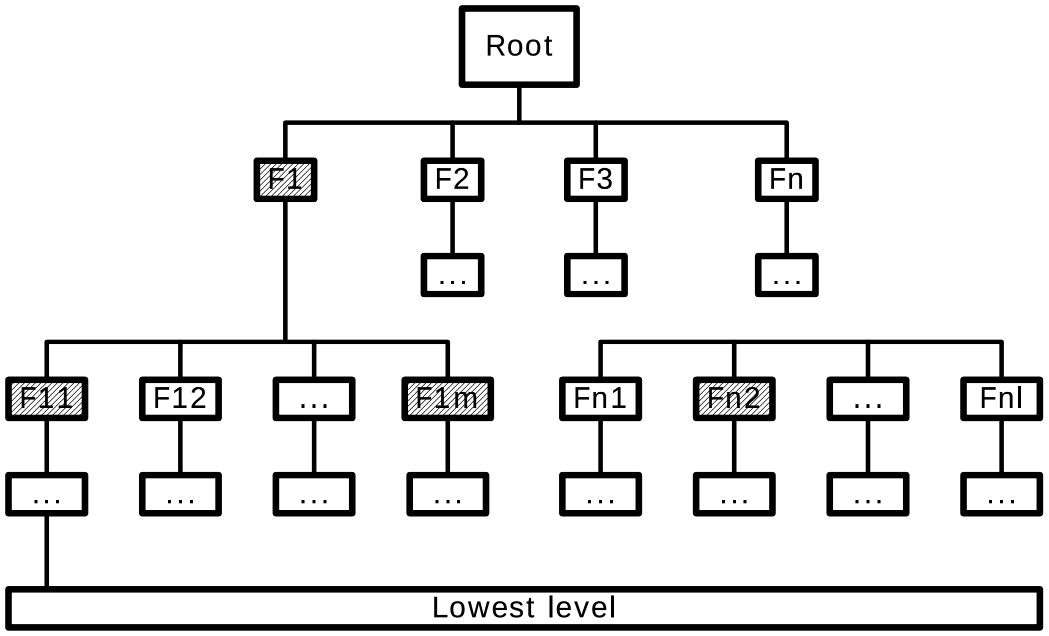

Figure 5. Software functional decomposition

The behavior model is an executable model. The deterministic behavior of the software is based on the information available. Error is introduced into this procedure if the information is not accurate, but it can be reduced when the analyst receives more information. The abstraction can be defined at different functional levels. The behavior needs to be clearly defined for each level of abstraction.

Consider, for example, a software system LOCAT[1] which calculates the projectile's coordinates. LOCAT receives real-time t from the TRAC hardware and computes the corresponding (x, y) Cartesian coordinates and outputs the results. The highest logic level system diagram is illustrated in Figure 6.

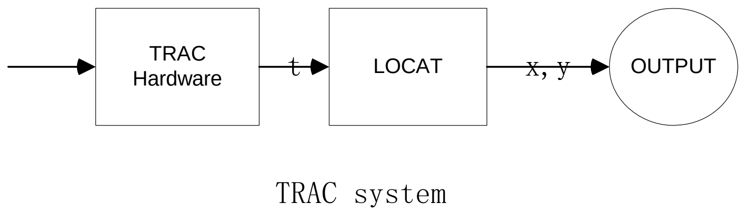

Figure 6. The highest logic level system diagram for LOCAT

LOCAT is composed of sub-functions realtimeCalculation and outputResult. Sub-function realtimeCalculation can be further decomposed to sub-functions get_time and cal_coordinate. Sub-function get_time retrieves time information from TRAC hardware and validates the time received from TRAC hardware. Sub-function cal_coordinate calculates x,y coordinates for the given time. Sub-function outputResult outputs the results to the external device.

[1] . The software is a part of a real-time simple projectile tracking system for the Army's all weather Doppler radar system called TRAC. It is part of a host software subsystem called COMP

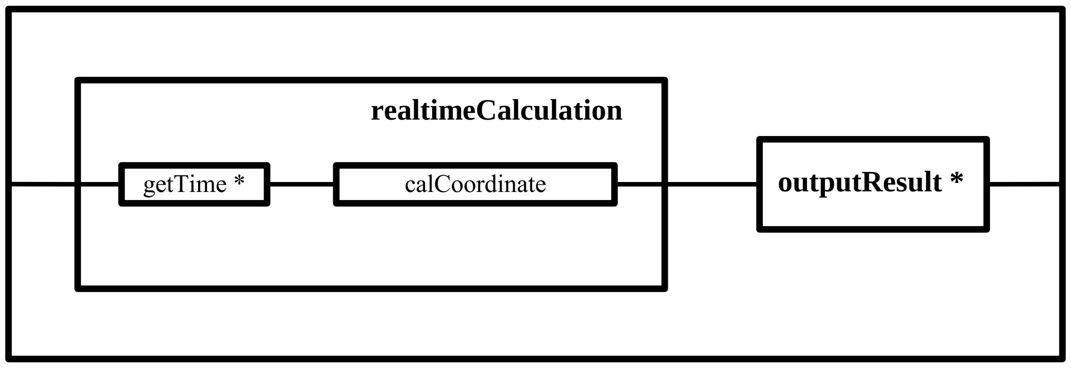

Figure 7. Example Software System LOCAT

The abstraction behavior has been defined for function LOCAT, also for sub-function realtimeCalculation. In this system the software function LOCAT can be modeled at the abstraction level of LOCAT or at the lower abstraction levels realtimeCalculation and outputResult, or at the detailed levels getTime, calCoordinate, outputResult. For each level, the detailed behavior needs to be defined deterministically. The level of detail is controlled by the software guidance model during simulation. Error is introduced when simulating at a high-level, but can be eliminated when simulating at the lowest level.

The software behavior model is constructed, based on an expected software behavior that omits all the failures introduced during software implementation. The implementation failures should be modeled also as stochastic events. The detailed failure information should be simulated in the abstraction model during simulation. The software failures can be injected at the selected level. The software function outputs are influenced by the failures, even when the detailed locations of the software faults are not available. So the software failures will be injected at the output side of the functions in our models.

Considering the example LOCAT system in Figure 7, from the information available we know that some faults exist in the function block getTime and the function block outputResult. The detailed fault location, however, is not available. Accordingly, the software failures can be injected at the output side of LOCAT, or at the output side of getTime and outputResult, or at the output side of getTime and outputResult. The detailed injection rules are discussed in the guidance model section (section 4.4). The failure injection level differs from the abstraction level. Even if the software is simulated at the lowest level getTime, calCoordinate, outputResult, the failure can still be injected at the output side of function LOCAT.

In this sense the software-behavior model is a combination of a deterministic model and a stochastic model. The deterministic model is used to simulate the behavior of the software, as well as the interaction between the software and other parts of the system. The stochastic model should be superimposed onto the deterministic model to represent the uncertain behavior of the software, e.g., software failures.

4.3.2 Simulation-based Finite State Machine (SFSM)

The software-behavior model is built using the FSM notation established by Harel [6]. The simulation-based concept is built into the basic FSM to form the SFSM.

The machine will be built using Matlab/Simulink [50]. Stateflow toolbox has been used to build the SFSM for our application software.

MATLAB, a very powerful tool designed by MathWorks, integrates mathematical computing, visualization, and a powerful language to provide a flexible environment for technical computing. The open architecture makes it easy to use MATLAB and its companion products to explore data, create algorithms, and create custom tools that provide early insights and competitive advantages.

Simulink, a toolbox extension of Matlab, is an interactive tool for modeling, simulating, and analyzing dynamic, multi-domain systems. It allows the user accurately describe, simulate, evaluate, and refine a system's behavior through standard and custom block libraries. Simulink integrates seamlessly with MATLAB, providing immediate access to an extensive range of analysis and design tools. Simulink is a very good tool for control-system design, signal-processing system design, communications-system design, and other simulation applications. Stateflow is another toolbox for MATLAB. It is a graphical design and development tool for simulating complex reactive systems based on FSM theory. Stateflow and simulink together will be used to construct a software representation for our examples.

Some key notions of SFSM are defined in the following:

[State]

State is defined as a condition or mode of existence that a system, component, or simulation may be in [5]. A state can be dissected into sub-states. There are two types of states: *exclusive state* and *parallel state*. Exclusive states are used for the software models that are mutually exclusive. Parallel states are used to model parallel software, which means that two or more states can be active at the same time [50].

States have labels that can specify actions executed in a sequence based upon action type. The action types are “entry”, “during”, “exit” and “on”.

"Entry" action is executed when the state is entered. "During" action is executed when the system stays in the state. "Exit" action is executed when the system exit the state. "On event" action is executed when the given event occurs and the system stays in the state.

[Transition]

Transition can be separated into two parts: the conditions and the transitions. The transitions are triggered when the conditions are true. Actions can be associated with both conditions and transitions. Transitions are not decomposable, and all of the transition is executed instantaneously.

[Action]

Actions can be associated with states, conditions, or transitions. An action can be a function call, the broadcast of an event, the assignment of a value to a variable. It can be served as an interface to load the real software.

[Internal Variables]

Internal variables are defined inside the SFSM. They will be used to describe the internal states of the software. They are also used to define control information for the guidance model.

The basic concept of the SFSM is discussed above. Simulation-based elements are added in the following sections.

4.3.3 Deterministic Model

Construction of the deterministic model is based on the information available. Multi-layer abstraction can be employed during different stages of the software development life cycle. Construction of the behavior model can be based on the software-requirement document, the software-design document, and the software code. The model is continually refined as more information becomes available.

Given the available information, the behavior model is also a multi-level model. Multi-level abstraction is defined for selected functions which meet the following criteria:

1) The execution of the functions is time-consuming (during simulation), and
2) The selected functions are not important for certain scenarios.

Different function blocks have different simulation priorities. The simulation level of detail may be different for different sub-function blocks. Even for the same function block, the priority changes in different contexts. The software guidance model (section 4.4) dynamically adjusts the simulation level of detail.

The simulation level of detail is defined as an internal variable. The simulation environment controls the values of the internal variables. The software is executed at different levels based on the value of the control variables. (See Figure 8)

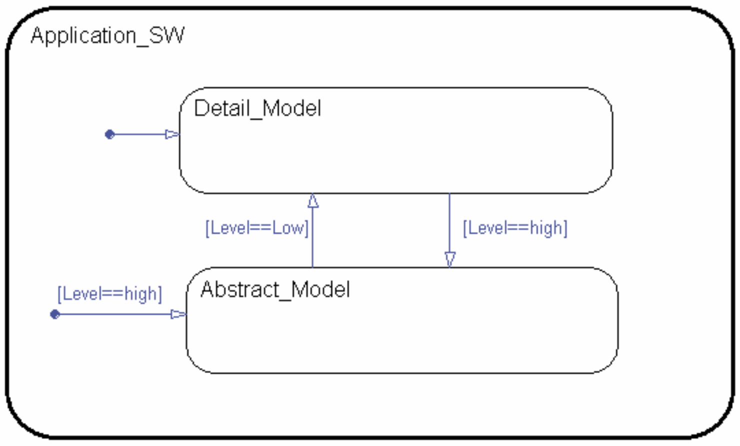

Figure 8. Typical structure used to control the level of model detail used in simulation

An abstraction knowledge base (AKB) needs to be defined before the simulation. A tree structure is used to construct the AKB (See Figure 9). Use of high-level abstraction will automatically disable all the low-level abstraction. The reason is obvious; the use of “Abstract_Model” (see Figure 8) disables all details in the software state “Detail_Model”.

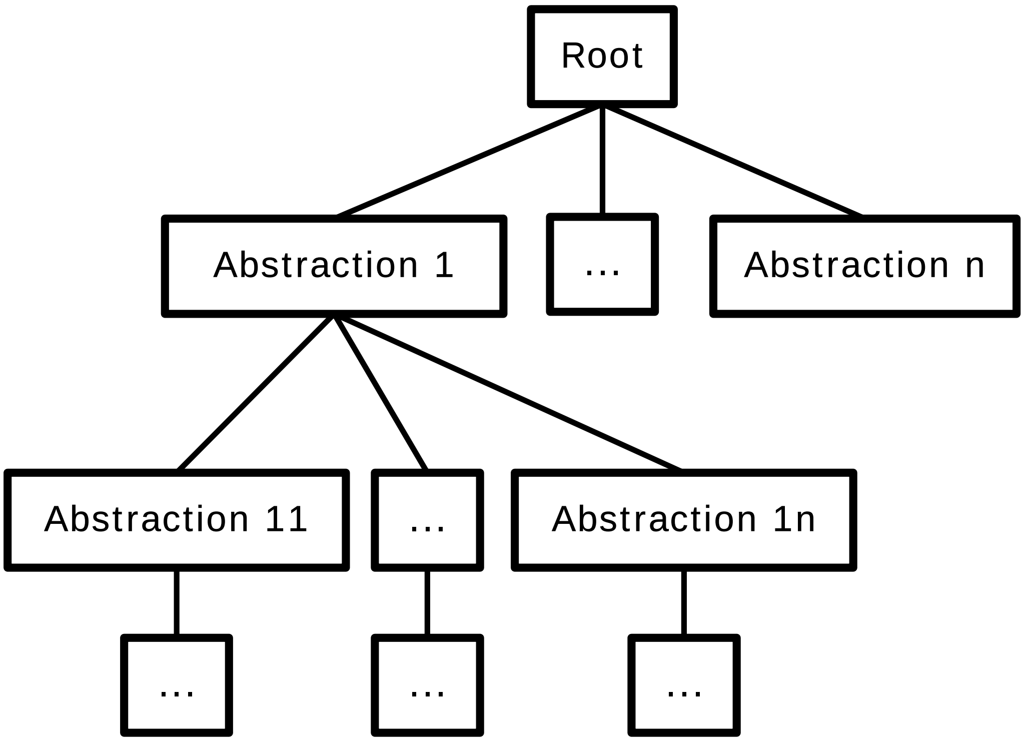

Figure 9. Abstraction Knowledge Base

A node of the AKB tree is described by the following equation:

$$AKB = \left\{i, f_i, f_l, N_p, \left\{N_{c1}, N_{cj}\right\}_{j=1,\cdots,n}\right\} \quad (4.3)$$

I is the abstraction-function index; the index uniquely defines the abstraction function; the index value for Root is always 0;

f_i represents the function name in the functional-decomposition structure (see Figure 5);

f_l represents the function level in the functional-decomposition structure (see Figure 5);

N_p represents the parent node of the current node; the value is -1 for the Root node;

N_{cj} represents the child nodes of the current node; the value is -1 if there is no child node available;

n represents the number of child nodes of the current node.

Only the structure-related information is stored in AKB. The simulation-related information about the abstraction level of detail is stored in a separate knowledge base. The detail of this knowledge base is introduced in the guidance model (section 4.4).

Considering the software example in Figure 5, the tree structure of AKB can be represented by the following figure:

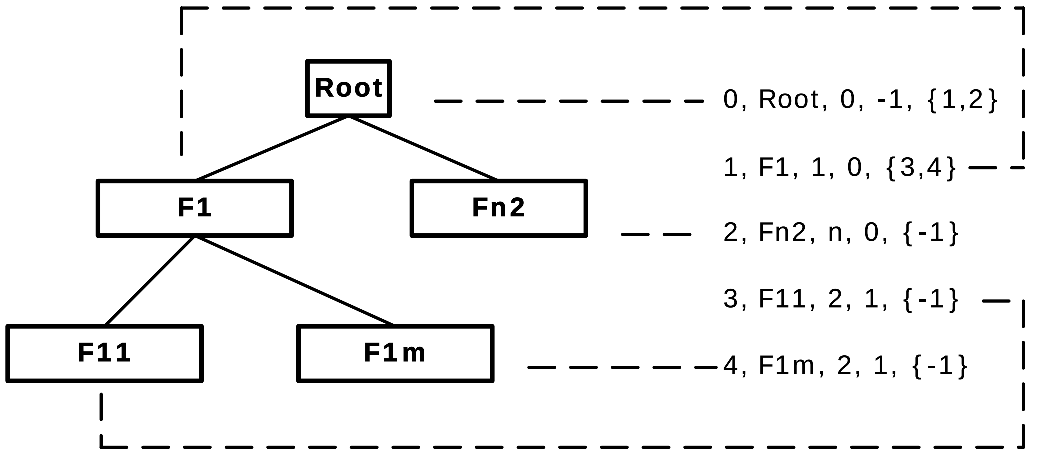

Figure 10. AKB for software example in Figure 5

The nodes of the AKB tree are described on the right side of Figure 10.

4.3.4 Stochastic Model

The stochastic model simulates the uncertain behavior of the software, e.g., software failures. Uncertain behavior should be controlled by the software scheduler and the high-level system scheduler. Using this mechanism, the simulation environment can simulate the implementation failures in the real software and analyze their impact on the whole system.

Failure Modes

Failure modes are defined as the observable ways in which a system, a component, an operator, a piece of software, or a process can fail. A taxonomy of software-related failure modes has been proposed in [4]. Software failures may originate either within the software itself or from the software interface with its operational environment. Failure modes, therefore, can be classified as either software functional-failure modes (failure modes of the software itself) or software interaction-failure modes (input/output failure modes, support-failure modes and environmental-impact factors). In this research, input/output (I/O) failure modes are considered first. The I/O failure modes include value-related failure modes (amount, value, range and type) and time-related failure modes (time, rate, duration and load). Function failure modes generate different function outputs and, as such can be covered by the above failure modes.

The effect of a support failure[2] will be covered in future research. The definition of the following failure mode set is based on the above information.

$$F_s = \{T_v[value, amount, range, type], T_t[time, rate, duration, load]\} \qquad (4.4)$$

The above set is used as a pre-defined generic failure-mode set in this research.

The value-related failure model uses the SFSM structure in Figure 11:

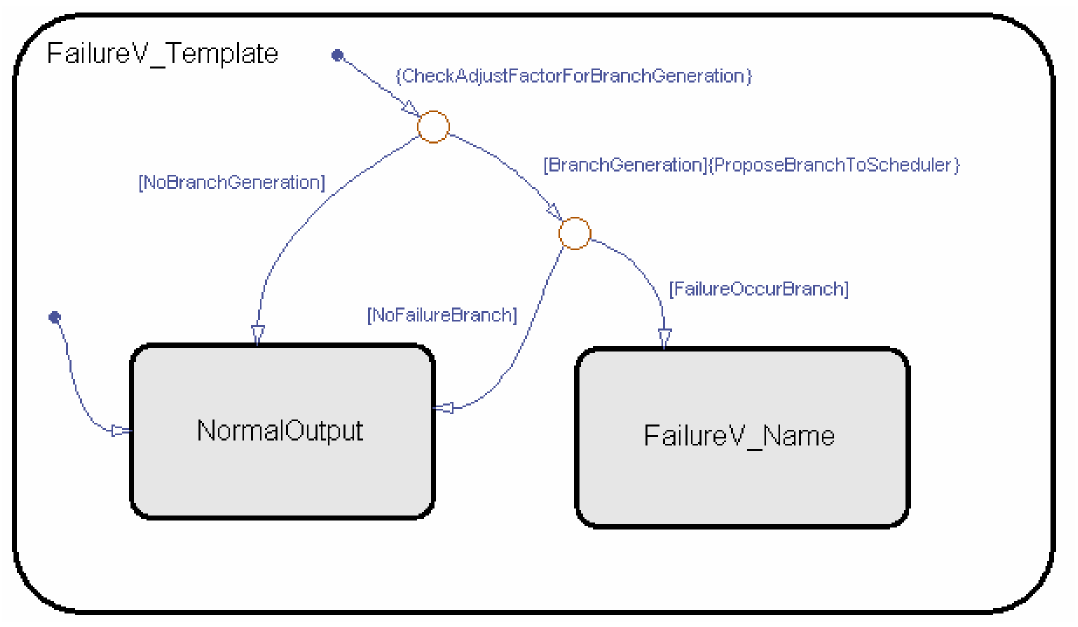

Figure 11. Value-related failure modeling in SFSM

Time related failures are complex, compared with value-related failures. Figure 12 presents the structure used for modeling a delay failure. Figure 13 shows the structure for the delay unit.

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[2] The "support" failure modes include failures due to competition for computing resource and the computing platform physical features. The failure modes due to resource competition are deadlock and lockout. The impact of physical failures on software can be decomposed further into the impact of CPU failures, memory failures and I/O devices failures

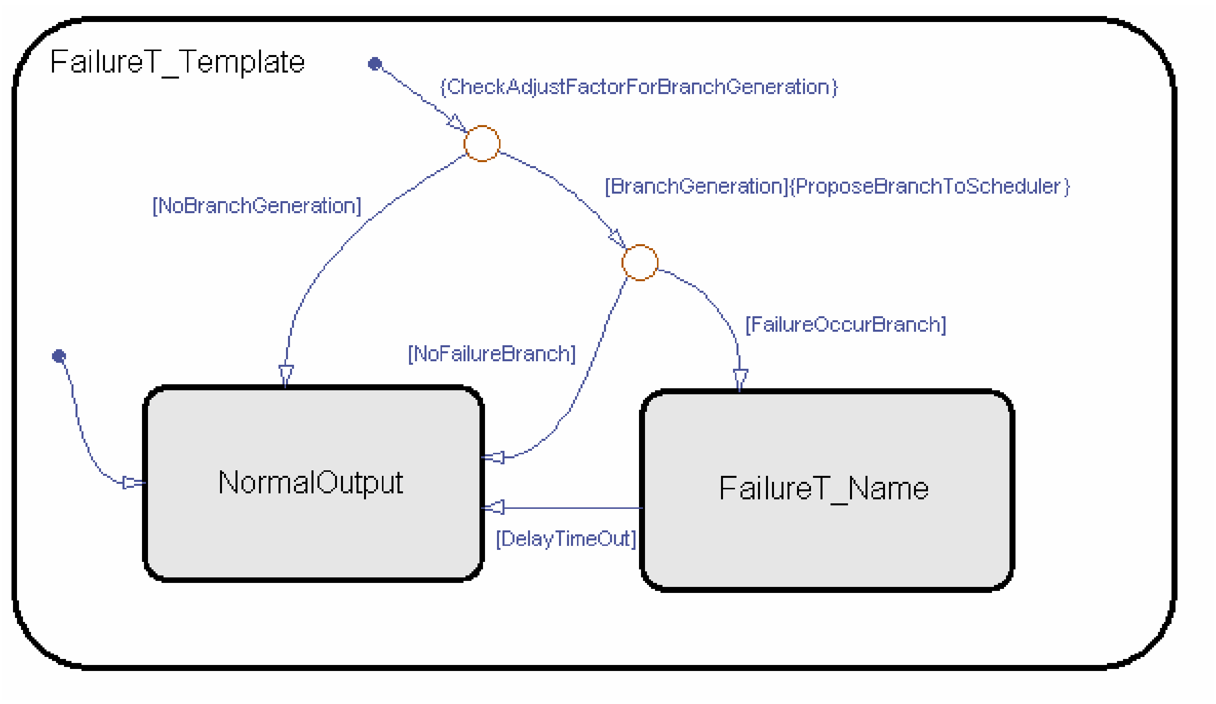


Figure 12. Delay failure modeling in SFSM

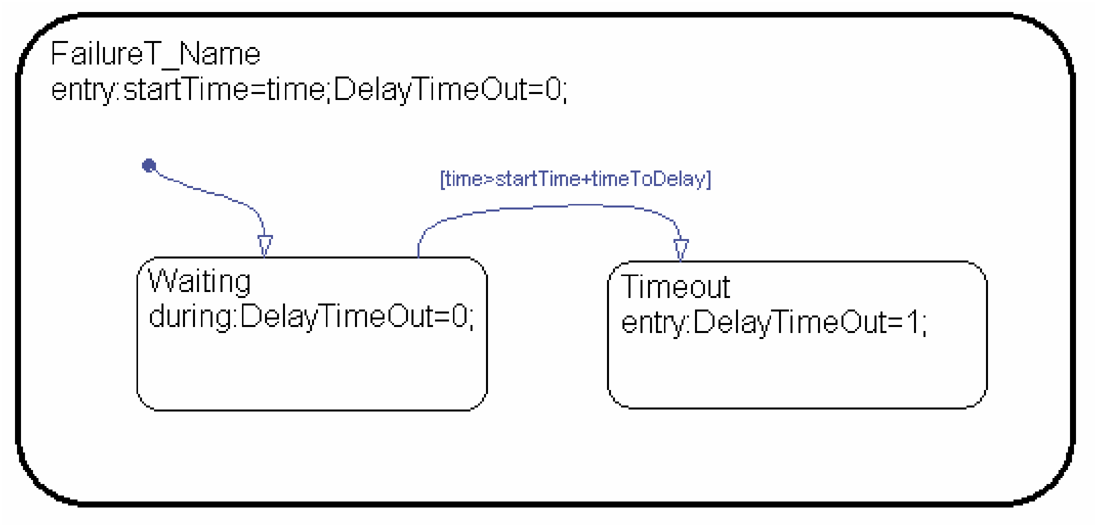


Figure 13. Delay component for time-related failure in SFSM

The detailed description for each transition will be discussed in the section discussing the integration of the software model into the SimPRA environment (chapter 5).

Failure Injection

The selected software failures are injected into the software behavior model. Failures are injected at the output side of software functions. They can be injected at different software levels.

Considering the software example in Figure 7, it is known that some faults exist in sub-function getTime and function outputResult.

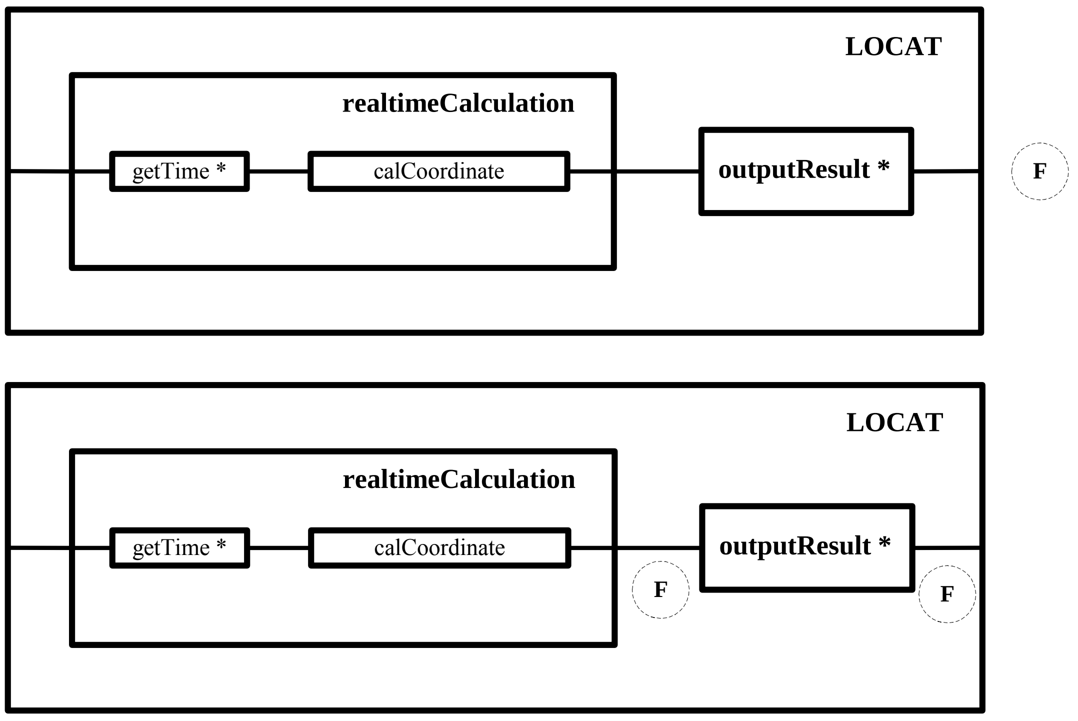


Figure 14. Different fault injection methods for an example system LOCAT

For the same type of failure mode, a high-level software failure is the combined result of low-level failures. In the example system, the software failure at the function LOCAT level is the abstraction of software failures at the sub function realtimeCalculation and outputResult levels. Software failures belonging to similar failure modes should not be modeled at different levels simultaneously.

The failure-injection level is different from the abstraction level Li. For example, in Figure 14, the output failure can be injected at the level of function LOCAT. However, the abstraction level of detail may be at the lowest level. In other words, the failure can still be injected at the high-level, even if the detailed code is used in the behavior model. The level of failure injection cannot go lower than the level of abstraction for an obvious reason. The failure cannot be injected at the sub-functions getTime and calCoordinate levels if they are not modeled at all.

The failure-injection location is determined by the analysts. The different injection level is dynamically adjusted by the guidance model.

Failure Probability Quantification

The selection of software failure modes is based on expert opinion and previous experience. Failure probabilities are estimated using statistical data, expert judgment, or the test-based methodology mentioned in section 2.1, once the code is available. For example, there are two databases for the Space Shuttle Group Project: one for the history of the software code and another that records every error ever made on the software project. As a result of the vast amount of data collected in the databases, the Space Shuttle Software Group has written software that predicts the amount of errors that should be expected. The data in the database is quite detailed: it contains information on possible failures in the software code, and the probability of failure. That information can be used to inject failures into the software representation and also to quantify the failure probabilities [51].

Software failures can only be triggered for the specified input domain. To inject a failure at the high-level, the analyst needs to define the decomposition of the input domain into a minimum input set. The failure probability in each of the sub-domains of the minimum input set is a fixed value. The triggering of software failures will be based on probabilities.

The minimum input set is defined as the set of sub-domains of the input domain I, such that:

$$I = \bigcup_{j=1}^{n} I_j$$

$$I_j \cap I_k = \Phi \qquad \text{for all } j \neq k \qquad (4.5)$$

For each $x_k, x_l \in I_j$

The failure probability $P(x_k) = P(x_l)$

A Failure Injection Knowledge Base (FIKB) needs to be constructed for the failures injected. Each injected failure is related with one software function. The minimum input set needs to be defined for those functions. The relationship between failure probability and each sub domain inside the minimum input set needs to be defined inside the knowledge base. A tree structure is used to construct the FIKB (see Figure 15).

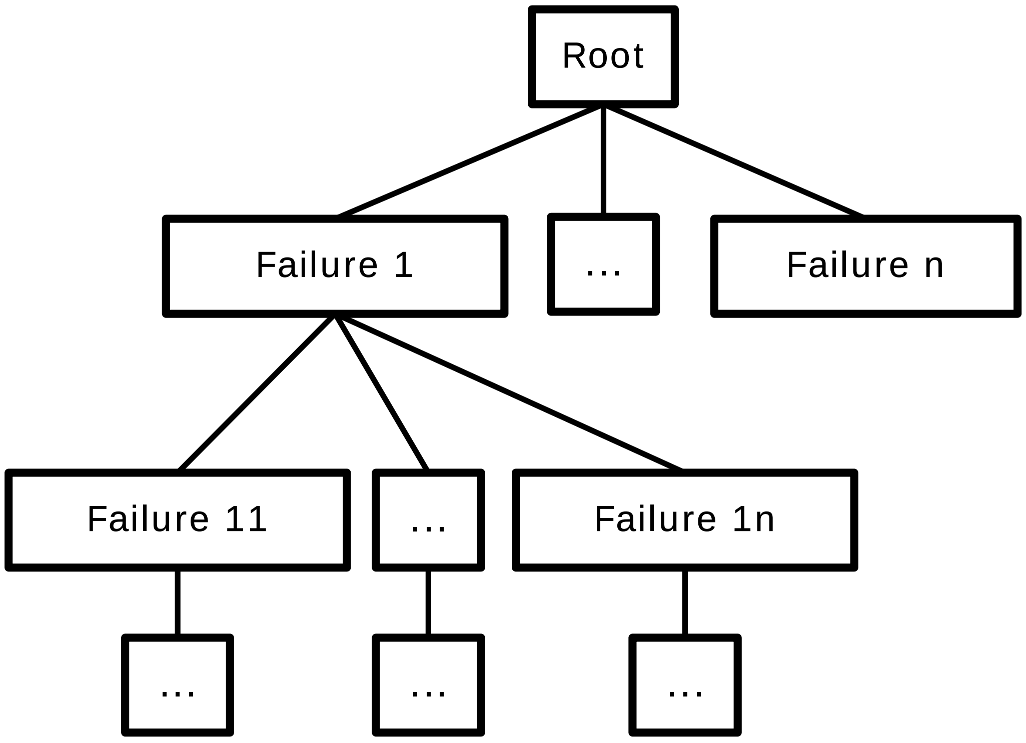


Figure 15. Structure of the Failure-Injection Knowledge Base

Each node inside the FIKB can be presented using the following equation.

$$FIKB = \left\{ i, f_{mi}, f_l, N_p, \left\{ N_{c1}, \cdots, N_{cj} \right\}_{j=1,\cdots,n}, I_i, \left\{ I_{ji}, pf_{ji} \right\}_{j=1,\cdots,n} \right\} \qquad I_i = \bigcup_{j=1}^{n} I_{ji} \qquad (4.6)$$

I is the software-failure index; the index uniquely defines the injected software failures;

f_{mi} represents the name of the injected software-failure modes (see

Figure 5);

f_l represents the injected software-failure level in the functional-decomposition structure (see

Figure 5);

N_p represents the parent node of the current node; the value is -1 for the Root node;

N_{cj} represents the child nodes of the current node; the value is -1 if there is no child node available;

n represents the number of child nodes of the current node.

I_i represents the input domain of the software-failure related function;

I_{ji} represents each sub-domain of the minimum-input set; the size of the minimum-input set is n;

pf_{ji} represents the failure probability for the sub-domain I_{ji};

n represents the number of sub-domains.

F_{mi} and f_l are used in the guidance model to control the activation of the software failures at different levels. Once the failures are activated, the relationship between I_{ji} and pf_{ji} is used to decide whether or not the failures are to be triggered for specific input from the simulation environment.

Considering the example system in Figure 14, the failure can be injected at the level of LOCAT as failure failure_LOCAT; it can also be injected at the level of sub-function realtimeCalculation as failure_realtimeCalculation and sub-function outputResult as failure_outputResult. FIKB can be represented using the tree structure in Figure 16

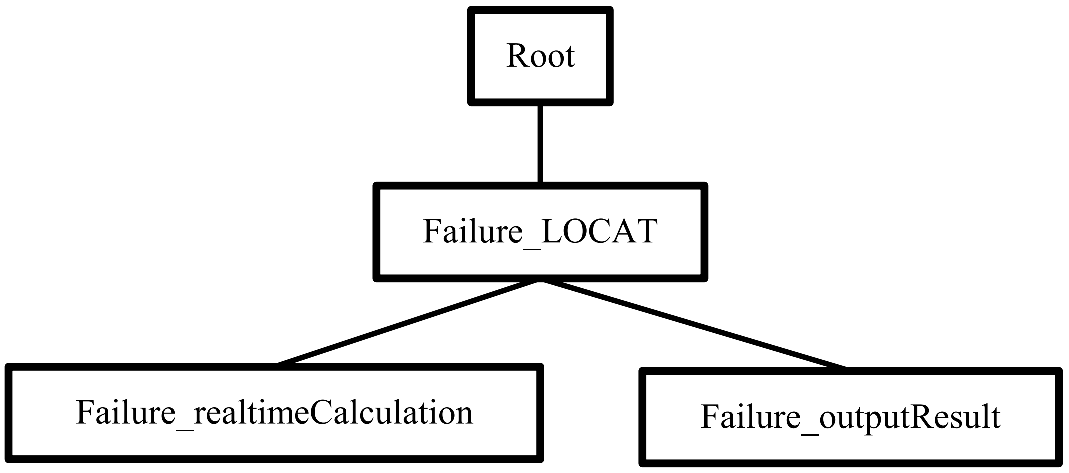


Figure 16. AKB for software example in Figure 14

The guidance model controls the activation of software failures. High-level failures and low-level failures can not be actived at the same time. In Figure 16, Failure_realtimeCalculation and Failure_outputResult become invisible once Failure_LOCAT is actived. Once the failure is activated, the relationship between I_{ji} and pf_{ji} defined for that failure is used to decide whether or not the failures are to be triggered for specific input from the simulation environment.

4.3.5 Summary

The deterministic model and the stochastic behavior models were introduced in previous sections. Several controllable variables are defined inside the behavior model. Multi-level abstraction structure is constructed in the deterministic model. The simulation level of detail is controlled by the guidance model (section 4.4). Software failures are injected through the stochastic model. The failure modes and locations are selected by the analysts. Different failure-injection levels are defined in the stochastic model. The software failures are triggered in the guidance model. The detailed mechanism used is discussed in the following sections.

To summarize, we can use the following equation to represent every component in the software behavior model.

$$\begin{aligned}
&S_i(L_i) = \left\{ i, L_i, [B_i(L_i+1), f_{is}] * d_i + \left[\tilde{B}_i, \tilde{f}_{is} \right] * (1-d_i) \right\} \\
&f_{is} = \{ f_k, f_{kd} \} \qquad k = 1, \cdots, m \\
&B_i(L_i+1) = S_{i1}(L_i+1) \oplus S_{i2}(L_i+1) \oplus \cdots \oplus S_{ij}(L_i+1) \qquad j = 1, \cdots, n
\end{aligned} \tag{4.7}$$

I is the software component name or (index), which uniquely defines the software components;

d_i is a Boolean variable indicating whether one will simulate S_i at an abstract level ; d_i is controlled by the scheduler;

L_i is the current level of detail of the function S_i in the software representation; L_i is a relative value. (For a given component, the current level of detail may be different, depending on the definition of the baseline in the software representation. The baseline is defined as level 0 of the software component. The baseline needs to be unified for the whole software representation before the simulation);

B_i is the detail behavior model of the software component S_i;

$\tilde{B}_i$ is the abstract behavior model of the software component Si;

f_{is} is a set of stochastic failures injected at the output side of the normal behavior model of the software component S_i;

$\tilde{f}_{is}$ is a set of stochastic failures injected at the output side of the abstract behavior model of the software component S_i (The structure of $\tilde{f}_{is}$ is similar as that of f_{is}) ;

f_k is a single software failure injected for this software function;

f_{kd} is a Boolean variable indicating whether this failure is activated or not (f_{kd} is controlled by the simulation guidance model) ;

m is the total number of software failures injected for this software function;

$\oplus$ represents that B_i is composed by the sub-function S_{ij}.

If no abstraction is defined for the software component, equation 4.7 becomes a solely functional decomposition of the software component. To explore the system vulnerabilities, the software simulation-guidance model controls all the controllable variables inside the behavior model.

4.4 Simulation Guidance Model

4.4.1 Overview

The high-level guidance model guides the simulation to explore scenarios of interest, in lieu of doing a wide-scale exploration. In this sense the guidance model is not necessarily a complete representation of the software system. Instead, it may be fragmentary, covering only specific parts of the system. The key elements of the software can be identified and built into the guidance model. General knowledge about the software and common vulnerabilities should also be defined in the guidance model. Meanwhile, a software scheduler needs to be constructed inside the guidance model to control the stochastic behavior of the software and to communicate with the high-level system scheduler.

The guidance model simultaneously interacts with the system-behavior model, the software-behavior model, and the high-level system scheduler (See Figure 1). The high-level scheduler provides high-level simulation requirements. The system-behavior model provides hardware inputs and human inputs. The software-guidance model adjusts the software-behavior model, based on the inputs from the system-behavior model and the high-level system scheduler. The software-behavior model generates the software outputs, based on the inputs from the guidance model.

4.4.2 Interactions with other models

Guidance Model vs. System Behavior Model

The relationship between the guidance model and the system behavior model is relatively clear. The system-behavior model provides the input to the software and receives the output from the software. The guidance model works as an intermediate layer. Let $I_{s\text{-}sw}$ be the input from the system-behavior model to the software-behavior model. Let $O_{sw\text{-}s}$ be the output from the software-behavior model to the system-behavior model.

The input/output for the software-guidance model is:

Input from the system-behavior model	$I_{s\text{-}sw}$
Output to the system-behavior model	$O_{sw\text{-}s}$

Table 2. Software-guidance model vs. System-behavior model

Guidance Model vs. Multi-level Software-Behavior Model

The software-guidance model provides the software input to the software-behavior model and controls the execution of the multi-level software model using control variables. The system input to the software $I_{s\text{-}sw}$ comes from the system-behavior model. The control variables include abstraction level of detail L, which of the pre-existing software failure types f_t should be activated and also the failure simulation level of detail f_L. The values of L, f_t and f_L are calculated based on the detailed guidance rules.

The input/output for the software guidance model is:

Input from the software-behavior model	$O_{sw\text{-}s}$
Output to the software-behavior model	$I_{s\text{-}sw}$ L f_t f_L

Table 3. Software-Guidance model vs. Software-Behavior Model

Guidance Models vs. High-Level System Scheduler

The relationship between the guidance model and the high-level system scheduler is the most complex. The high-level system scheduler provides the high-level requirements. The guidance model calculates the value of the control variables, based on the simulation requirements and the inputs from the system model. It provides the system scheduler with the simulation-level control information and the failure-injection information. Also, the guidance model decides branch generation and provides the result back to the high-level system scheduler. Let R_h be the high-level requirements from the system scheduler. Let B be the branch-generation information. The input/output for the software guidance model is:

Input from High-Level System Scheduler	R_h
Output to High-Level System Scheduler	B L f_t f_L

Table 4. Software-guidance model vs. System Scheduler

R_h includes:

- Simulation level of detail control factor R_L
- Injected failure type R_{ft}; Injected failure level of detail R_{fl}
- Simulation time requirement factors R_t

There is no direct control from the high-level scheduler for a particular variable, if the value of that variable is -1

The guidance model interacts with the enhanced SimPRA environment to adjust the controllable variables. The enhanced high-level planner and scheduler are presented in Chapter 5. The detailed guidance rules are discussed thereafter.

4.4.3 Simulation Knowledge Base (SKB)

A Simulation Knowledge Base (SKB) is constructed inside the software-guidance model to store prior knowledge about the software system. SKB, AKB, and FIKB together serve as the knowledge base for the software model.

The following information is stored in the SKB as prior knowledge:

1. Time-factor related information

The relationship between the high-level scheduler Simulation time requirement factors R_t and the simulation level of detail control factor R_L are stored in the knowledge base. When there is no direct control from the high-level system scheduler, the guidance model decides the simulation level of detail based on the time requirements factor from the high-level system scheduler.

The relationship between R_t and R_L is not necessarily a 1-to-1 relationship. When the relationship between R_t and R_L is 1-to-many, the probability for each pair should also be defined in SKB.

That type of node in SKB can be described using the following equation:

$$SKB = \{i, type_i, R_t, \{R_{L1}, \cdots R_{Ln}\}\} \tag{4.8}$$

I is the node index (the index uniquely defines the node in the SKB);

$type_i$ represents the type of node;

R_t represents the simulation time requirements factor from the high-level scheduler;

R_L represents the simulation level of detail;

2. Prior knowledge

The relationship between the pre-defined condition and the simulation level of detail is stored in this part. It is an interface that can be modified by the analysts for different applications. The pre-defined condition can be configured differently in different environments. For instance, in the example system in Figure 17, let us assume that the pump-control software is designed to maintain the life-support system for the Space Shuttle, based on the temperature, pressure, and time. When the system is in a relatively safe range, there is no need to simulate the control software in detail. A high-level lookup table is used to simulate the software-deterministic behavior. The lookup table is a continuous abstraction for the detailed control equation. When the system reaches the danger area, the lookup table is not accurate enough, so the low-level detailed control equation is used to simulate the software behavior.

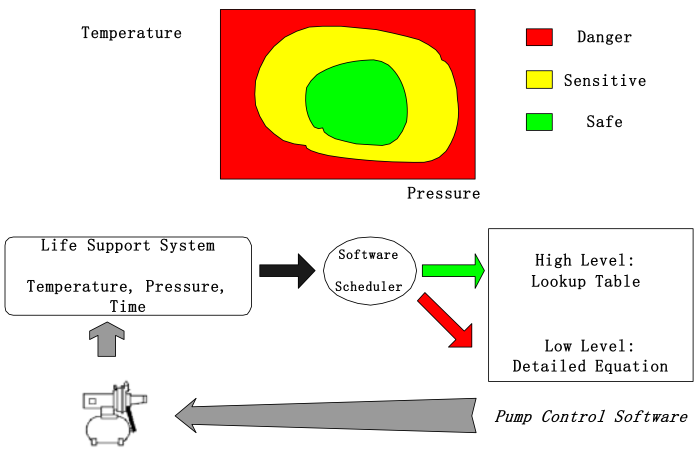


Figure 17. Pump control system

The relationship between the simulation level of detail (High/Low) and the predefined condition (Range of Temperature + Pressure) is defined in this part of SKB.

This type of node in SKB can be described using the following equation:

$$SKB = \{i, type_i, C, \{R_{L1}, \cdots R_{Ln}\}\} \tag{4.9}$$

I is the node index (the index uniquely defines the node in the SKB);

$type_i$ represents the type of node;

C represents the pre-defined condition in the system model;

R_L represents the simulation level of detail;

The above information is simply the type of information we studied to this point. SKB can be further enriched later to store more simulation-related prior knowledge.

Chapter 5: Integrating the Software Representation into SimPRA

5.1 State Explosion Issue

Dynamic Probabilistic Risk Assessment (DPRA) of complex systems is considered to be the next generation of PRA techniques. It is not currently in wide use because of state explosion issues that need resolution. DPRA is a set of methods and techniques in which executable models representing the behavior of the elements of a system are exercised in order to identify risks and vulnerabilities of the system, by simulating a variety of sequences of events that are representative of the possible true behaviors of the system. The event sequences typically share a single initial condition but are varied by introducing, at various points in the event sequence, possible deviations due to hardware and software failures, as well as human actions. The set of simulated sequences is then analyzed to gain insights into courses of events leading to undesirable end states, as well as their likelihood.

State explosion is a well-known problem that impedes the implementation of DPRA techniques. The major weakness of the approach based on state space-exploration is that the size of the state-space grows exponentially with the number of branches generated and thus creates the state space explosion problem.

Different approaches have been proposed to solve the state explosion issue. One approach is to employ a conservative assumption and merge the system states or the end states, thus reducing the branch generations. A second approach is through distributed computing which would reduce the loads on a single computer. Another approach is to bias the simulation toward interesting events and end states. That approach would include the use of a knowledge-driven high-level planner to guide the simulation, as well as an entropy-based biasing of the scenarios. The simulation scheduler drives the actual-risk scenarios. The SimPRA environment is a real implementation of the third approach.

5.2 SimPRA environment

5.2.1 Overview

SimPRA is an adaptive scheduling simulation-based DPRA environment developed by the University of Maryland under a grant from NASA Ames Research Laboratory. [38] Prior knowledge of the systems and knowledge gained during simulation are used to dynamically adjust the exploration rules in the DPRA environment. In SimPRA, a high-level simulation scheduler is constructed to control the simulation process, generally by controlling the occurrence of the random events inside the system model. Instead of using a generic wide-scale exploration, the scheduler is able to pick out important scenarios, which are essential to the final system risk, thus increasing the simulation efficiency. To do this, a high-level simulation planner was constructed to guide the scheduler.

5.2.2 Guidance Rule in the single-level SimPRA environment

The adaptive exploration strategy used in SimPRA is based on an adaptive learning procedure. A general framework of adaptive learning procedure is described in Figure 18. It is believed that there is always information available prior to the experiments. The information gained from past data can be used to alter the exploration strategy of future exploration to more efficiently address the area of interest.

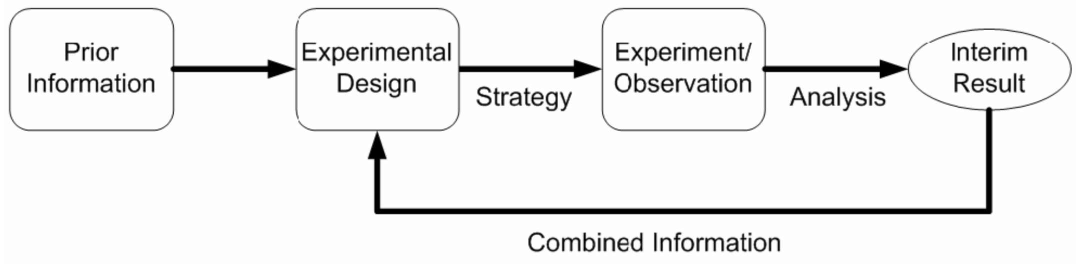


Figure 18. General framework for adaptive learning

In the current SimPRA environment, two kinds of knowledge are used to guide the simulation. The first category is prior knowledge, including the system-specific knowledge, such as the design of a system, plus generally applicable knowledge, such as the experience from similar systems. The second category is knowledge obtained during simulation, which is used to adaptively guide the simulation towards the scenarios of interest and to fairly distribute the simulation among possible scenarios. For instance, the event sequences generated can be used to modify the focus of exploration.

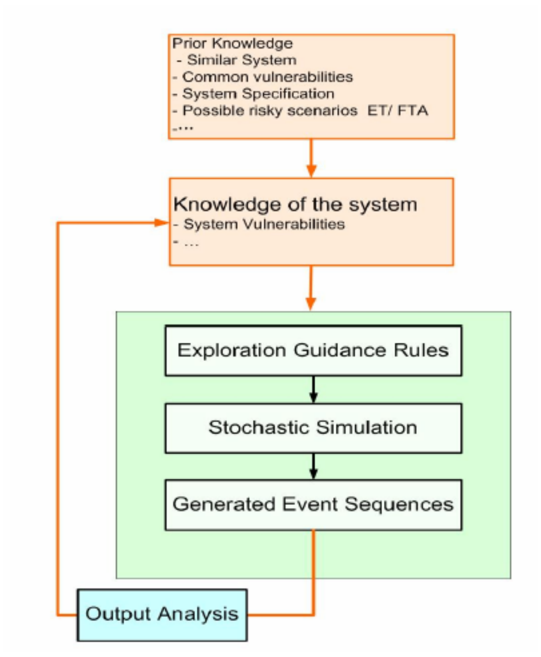


Figure 19. The use of information in the SimPRA environment

The SimPRA environment includes a planner, a scheduler, and the system simulator (see Figure 20).

The planner serves as a map for exploration. The scenarios of interest are highlighted in the planner. The map should not necessarily be accurate and complete; it will be updated after each round of simulation. There are two types of updating. The first type is automatic updating after simulating a specific number of event sequences. A second type of updating needs the analysts' intervention. The result of simulation may disagree with the plan. The discrepancy is highlighted for further investigation by the analysts [52].

The scheduler manages the simulation process, including saving system states, deciding the branch selection, and restarting the simulation. The scheduler guides the simulation toward the plan generated by the planner. The scenarios with high importance would be explored with higher priority, while all other scenarios also have a chance to be simulated. The objective of the scheduler guidance includes [40]:

- Maintain sufficient coverage of important scenarios in the plan
- Guide simulation toward areas of greatest uncertainty
- Continuously adjust priorities, based on simulation results
- Avoid test areas known to definitely lead to a specific end state
- Cover all possible event-sequence space

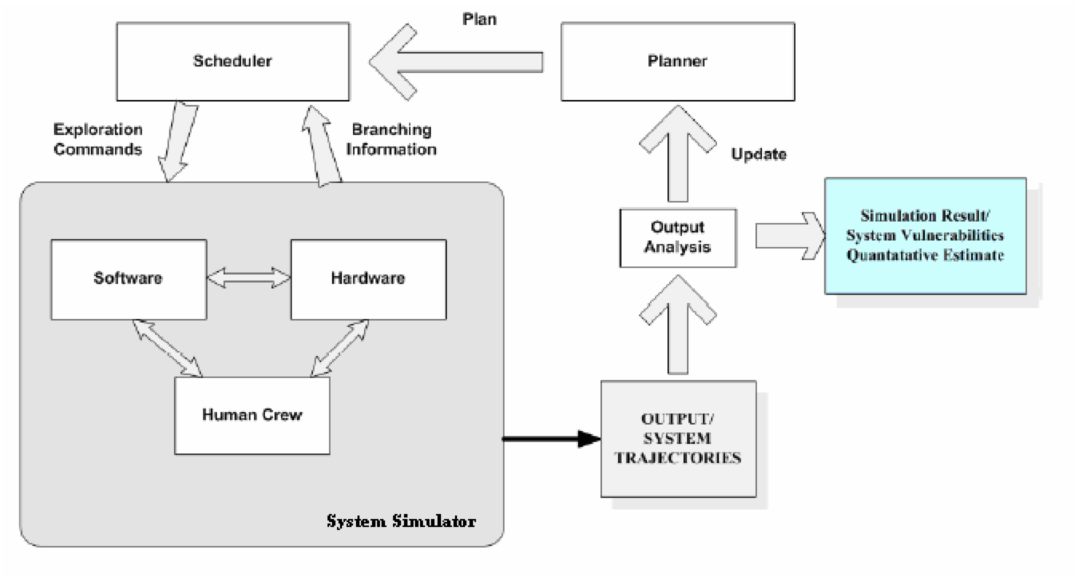


Figure 20. SimPRA environment

Whenever it comes to a branching point, the system simulator proposes transitions (branches) to the scheduler. The scheduler retrieves the information of the proposed transitions and decides which branch to explore. The exploration command is sent back to the simulation, and the simulation model executes the command, continuing the simulation until another branching point or end state is reached.

There are two types of stochastic events in the system model: time-based events and demand-based events. One type of stochastic behavior of a component can be described by the probability distribution function of time-to-failure. There is another class of failure. The probabilistic branching stochastic process has a set of outcomes, each with of a probability of occurrence. The timing of the occurrence is not random; instead, the outcomes at that point of time are random [38]. In our model, software failures are considered to be demand-based failures[3], which means the software failure is not triggered unless that part of the software is executed in the simulation environment.

Software aging is another phenomenon discussed in the literature, where the error conditions actually accrue with time and/or load, resulting in performance degradation and/or failures. The typical causes include memory bloating and leaking, unreleased file-locks, data corruption, storage space fragmentation and accumulation of round-off errors [53]. This type of failure is not considered in this dissertation.

5.2.2 Integrating Software into the single-level SimPRA

Software reliability is defined in [54] by the Institute of Electrical and Electronics Engineers as:

[3] One should not confuse the concept of time-based event with the concept introduced later of delayed software execution.

“Software reliability is the probability that the software will not cause the failure of a product or of a mission for a specified time under specified conditions; this probability is a function of the inputs to and use of the product, as well as a function of the existence of faults in the software; the inputs to the product will determine whether an existing fault is encountered or not.”

From the definition, it is clear that software reliability is a function of the context in which the software operates. Software faults are triggered by specific input conditions. Unlike hardware, software does not deteriorate with operation time. However, the passing of time is still used as a parameter in some software reliability models due to the fact that it usually associates with the count of software execution cycles, which has a direct link with the probability of occurrence/non-occurrence of a specific input condition.

Software risk models have been categorized as black-box unconditional software reliability formulations and conditional risk formulations in the “Probabilistic Risk Assessment Procedures Guide for NASA Managers and Practitioners” [10]. In the conditional risk model, the presence of a software failure event is determined by two basic constituents, namely:

- The “input condition” event that triggers the execution of a certain logic path in the software
- The “software response” to that condition, as determined by the internal logic path execution.

In our software representation, software failures are injected at the output of the selected functions. The logic path from the beginning of the software input to that selected function is already modeled inside the software behavior representation. The internal logic of the selected function and the detailed location of the failure are unknown to us. The failure probability is related with the input condition. The analyst needs to divide the input domain into minimum input sets. Within each minimum input set, the failure occurrence probability is treated as a uniform distribution.

All the failure-related information is stored in FIKB. The detailed structure of FIKB is defined in chapter 4. Software failures are treated as demand-based failures. There are some differences between software failures and hardware failures.

The first difference is that demand-based software failures are usually loaded more frequently compared with other demand-based components in the simulation environment.

In SimPRA, a branch point is proposed when a component with demand-based failure is demanded in the system simulation. For instance, human action can be considered as a demand-based component. When a human action is required in the simulation environment, the human proposes different actions with different probabilities to the scheduler. The scheduler picks one branch based on the scheduling rule. A branch point is generated whenever the human action is demanded.

Software is different due to the reason that software requests are much more intensive compared with other components. Considering the space shuttle thrust control software, a software output is needed for every single step of the simulation. If there is a software failure injected at the output of the thrust control software, it means a branch point request is generated for every single time step in the simulation, which is not efficient and is very time-consuming. The branch point request should be reduced to an acceptable level.

In order to get unbiased estimation of the final system risk, we introduced the concept of adjustment factor w_a. Adjustment factor w_a is a weigh factor ranging from 0 to 1. It is used to adjust the number of software branch point requests (See Figure 21)

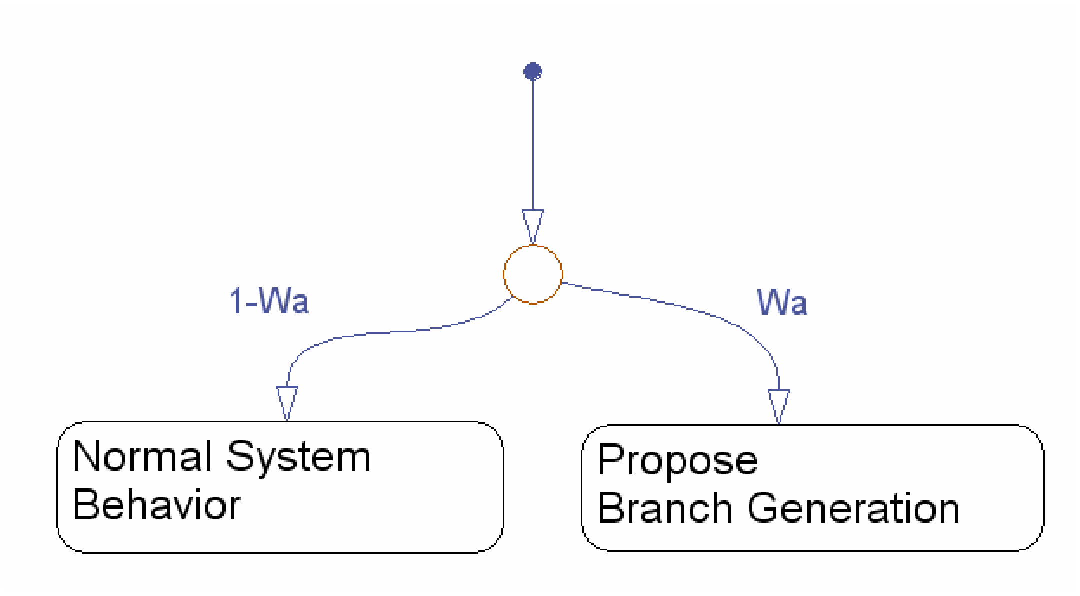


Figure 21. Software branch point generation adjustment factor

In Figure 21, only w_a percent of software execution proposes a branch point to the system scheduler. In order to make the final result unbiased, the adjustment factor should be considered when the software proposes a transition to the system scheduler. Assume the natural software failure probability is P. When the software proposes a transition to the system scheduler, the probability used should be P/ w_a. In this way, the final branch probability remains identical. Indeed:

$$\frac{P}{w_a} \times w_a = P \tag{5.1}$$

Also the occurrence of the branch points remains the same. Assume that the software is executed n times. Before applying the adjust factor w_a, the probability for the ith execution to be selected is:

$$p_s(i) = P \tag{5.2}$$

After applying the adjust factor w_a, the probability for the ith event to be selected into the group proposing branch generation requests is

$$p(i \in g) = w_a \tag{5.3}$$

Within the group, the probability for each event to be selected is

$$p_s(i \mid i \in g) = \frac{P}{w_a} \tag{5.4}$$

So the probability for the the ith execution to be selected is

$$p_s^{'}(i) = p(i \in g) \times p_s(i \mid i \in g) = w_a \times \frac{P}{w_a} = P \tag{5.5}$$

Comparing the equation (5.2) and equation (5.5), one can see that the probability for the ith execution to be selected remains the same. Thus the occurrence of the branch points remains the same.

The total branch generation requests decrease after applying the adjust factor w_a. Before applying w_a, the branch generation requests are proposed to the system scheduler at every time step when the software is executed. Two branches are generated if there are only two possible branches for each request. See Figure 22 a)

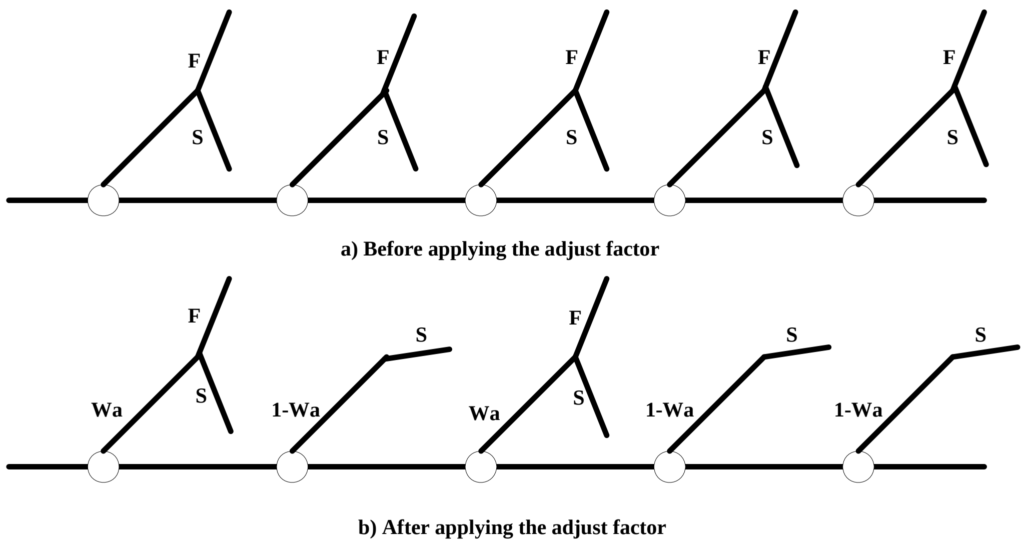

F
S
F
S
F
S
F
S
F
S
a) Before applying the adjust factor
F
S
Wa
S
1-Wa
F
S
Wa
S
1-Wa
S
1-Wa
b) After applying the adjust factor

Figure 22. The effect of the adjust factor to the branch generation

After applying w_a, only w_a percent of the software execution proposes the branch generation requests to the system scheduler. Two branches are generated for each request. For the rest of the software execution, no branch generation requests are proposed to the system scheduler. Thus only one branch is generated. (See Figure 22 b)

Assume that the actual software execution can be represented using a Poisson distribution with parameter λ. The number of branches generated after time T is:

Before applying w_a $\lambda T \times 2$

After applying w_a $\lambda T \times (w_a \times 2 + (1 - w_a)) = \lambda T \times (1 + w_a)$

The adjustment factor can be selected by the analyst. But the value of the adjustment factor should be greater than the natural probability of the software failure P.

$$1 \geq w_a > P \qquad (5.6)$$

Considering a software function with the following input domain, the failure probability is defined for each minimum input set as:

$$I, \{I_j, pf_j\}_{j=1,\cdots,n} \qquad I = \bigcup_{j=1}^{n} I_j \tag{5.7}$$

We can define:

$$w_a = \min((m * \max(pf_j)_{j=1,\cdots,n}), 1) \qquad m > 1 \tag{5.8}$$

Considering a software function with the following input domain:

$$I, \{(I_1, 0.01), (I_2, 0.02), (I_3, 0.001), (I_4, 0.05)\}$$

We can get:

$$w_a = \min((m * \max(pf_j)_{j=1,\cdots,n}), 1) = \min(m * \max(0.01, 0.02, 0.001, 0.05), 1) = \min(m * 0.05, 1)$$

The factor m is defined by the analyst for different software failures. The increase of the value of m increases the total number of branch points. A small value of m decreases the stochastic characteristic of the software failures. Figure 23 shows the relationship between w_a and the total number of branch point requests in the space shuttle example [38].

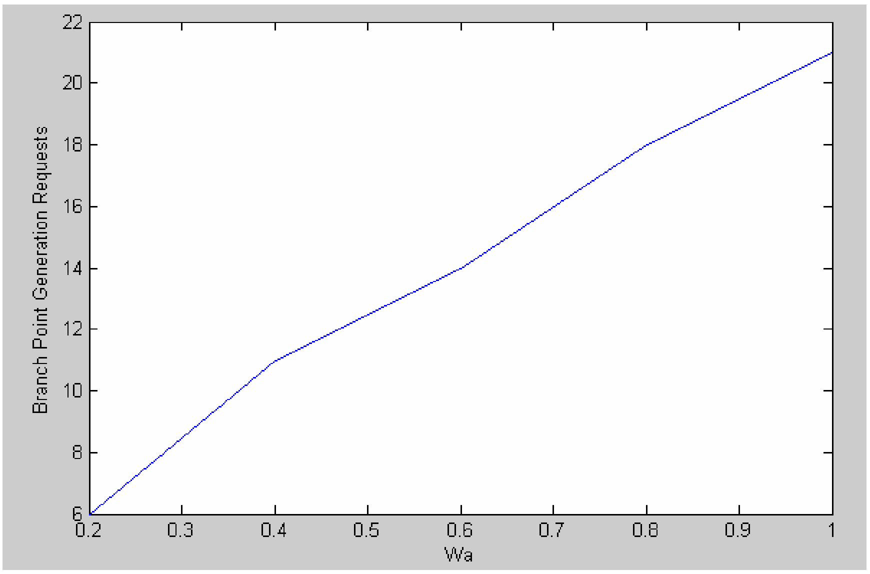


Figure 23. w_a vs. the total number of branch point requests in the space shuttle example

Comparing Figure 21 with the software failure template of Figure 11 and Figure 12, the transitions within the template should be clear at this point.

The second difference is that the software failure probability is not a fixed value as in other demand-based components. The failure probability is input condition dependent. In FIKB, different failure probabilities are defined for different minimum input sets. When the software-behavior model proposes a branch point to the scheduler, the request is sent to the software-guidance model to get the failure probability based on the input value. The guidance model queries FIKB to get the actual failure probabilities and further sends the request to the system scheduler. (See Figure 24)

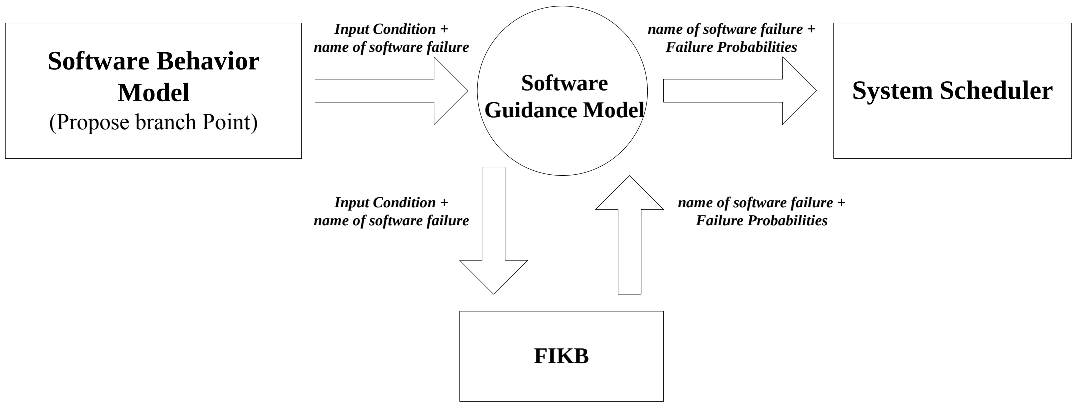

Software Behavior Model
(Propose branch Point)
Input Condition + name of software failure
Software Guidance Model
name of software failure + Failure Probabilities
System Scheduler
Input Condition + name of software failure
name of software failure + Failure Probabilities
FIKB

Figure 24. Software failure branch point generation procedure

The detailed rules used in the system scheduler to select a branch based on its value measure can be found in [38].

5.3 Enhanced SimPRA environment

5.3.1 Overview

The state explosion issue was discussed in section 5.1. Three different approaches to solve the problem were introduced. In this section, an alternative approach is presented, in which a multi-level simulation environment is constructed; multi-level objects are defined within the simulation environment; multi-layer planner and scheduler are constructed and dynamically used to guide the risk simulation at the right level of detail and abstraction. That reduces the branch generation and mitigates the state explosion problem.

The initial levels of the multi-level objects are defined by the analysts in the plan. The simulation results are used to adjust the level of detail to an appropriate level. The multi-level objects are simulated at a relatively high-level when they are not important for the end states of interest (see Figure 25).

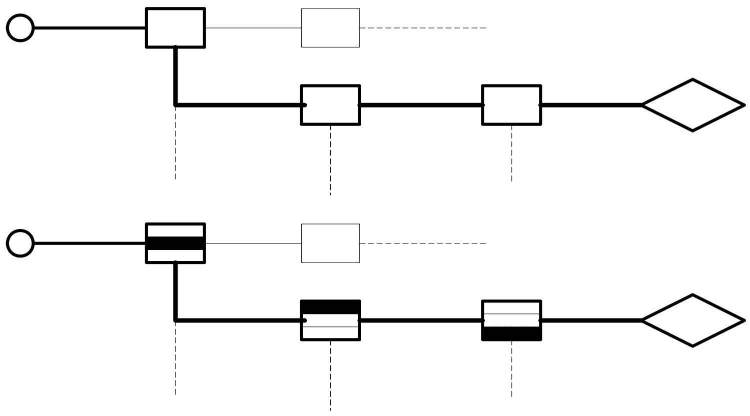


Figure 25. Sample scenarios consisting of multi-level objects

An enhanced multi-level SimPRA environment is constructed and provisions are provided to use software models at different levels of detail and fidelity. The innovative aspect of the approach is that the selection of the most appropriate level of detail is initially specified by the analyst in the Planner, but then automatically adjusted during the various rounds of simulation according to an entropy-based rule.

5.3.2 Enhanced Planner

As we discussed before, the planner is designed to guide the simulation towards a smarter and faster way to assess the risks of the system and generate useful knowledge about the contribution of different classes of scenarios. The goal of the plan is to guide the system to fail in such a way that the user's knowledge about the system is increased. The planning process that is suggested is dynamic, meaning that the plan is updated by the results of the simulation. Figure 26 shows the cycle that the planner goes through to guide the simulation in a dynamic way [38, 52].

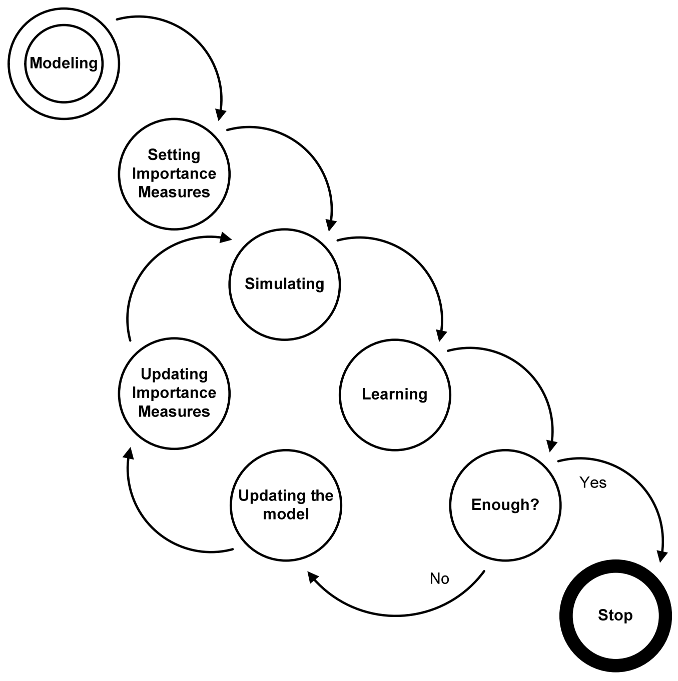


Figure 26. Planner update cycle

A high-level Scripting Language (SL), similar to a programming language, is defined in [38, 55] to represent the types of knowledge including physical and mathematical knowledge as well as temporal knowledge.

In the enhanced SimPRA environment, a special Level Control Node (LCN) is added to SL to represent the level information for multi-level objects. The LCN is added to the scenarios generated in the plan. The structure of the LCN can be represented as:

$\{LCN, type, value\}$

The type of level control nodes includes:

1. Undefined: the level control information is undefined.
2. Direct level control: the direct value for the level of simulation
3. Time Factor: the time factor required at this point (see section 4.4.3)

LCN is used to control the simulation level of detail for the multi-level objects. For the direct level control, a System Level Knowledge Base (SLKB) is constructed separately to associate the value of the level control with the level of detail for the software, human and hardware. (See Table 5 for an example)

LCN Control Value	Hardware level	Software Level	Human Level
1	1	1	1
2	1	2	2
3	1	3	2

Table 5. An example for the system level knowledge base

Inside the knowledge base, each row represents a compatible combination of the level of detail for different sub-components. For each combination, the input/output of the connected components needs to be compatible. For instance, if the software output is connected to the human input, the number of output from the software model needs to be compatible with the human input requirements. In other words, the human model needs to be able to understand the software input and process the software input at the level used.

The planner is loaded into the scheduler at the beginning of the simulation. The simulation level of detail is adjusted adaptively based on the information in the plan, the information in the guidance model of different components, and the previous simulation results. After each round of simulation, the planner is updated, based on the prior simulation results. The detailed adaptive scheduling rule and the updating mechanism will be discussed in the following sections.

At the beginning of each simulation, the scheduler loads the plan from the plan file generated by the planner. An ESD is constructed based on the scenarios within the plan. LCN at the beginning of the scenario indicates that this plan is a multi-level model. For instance, the following is an example plan.

```
LCN,1,1
BP1|BP2|LCN|BP3|End_1!H
BP1|BP4|BP5|BP6|End_2!L
BP1|BP4|BP5|BP7|End_1!H
BP1|BP8|LCN|BP9|End_2!L
```

An enhanced ESD with LCN can be constructed using the multi-level plan (See Figure 27).

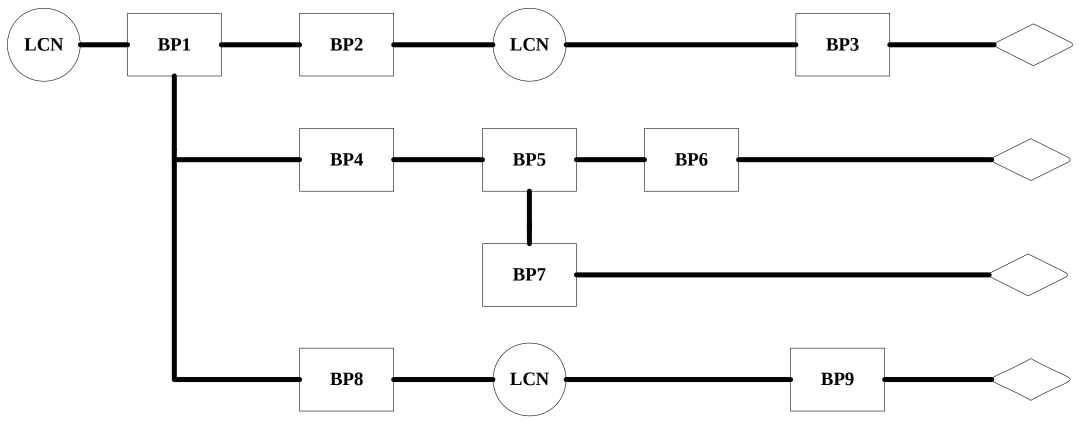


Figure 27. Example ESD constucted from a pre-defined plan

5.3.3 Enhanced Scheduler

The enhanced scheduler is established to handle multi-level objects in the simulation model. The scheduler loads the plan at the beginning of the simulation. If the ESD from the plan starts with LCN, the scheduler initializes the multi-level objects based on the information in the first LCN.

The scheduler controls the level of multi-level objects based on the following logic.

1. If LCN contains the direct control information, scheduler reads the level information from LCN; queries the system level knowledge base to get the detailed simulation level for each sub-component; sets the simulation level of detail for all multi-level objects. If there is no direct control information, go to step 2;
2. If LCN contains time factor requirements[4], the scheduler sends the time factor requirements to the sub-components guidance model. In our case, the system

[4] The time factor for different LCN is defined separately based on the input from the analyst. The value of time factor for different LCN may be different.

scheduler sends an information request to the software guidance model, the guidance model queries SKB to get the level control information based on the time factor requirement and sends it back to the high-level scheduler; the high level scheduler queries SLKB to check the compatibility of the level information received from each sub-component and obtain a valid combination; the scheduler sets the simulation level of detail for all multi-level objects based on the combination.

3. If LCN is undefined, the scheduler sends this information to the sub-component guidance models. The guidance model decides the simulation level based on the information in SKB and sends it back to the high-level scheduler; the high level scheduler queries SLKB to check the compatibility of the level information received from each sub-component and obtain a valid combination; the scheduler sets the simulation level of detail for all multi-level objects based on the combination.

As discussed before, the plan is updated during simulation. In SimPRA, user could specify the number of event sequences of one updating interval, and number of updating round.

After the simulation has started, the enhanced scheduler will control the simulation level of detail during each simulation. The simulation continues until it reaches a LCN node. The level control logic is the same for all LCNs within the plan. The simulation level of detail for multi-level objects only changes when the simulation reaches LCN. The level information is adjusted based on the logic in Figure 28.

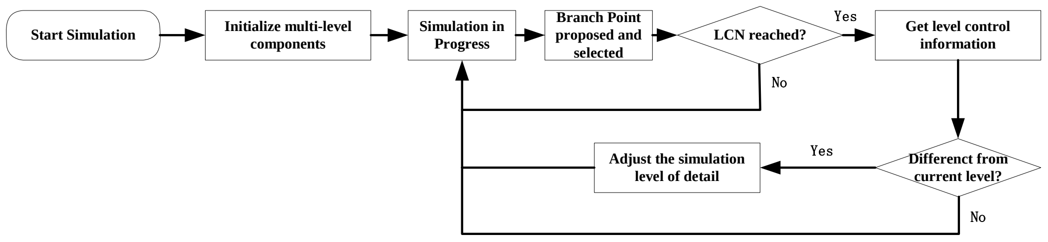

Start Simulation
Initialize multi-level components
Simulation in Progress
Branch Point proposed and selected
LCN reached?
Yes
No
Get level control information
Differenct from current level?
Yes
No
Adjust the simulation level of detail

Figure 28. Simulation level of detail adjustment logic

The plan is updated after one round of simulation. The information in LCN is updated based on the simulation results. A post simulation analysis is executed after each round of simulation. The switching mechanism is based on Shannon's entropy measure [56-58] and its application to simulation branch generation introduced in [38]. In this research the entropy-based branch control is extended to simulation level control.

For a event sequence with two end states, let *x* be our degree of belief that end state *E* will be reached, and let our belief regarding this probability be described by a Beta distribution

$$\pi(x \mid \alpha, \beta) = \frac{x^{\alpha-1} \cdot (1-x)^{\beta-1}}{Be(\alpha, \beta)} \tag{5.9}$$

where $\alpha - 1$ and $\beta - 1$ respectively represent the number of times that end states 1 and 2 are observed in a total of $\alpha + \beta - 2$ sequences. Then the entropy measure is equal to

$$I(x \mid \alpha, \beta) = (\alpha - 1) \cdot (\psi(\alpha) - \psi(\alpha + \beta)) + (\beta - 1) \cdot (\psi(\beta) - \psi(\alpha + \beta)) - \ln Be(\alpha, \beta) \tag{5.10}$$

where, $\psi(z)$ is the digamma function,

$$\psi(z) = \frac{d}{dz}\ln\Gamma(z) = \frac{\Gamma'(z)}{\Gamma(z)} \tag{5.11}$$

which for integer arguments can be computed as (Abramowitz)

$$\psi(\alpha) = -\gamma + \sum_{m=1}^{\alpha-1}\frac{1}{m} \tag{5.12}$$

such that

$$\psi(\alpha) - \psi(\alpha+\beta) = \sum_{m=1}^{\alpha-1}\frac{1}{m} - \sum_{m=1}^{\alpha+\beta-1}\frac{1}{m} = -\sum_{m=\alpha}^{\alpha+\beta-1}\frac{1}{m} \tag{5.13}$$

For large values of z, the digamma function can be approximated efficiently by

$$\psi(z) \approx \ln(z) - z/2 \tag{5.14}$$

After N simulation, the entropy reaches its maximum value when $\alpha - 1$ = N or $\beta - 1$=N. The entropy reaches its minimum value when $\alpha - 1$ = $\beta - 1$ = N/2. A small value of entropy indicates a state of ignorance about the outcome of the scenario. A large value of entropy indicates a good confidence about the outcome of the scenario. The entropy value is calculated for each multi-level object in the plan. It is used together with the conditional end state probability after this node. The conditional probability for end state of interest is calculated. It is a value ranging from 0 to 1. A large value indicates that the execution of the failure in this multi-level object has a large probability to lead the simulation to the end state of interest.

Considering the plan in Figure 29, software model is adjusted to the high-level after LCN1.

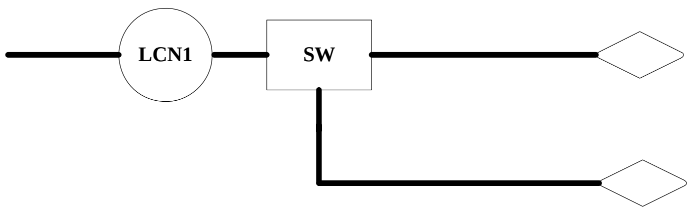


Figure 29. Part of an example plan

Software failures are executed after LCN1, the result of simulation indicates the entropy for the software failure is high and the conditional probability to the end state of interest is high, which indicates that we have a high confidence that the execution of the software failure greatly influences the simulation to the end state of interest. In this case, the software model should be further decomposed to get more accurate results. In the reverse case, it indicates that the execution of the software failure does not have a great influence to lead the simulation to the end state of interest. In this case, the software model should stay at a relatively high-level.

The threshold for entropy and the conditional probability is defined by the analyst before simulation begins. It can be further updated after each round of simulation. After each round of simulation, the entropy value and the conditional probability for each multi-level object is calculated and compared with the level information in the previous LCN. If the value of entropy indicates that the simulation level should be adjusted, the scheduler submits a request to the multi-level objects guidance models. In our case, the system scheduler submits a request to the software guidance model to check if any updates are available. If no further updates are available for the software, the plan is treated as the best plan available. The simulation results are calculated based on this plan.

Figure 30 describes a high-level overview of the data flows in the enhanced scheduler:

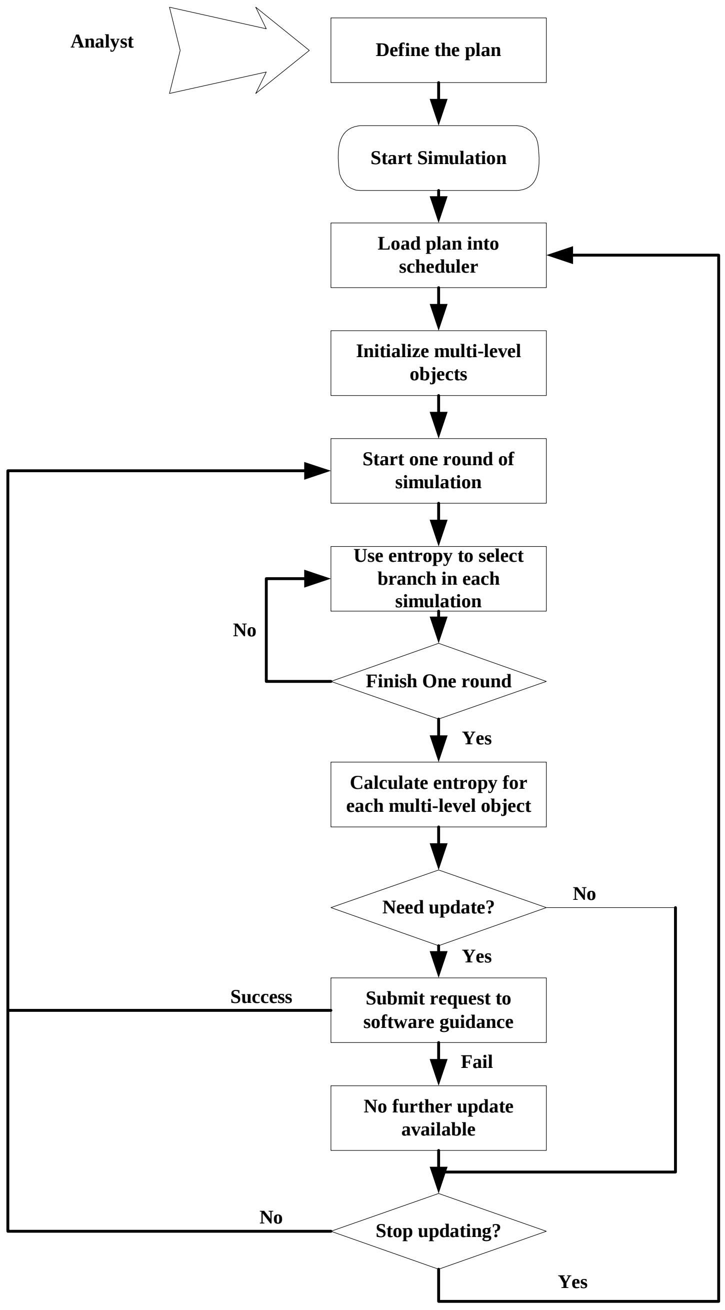

Analyst
Define the plan
Start Simulation
Load plan into scheduler
Initialize multi-level objects
Start one round of simulation
Use entropy to select branch in each simulation
No
Finish One round
Yes
Calculate entropy for each multi-level object
Need update?
No
Yes
Success
Submit request to software guidance
Fail
No further update available
No
Stop updating?
Yes

Figure 30 Data flow in the enhanced SimPRA scheduler

The use of entropy-based strategies in the dynamic PRA environment to select different branches is discussed in [39].

5.3.4 Software Guidance Model in SimPRA

The software guidance model receives the update request from the system scheduler. The basic updating algorithm is presented in Figure 31.

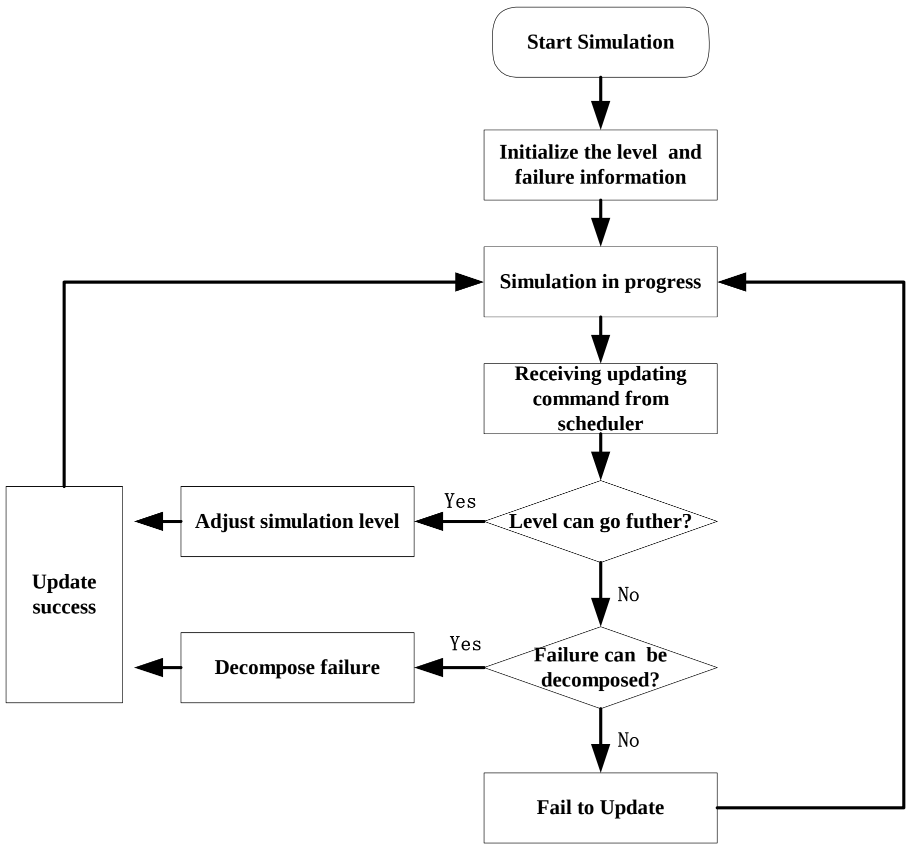


Figure 31: Software Guidance update mechanism

5.4 Integration

The approach to integrate the software model into the dynamic simulation environment is as follows:

1 Identify the boundary of the software. Decompose the software into independent software blocks. Each block is modeled separately.

2 Define the information available and construct the executable behavior model using SFSM. (section 4.3.2)

3 Define the multi-level structure for the selected functions. In this step, the analyst needs to choose the functions first. Then define the abstraction method and build the high-level abstraction model for the selected functions. (section 4.3.3)

4 Select the software failures based on the available information, including the failure type and different failure levels. Inject the software failures into the behavior model. (section 4.3.4)

5 Construct AKB and FIKB using the software modeling tool. (section 4.3.3 and section 4.3.4)

6 Build the software guidance model; establish the interface between the guidance model and other models. (section 4.4)

7 Establish SKB. The analyst needs to categorize the prior knowledge available, define the interface and summarize it in SKB. (section 4.4.3)

8 Integrate the software components in the high-level planner. The multi-level abstraction information should be included in the plan generated. (section 5.3)

9 Run the simulation and update the plan using the simulation results. (section 5.3)

Chapter 6: Experimental Demonstration --- Propulsion System Mission and Design Problem

6.1 Introduction

The benchmark problem is a multi-phase mission involving an ion propulsion system needed for a science mission to the outer solar system. The propulsion system is needed only in some of the phases, during which thrust is continually provided.

Mission Profile

An ion propulsion system is needed for a science mission to the outer solar system. Figure 32 depicts the mission phases, along with the propulsion system operating time during each phase in hours of Mission Elapsed Time (MET). Table 6 conveys the same information in tabular form. For those phases where the propulsion system only operates during part of the phase (e.g. Phases 4 & 5), thrust is continually provided from the beginning of the phase until the specified operating time expires.

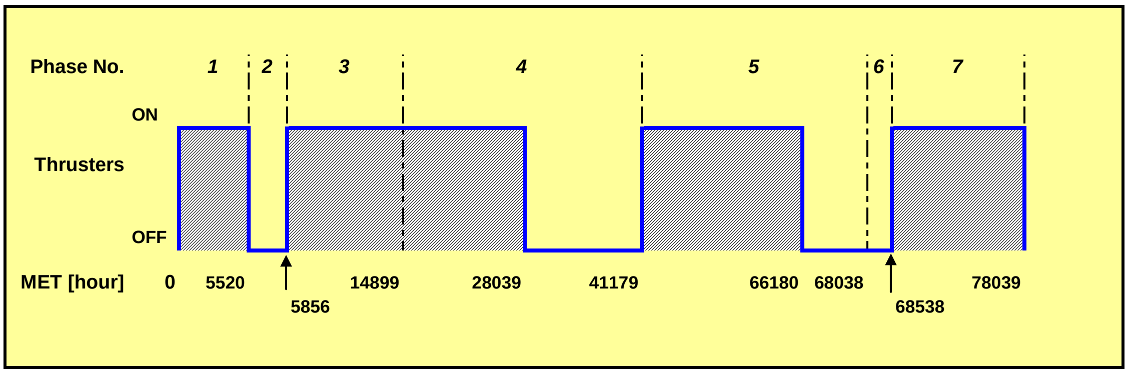


Figure 32. Propulsion System Mission Profile

Mission Phase No.	Duration (Hours)	Propulsion System Operating Time (Hours)
1	5520.0	5520.0
2	336.0	0
3	9043.2	9043.2
4	26280.0	13140.0
5	26858.5	25001.0
6	500.0	0
7	9501.5	9501.5

Table 6. Mission Profile (table used in previous version)

Design Description

The propulsion system consists of 5 thruster assemblies and a single propellant supply. Each assembly has:

1) propulsion power unit (PPU), and
2) ion engines

When an assembly is operating, the PPU provides power to just one ion engine. The other engine will be in a standby mode, unless failed.

During Phase 1 the success criterion is propulsion from 2 assemblies. In all subsequent phases where the propulsion system is operating, the success criterion is propulsion from 3 assemblies.

Relative to the assembly operation, the strategy is to use Assemblies 1 through 2 during the first phase. During subsequent phases, Assemblies 1 through 3 will furnish propulsion, if available.

Failure of an assembly causes it to be replaced by the lowest numbered standby assembly. For example, if assembly 1 fails in Phase 1, the strategy is to actuate

Assembly 3. If no further failures occur during Phase 1, assemblies 2, 3 & 4 will furnish propulsion at the beginning of Phase 3.

Basically, standby assemblies remain in standby until they are needed to replace a failed assembly, and they are actuated in series (i.e., the lowest numbered assembly is first selected).

Figure 33 is a schematic of a thruster assembly. In assessing the mission risk input power failures are modeled separately, so the propulsion system model can ignore a loss of power from that support system.

The strategy for thruster assembly operation is to begin with power from the PPU going to Ion Engine A. Ion Engine A will continue to be the operating engine of the assembly until the engine fails. At that time the strategy is to:

- shutdown the PPU;
- switch the PPU to Ion Engine B; then
- reenergize the PPU and operate with Ion Engine B.

There are no intermediate switches between a PPU and the ion engines. All switches are integral to the PPU.

Figure 33 also depicts a propellant supply to each engine. The propellant is a noble gas from a common storage tank. The engine ionizes and accelerates the propellant to produce thrust. Since the propellant supply is part of the propulsion system, it must be included in the system model.

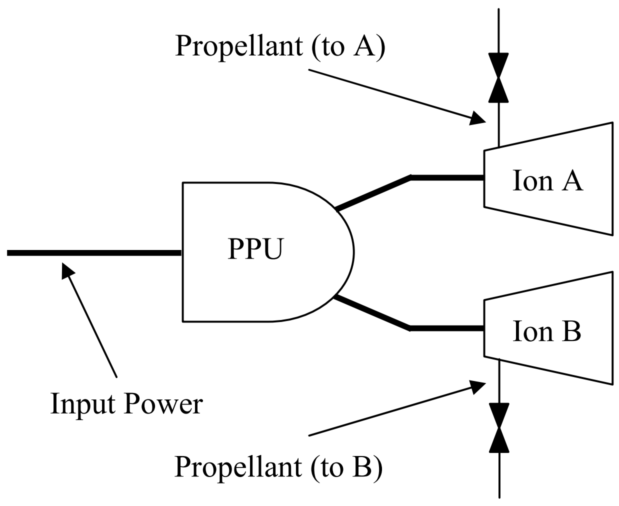


Figure 33. Thruster Assembly Schematic

Common cause failures (CCF) should be assessed using the conditional probability values from Table 7 by the CCF model of choice. No specific CCF model is endorsed, but any simplification or approximation of CCF probabilities must be based on calculations using the values below.

Group Size	Group Conditional Failure Probability [%]
2	8.0
3	4.0
4	2.0
5	1.0

Table 7. Common Cause Failure Modeling Values

Table 8 is a failure mode and effects analysis for the propulsion system. Reliability data are listed in Table 9.

Component	Failure Mode	Effect
PPU	Fails to start on demand	Assembly failure

Component	Failure Mode	Effect
	Failure to operate	
	Failure to shutdown on demand[5]	
Ion Engine A	Fails to start on demand[6]	Loss of redundancy
	Failure to operate	
Ion Engine B	Fails to start on demand	Assembly failure
	Failure to operate	
Propellant Valve A	Failure to open on demand	Loss of Ion Engine A
	Failure to close on demand	System failure
	External leakage	
Propellant Valve B	Failure to open on demand[7]	Loss of Ion Engine B
	Failure to close on demand	System failure
	External leakage	
Propellant tank	External leakage	System failure
Propellant distribution lines	External leakage	System failure

Table 8. Failure Mode and Effects Analysis

Component Type	Failure Mode	Value
PPU	Fails to start on demand	1×10^{-4} (per demand)
	Failure to operate	1×10^{-6} (per hour)
	Failure to shutdown on demand	1×10^{-5} (per demand)
	Fails to switch to Ion Engine B	2×10^{-6} (per demand)
Ion Engine	Fails to start on demand	3×10^{-5} (per demand)
	Failure to operate	2×10^{-5} (per hour)

5 Failure of a PPU to shutdown on demand will burn it out rather quickly. This results in an assembly failure because the PPU is permanently disabled.

6 An ion engine is shutdown on demand be shutting down its PPU and closing its propellant valve. Hence, failure to shutdown on demand is not an ion engine failure mode. However, the power surge experienced when an ion engine is started (i.e., when its PPU initially supplies power) subjects an ion engine to appreciable internal stresses that can result in failure to start on demand.

7 If Ion Engine A fails in an assembly, the strategy for transferring to Ion Engine B includes terminating propellant flow to the failed engine and opening Propellant Valve B.

Component Type	Failure Mode	Value
	Failure to shutdown on demand	3×10^{-6} (per demand)
Propellant Valve	Failure to open on demand	3×10^{-4} (per demand)
	Failure to close on demand	3×10^{-4} (per demand)
	External leakage	5×10^{-5} (per hour)
Propellant tank	External leakage	1×10^{-6} (per hour)
Propellant distribution lines	External leakage	1×10^{-6} (per hour)

Table 9. Reliability Data

Predicated upon the above mission and design descriptions, the time-dependent reliability of the propulsion system over the planned mission should be quantified.

6.2 Simulation Model

6.2.1 Overview

The benchmark system is a system with hardware components and software components. The whole software system is a parallel running software system with 6 sub software-components: 1 central control unit and 5 thruster assembly control software. The central control software controls the status of the 5 assemblies by sending control signals. The thruster assembly control software receives the command from the central control software; controls the working status of the assembly; and sends the status of the assembly back to the central control unit.

6.2.1 Software Model

Figure 34 shows a high level overview for the software model.

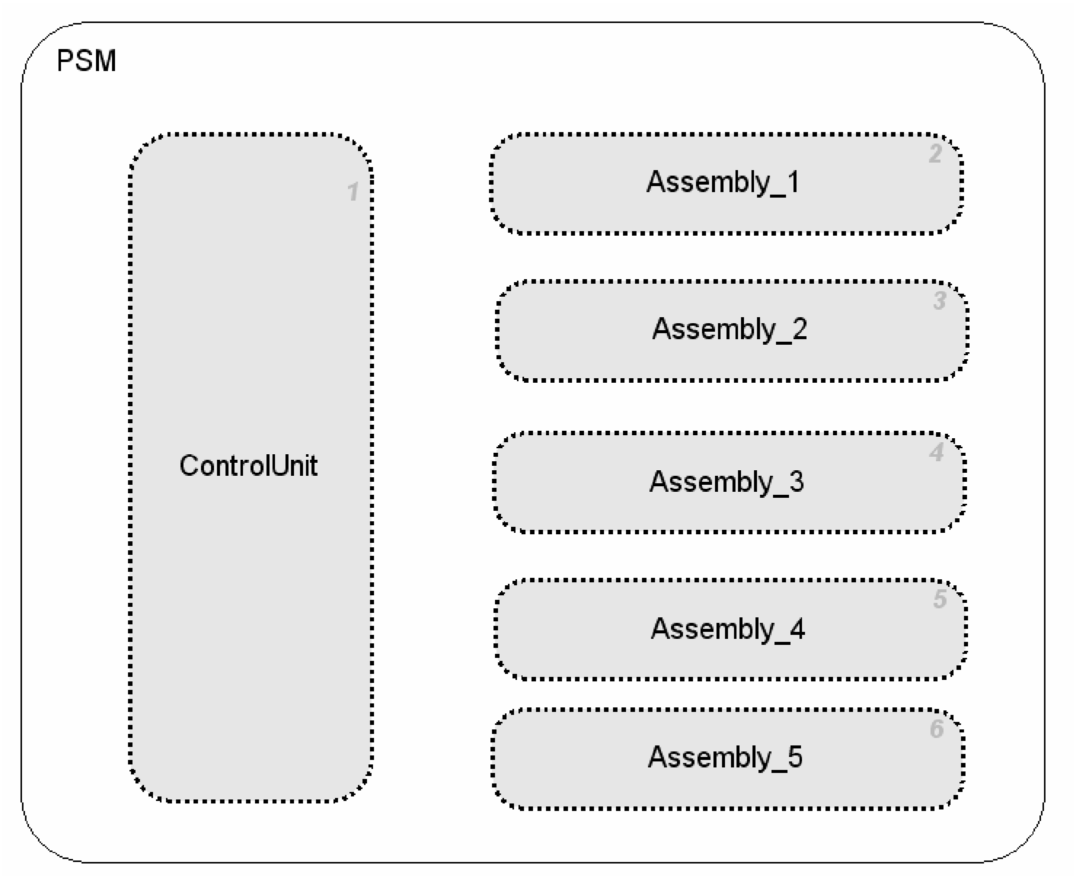


Figure 34. High level software overview for PSAM benchmark problem

The central control software controls the status of the assemblies during different phases of the mission (See Figure 35). During each phase, the central control software monitors the status of each assembly. If any working assembly fails, the control unit powers off the failure unit and turns on the backup assembly (Figure 36). If there is no backup assembly available, software control unit sends a signal to the simulation environment to indicate the system failure.

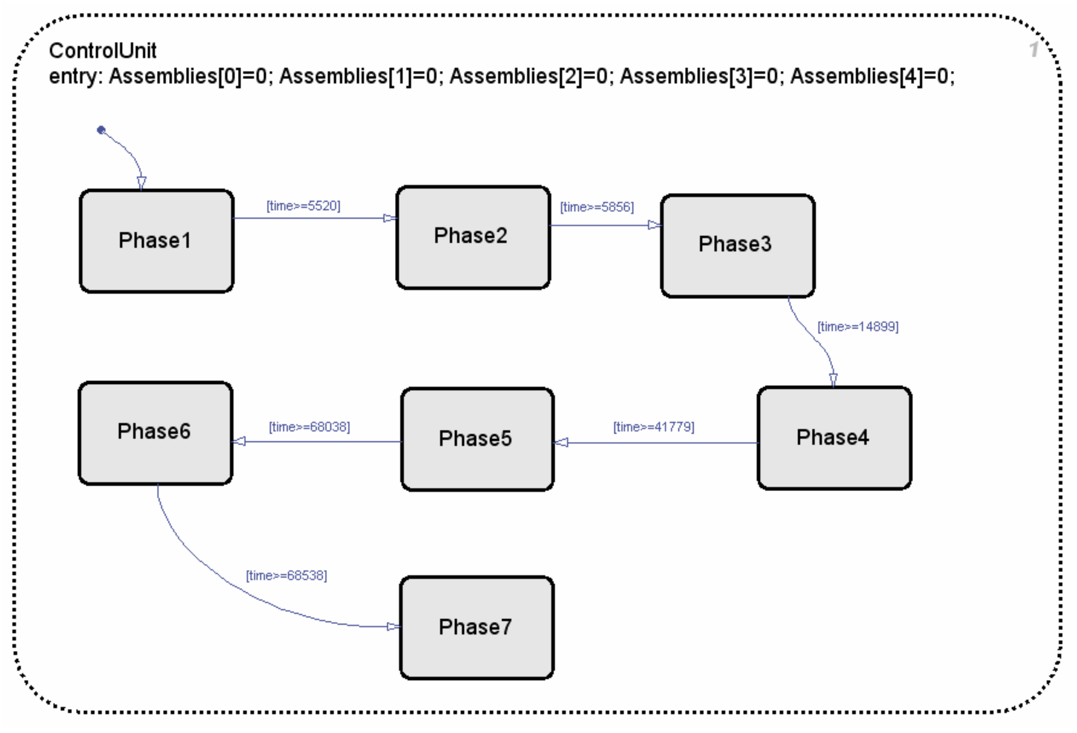


Figure 35. Central control software representation for PSAM benchmark problem

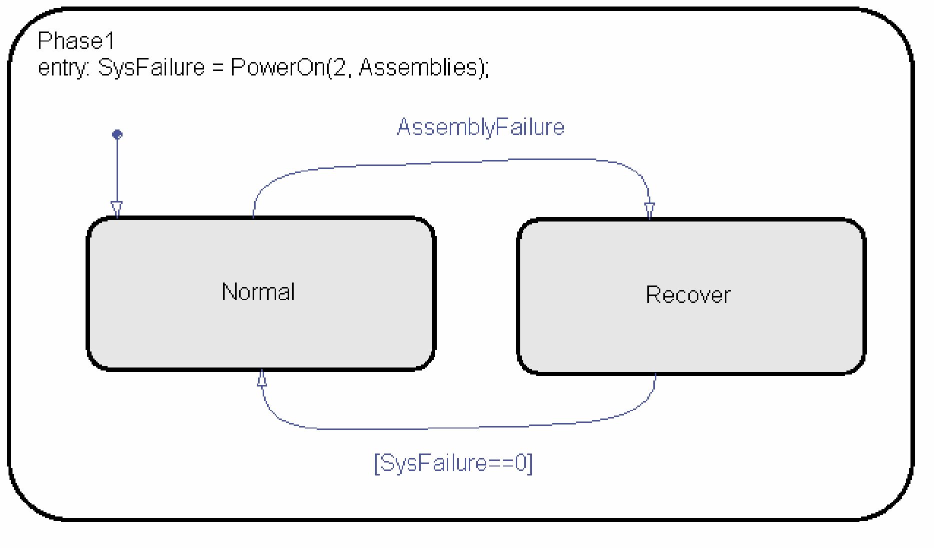


Figure 36. Failure recovery mechanism for PSAM benchmark problem

There are 4 different states for each assembly during the mission: Standby, working, switching and failure. A state diagram for the assembly is represented in Figure 37.

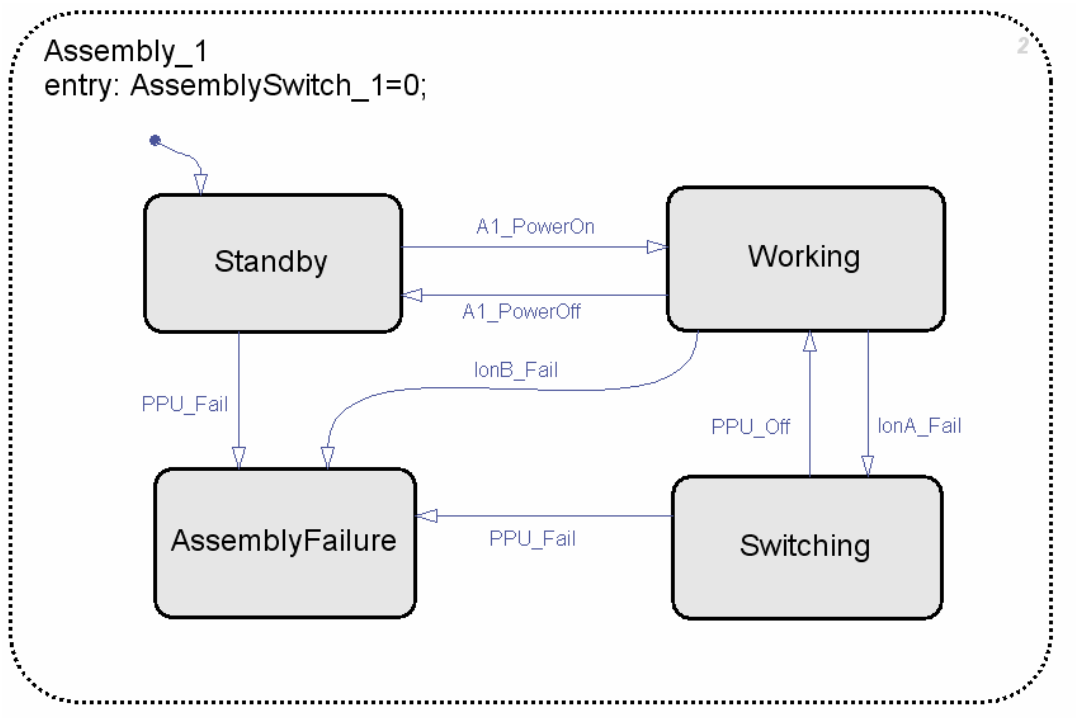


Figure 37. State Diagram for assembly control software

6.3 Discussion

In this chapter, a detailed software representation is presented to represent the parallel control software based on the mission profile. No software failure is represented in the original mission profile. But the simulation model can be easily extended to introduce software malfunction failure modes. The impact of the software failures to the system risk can be fully studied based on the simulation results, i.e., risk scenarios leading to predefined End States are in form of specific realizations of time dependent sequences of events. End State probabilities are based on grouping of such realizations [59].

In the next chapter, a software model is constructed for a complex system. Different types of software failure are injected in the software model. Three levels of abstraction are defined. The whole integration process is studied in detail.

Chapter 7: Experimental Demonstration --- PACS

7.1 PACS System Introduction

The PACS system is a simplified version of an automated personnel-entry-access system (gate) used to limit physical access to rooms, buildings, or other facilities to authorized persons, to whom coded identification (ID) cards have been issued. The ID card contains the person's name and social security number. Users insert their ID cards into a reader. The system searches for a match in the system's updateable database, requests the user's four-digit Personal Identification Number (PIN), validates the PIN, and unlocks a turnstile gate for entry. A single-line display screen and a 12-key keyboard provide communication between the system and its users. A security officer monitors a duplicate message on his/her console with override capability.

The software system initially displays the message "INSERT CARD," then checks a register for a 0 or 1 value to determine if the card has been inserted into the card reader. Given a positive response (value 1), it reads the nine-digit social security number and the twenty-character last name and validates that data against the information in the card database. If the card is valid, the software displays the message "ENTER PIN". Should the card not be readable then the message "RETRY" is posted for a maximum of three tries, after which the system posts the message "See Officer". A duplicate message is sent to the officer.

The PACS system involves two humans (the user and the guard) and six hardware components (the card reader, keyboard, single-line digital message display unit, the guard's display unit, guard reset unit, and a gate).

In the event of fire, the user needs to pass through the gate within sixty seconds. The guard may notice the fire right away and open the gate directly. If the guard does not open the gate, the user needs to pass through the gate using his ID card and PIN. The user's stress increases as the remaining time decreases. The guard may leave his position in case of fire. Even when the actions of the user are correct, hardware failures may generate incorrect inputs to the software. Software implementation or requirements failures may be another reason for a delay in the opening of the gate. The complex interaction among software, hardware, human and environment finally leads to two end states. The end result may be either loss of occupant or successful escape.

7.2 Simulation Model

7.2.1 Overview

Let us model the example system at the requirements stage. The software, human, hardware and environment factors are modeled separately. Figure 38 shows a high-level overview of the final system model.

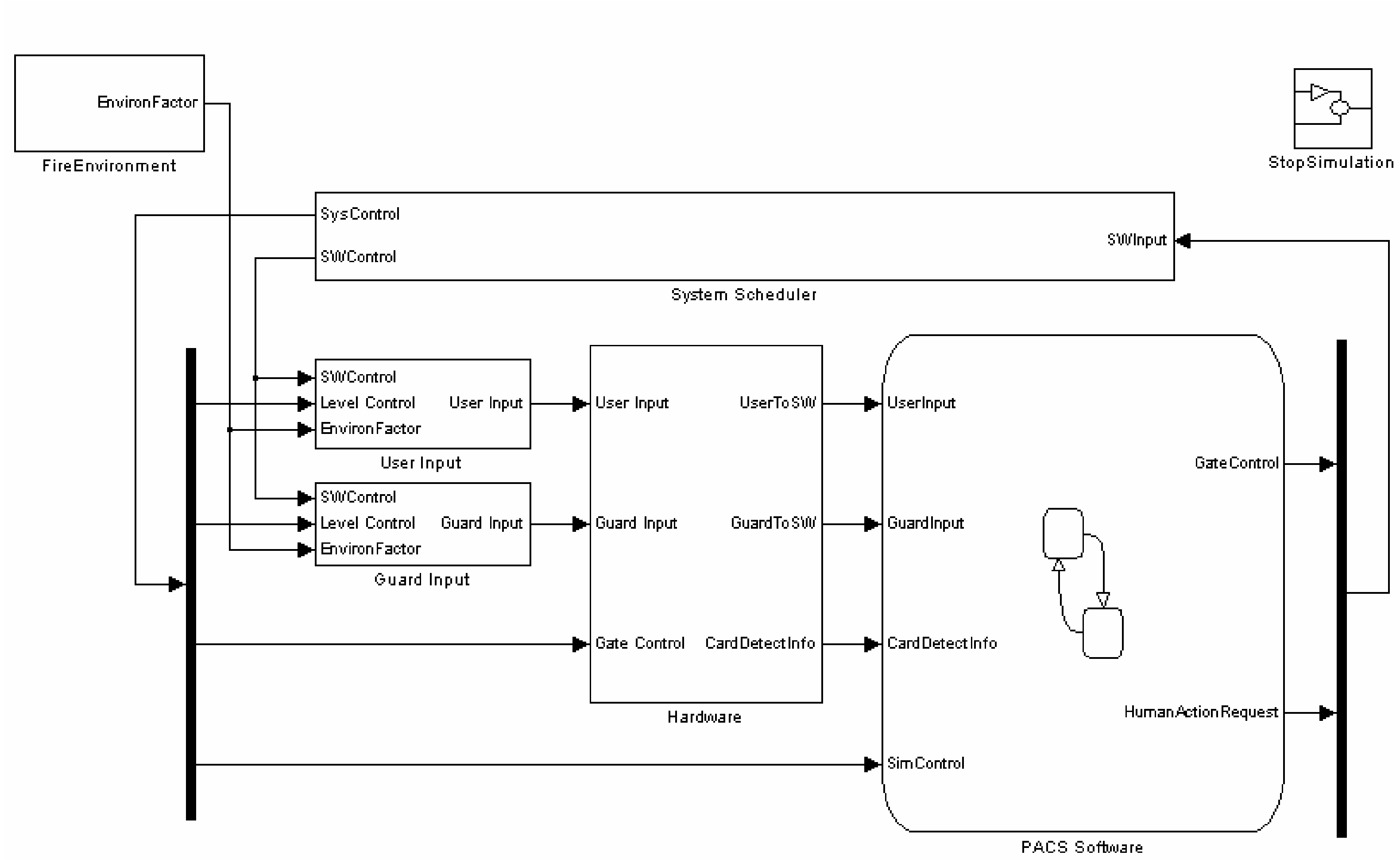


Figure 38. High-level model overview for the PACS system

There follows the description of each block:

- FireEnvironment: This block simulates the fire initiator. The environment factor evolves as the fire unfolds and so does the Human Performance Influence Factor Stress. From Figure 38, we can see that the output of this block serves as an input to the human modeling blocks.
- UserInput, GuardInput: These two blocks are human modeling blocks. The human receives input from the software and control command information from the high-level system scheduler. The human then performs different actions, based on the inputs. For instance, the user may insert card, input PIN, etc. Human stress increases as the time remaining decreases, causing the user and the guard to be more prone to errors. The guard will leave his position when the time remaining is less than 10 seconds.
- Hardware block: The hardware components are simulated in this modeling block. The hardware serves as a bridge between humans and software. If a hardware failure occurs, the corresponding software input may be incorrect even if the human's input is correct. The gate may not open even if the software generates the right open gate command when a failure of the turnstile gate hardware occurs.
- Software block: The software representation. Detailed procedures for building the model are discussed in the following sections.

The hardware and human modeling blocks are not the focus of this research; therefore, they are not discussed in detail.

7.2.2 Software Model

Below are the detailed steps for building the software representation.

Step 1: Identify the boundary of the software. PACS is an independent software system; therefore, PACS is modeled as a whole unit.

Step 2: Model the PACS behavior, based on the software requirements specification. The PACS model is implemented using Matlab/Simulink. Figure 39 shows a high-level view of the PACS software model:

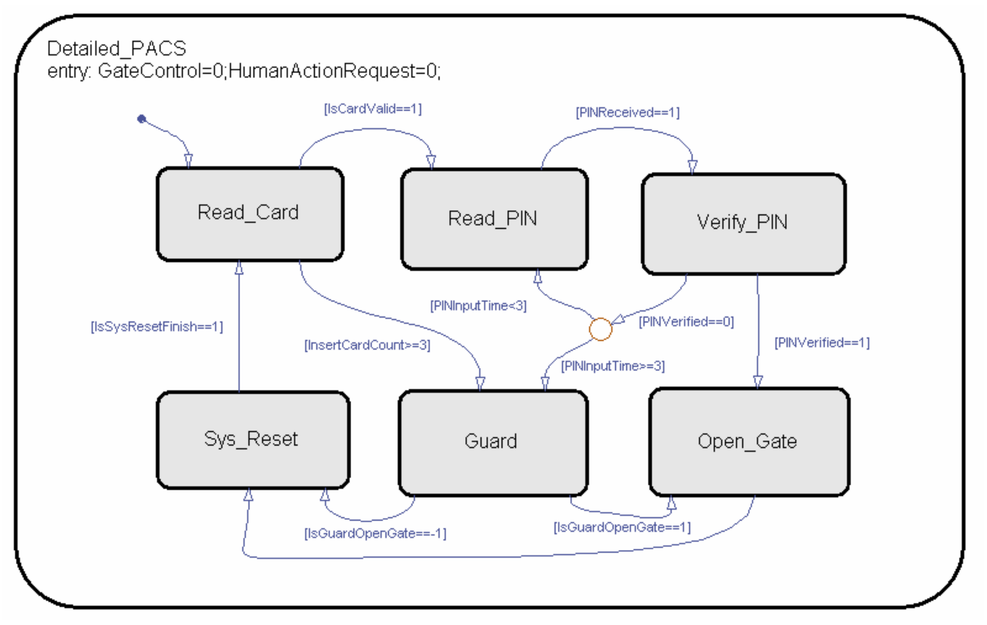


Figure 39. Detailed PACS behavior model

Step 3: Define the multi-level structure for PACS. Three levels are defined.

The highest level is to treat PACS as a single block (Abstract PACS in Figure 40). User card information, User PIN input, and guard inputs are treated as one single input. The output is gate status (open or not). The time necessary for human input and software execution is added as the PACS execution delay.

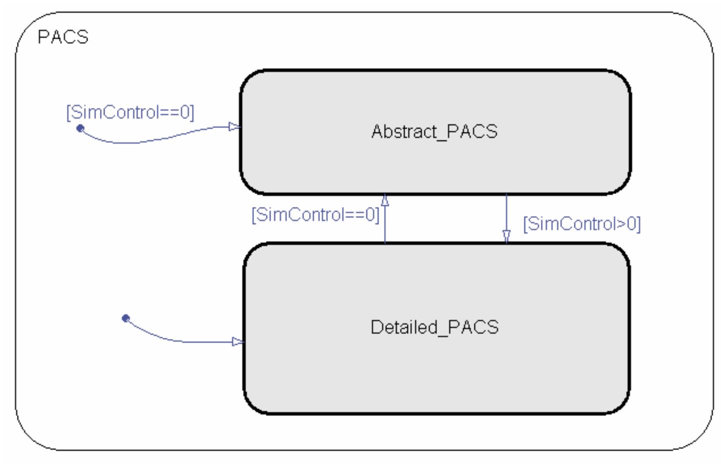


Figure 40. Level 1 abstraction for PACS

The second level goes inside PACS. PACS is decomposed into Insert_Card, Read_Card, Read_PIN, Verfiy_PIN. The structure of Detailed_PACS is similar to that in Figure 39. All sub-functions are at the lowest level, except Read_PIN. An abstraction of Read_PIN is used at this level. The input to this sub-function is the correctness of the PIN value (true or false). No detailed PIN input is simulated at this level. The output of Read_PIN is the PIN status. The human input time and the software execution time are added as the Read_PIN execution delay.

The third level corresponds to a detailed view of Read_PIN. The PIN input is processed digit by digit. Figure 41 is a detailed simulation model for function Read_PIN. At this level, each digit of the PIN is simulated separately.

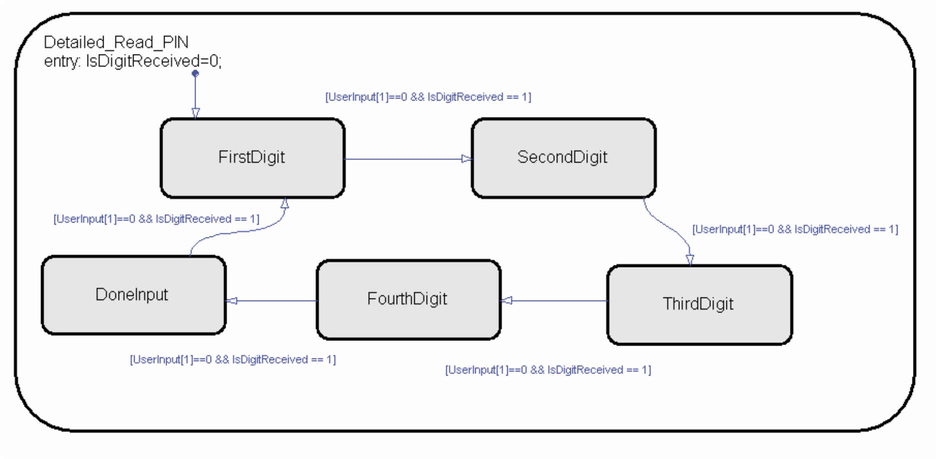

Detailed_Read_PIN
entry: IsDigitReceived=0;
[UserInput[1]==0 && IsDigitReceived == 1]
FirstDigit
SecondDigit
[UserInput[1]==0 && IsDigitReceived == 1]
[UserInput[1]==0 && IsDigitReceived == 1]
DoneInput
FourthDigit
ThirdDigit
[UserInput[1]==0 && IsDigitReceived == 1]
[UserInput[1]==0 && IsDigitReceived == 1]

Figure 41. Detailed simulation model for Read_PIN

Step 4: From past experience, typical software failures are selected for different abstraction levels. Below are some of the failures injected:

Level	Function	Failure Modes	Failure Description
1	PACS	Value	A value failure is injected at the output of PACS; gate does not open even if the user inserts the correct card and inputs the correct PIN.
1	PACS	Time	A delay failure is injected at the output of PACS; gate opening is delayed even if the user inserts the correct card and inputs the correct PIN.
2	Read_PIN	Time	An infinite time delay is injected for any abnormal PIN input.
3	Done_Input	Function [8]	If the input is not "enter" as expected, Function Done_Input leads the software to a crash state.

Table 10. Software failure examples for PACS

Step 5: The Software AKB and FIKB are constructed automatically, based on the PACS software model. PACS is a small example with only a three-layer abstraction;

[8] This is a real fault at the lowest code level which is not controllable.

so, the structure of the knowledge base is relatively simple. Figure 42 is the structure for the abstraction knowledge. Because of the nature of the abstraction knowledge base, only the functions with abstractions are modeled in the knowledge base.

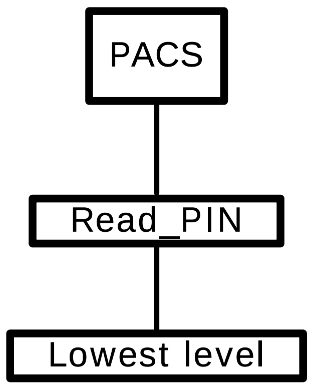


Figure 42. Abstraction knowledge base for PACS

Step 6: Build the software guidance model; establish the interface between the guidance model and other models. The software model is integrated in the whole system model (see Figure 38). The input/output interfaces are defined and connected to the rest of the system model.

Step 7: Establish SKB. The analyst needs to categorize the prior knowledge available, define the interface and summarize it in SKB.

Two types of information are categorized and stored in SKB. The first type is the time-related information. A simple knowledge base is constructed to build the relationship between the high-level system scheduler time requirements and controllable variables. In the PACS example, the time requirements factor from the high-level scheduler includes three different values.

Time Requirement Factor	**Simulation Level**
Low	3

Medium	2
High	1

Table 11. Time requirement factor table for PACS

The second category is the prior knowledge information. Based on prior knowledge, the user has a very low probability to exit the gate if the time remaining is less than 10 seconds since the guard is no longer available and the user will easily make a mistake in such a short time. PACS is simulated at the highest level if the pre-defined condition is true.

$T_{remaining} < 10s, R_L = 1$

Step 8: Integrate the software components in the high-level planner. Software input and output vary, depending on the software level. The human input should also be defined separately for different levels. The multi-level abstraction information is included in the plan generated. The following scenario is part of the plan generated.

In the event of a gate failure, the probability that the gate will open is low even if the software issues the gate open command. In this scenario, PACS is executed at the highest level. In the case of a keyboard failure, PACS is executed at the second level since there is a high probability that the software will receive a wrong PIN even if the user inputs the right PIN through the keyboard (See Figure 43).

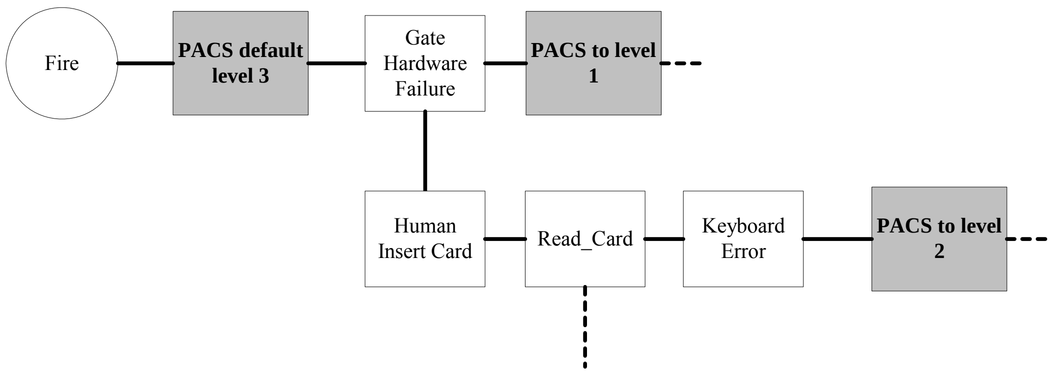


Figure 43. Extract of the plan for the PACS simulation

In the high-level system scheduler, a knowledge base is constructed to store the relationship between the software simulation level of detail and the human simulation level of detail. The human simulation level of detail is adjusted automatically with the software simulation level of detail by the high-level system scheduler.

Step 9: Run the simulation and update the plan using the simulation results. The initial plan for the multi-level objects may not be perfect. The plan is updated automatically based on the simulation results.

Running the simulation model based on the pre-defined plan, the cumulative distribution of the two end states are obtained through SimPRA. (See Figure 44)

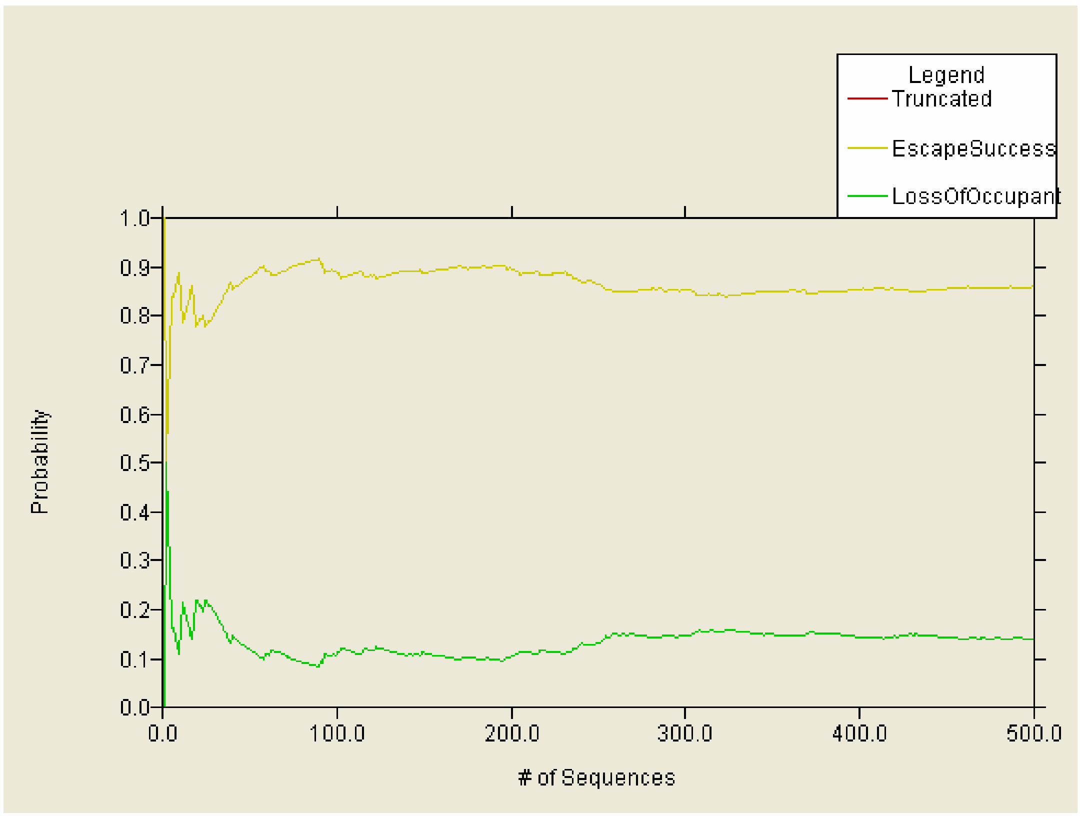


Figure 44. Probability estimation from SimPRA

A list of scenarios is generated as part of the simulation results. Here is one example scenario:

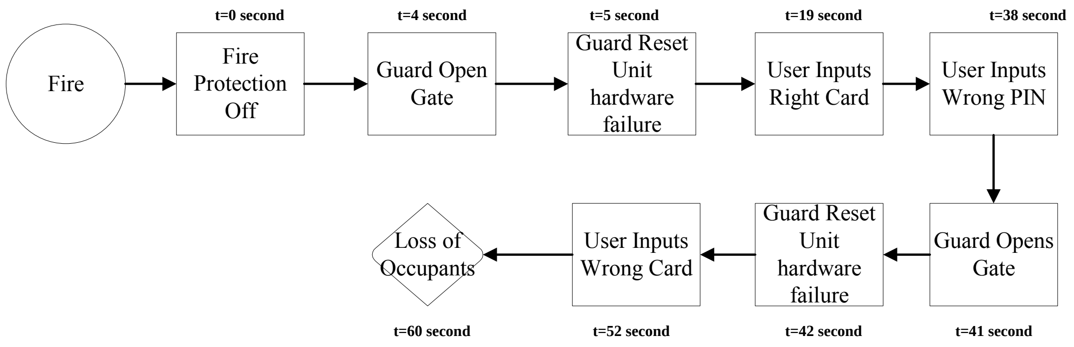


Figure 45. Example scenario for PACS

7.3 Traditional vs. Dynamic

PACS has been studied in [3] using the traditional PRA methodology. The ESD in Figure 46 is used to model the system evolution. Software components are included in the ESD and quantified using the test-based methodology.

The ESD in Figure 46 is a simplified version with conservative assumptions. The guard intervention is restricted to the beginning of the fire. If the guard fails to take action, the user will only have one chance to escape the gate using his card or PIN. Failure to insert the right card or to input the right PIN all lead to loss of occupants. The assumption here is that the guard always opens the gate directly in case of fire if the guard is in his position. If the guard is not in his position, no one is going to open the gate or reset the system thus the user only has one chance to insert the right card and input the right PIN. The logic here seems clear and complete under this assumption. But it is not. For instance, the dynamic scenario in Figure 45 is not covered in this ESD. The following story can be retrieved from Figure 45:

The guard noticed the fire immediately and decided to open the gate directly. He pressed the gate open button but the gate did not open due to a hardware failure in the guard reset unit. The user tried to exit the gate using his card and PIN. The guard stayed in his position to reset the system if needed. Even if the guard can not open the gate directly, he can still reset the system and allow the user multiple trials. The user inserted the right card but input the wrong PIN due to stress. The guard reset the system but the user failed to get out before 60 second.

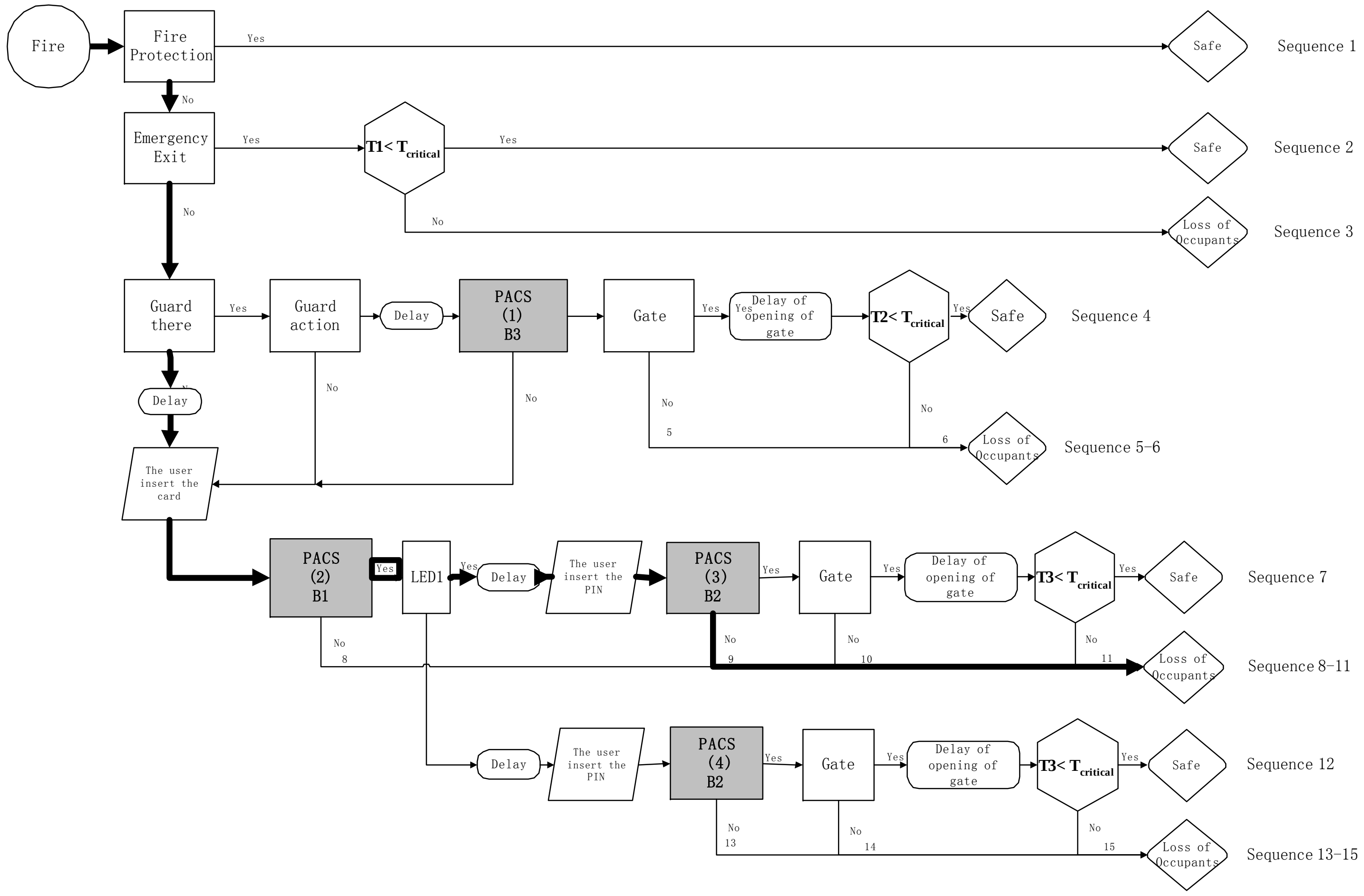


Figure 46. ESD for the PACS System (The initiator is fire. Gray place holders indicate the presence of software contributions).

Apparently this scenario fits into the assumptions used to create Figure 46 but is not covered in the ESD. The reason is complex. The dynamic interactions among the components make it difficult for the analyst to identify and predict all the possible scenarios. Meanwhile the count of scenarios increases dramatically if the analyst needs to consider the details of the system. The analyst has to model at a relatively high-level to explore all possible scenarios. In the ESD in Figure 46, the software related blocks B1, B2, B3 in the ESD represent a group of events. For instance, block B1 in Figure 46 represents the Read Card function. Two different branches originate from block B1: correct card is read or failure to read card. Considering the second branch, the possible reason for failing to read the card includes a failure of the software function Read_Card, a failure of the card reader hardware, and human failure. If the analyst needs to unfold all these blocks, the size of the ESD will increase dramatically. Using the dynamic PRA methodology, the analyst only needs to construct the behavior model and the simulation environment explores all the scenarios automatically. The level of detail can be easily changed. Meanwhile, once the system model has been constructed, only small modifications are needed to obtain results under different assumptions.

Compared with the traditional PRA methodology, software modeling in the DPRA environment has the following benefits:

- The dynamic methodology generates more information in the output.

The scenarios generated in the dynamic environment include time-related information. The ESD used in the traditional methodology is conservative. Time-related information is generated in the ESD.

- The system model generated using the dynamic methodology can be easily and economically maintained and modified.

If a new failure needs to be included in the system analysis, the entire ESD in the traditional methodology may need to be reconstructed and all components may need to be re-quantified if the operational profile is different. In the dynamic environment, the result can be obtained easily by running the simulation after adding the new failure in the system model.

- The system and software models generated using the dynamic methodology are reusable.

The system and software model generated in the dynamic environment can be easily reused for a different system if similar components exist.

7.4 Multi-level Simulation

The system model for PACS is a multi-level model, as described in section 7.2. Running the simulation at different levels generates different results. PACS has been executed under the following three different cases:

Case 1: The execution of PACS has been maintained at the highest level: level 1;

Case 2: The execution of PACS has been maintained at the lowest level: level 3;

Case 3: The simulation level of detail is dynamically adjusted by the simulation environment.

The following results are generated after 500 runs:

	Time Used (s)	Success	Loss of Occupant
Case 1	412.26	0.891	0.109
Case 2	463.61	0.947	0.053
Case 3	447.28	0.928	0.072

Table 12. Multi-level simulation: Run-time for different levels of detail (within SimPRA)

In Table 12, the "time used" factor is influenced by both the software model and other parts of the simulation environment. Table 13 displays the run time obtained when the contribution of the software model is isolated from the simulation environment.

	Time Used (s)
Case 1	187.985
Case 2	219.063
Case 3	213.469

Table 13. Multi-level simulation: Run-time for different levels of detail (in Isolation)

7.5 Comparison of software model vs. Real code

In this section an experiment is designed to validate the software model when compared with the real code. All hardware failures are removed from the PACS system model. The guard action is restricted to responding to the user's requests. In other words, the guard will not open the gate before the user inserts his card, or inputs his PIN. Also the guard will not leave when the time left is small. The software models are built based on different levels of knowledge from analysts. The profile for PACS is completely defined. Value-related failures are injected into PACS and testing is performed on the real code. Analysts design the software model based on the results from different levels of test results. The models are integrated into the simulation environment. The results are obtained and compared with those obtained using the code directly in the simulation environment.

Here are the basic procedures for this experiment:

1. Define a complete operation profile for PACS
2. Inject software failures into PACS code
3. Test PACS; different levels of results are obtained based on the number of rounds of tests performed
4. Build a software model based on different levels of knowledge; integrate the software model into the simulation environment and run the simulation
5. Integrating the software code into the simulation environment; the IO part of the software model is modified to fit the simulation environment; compare the simulation results with the results from step 5.
6. Calculate quantitative coverage information through the comparison of scenarios generated

Step 1: Define a complete operation profile for PACS

All hardware failures are removed from the current PACS system model. In that way, the influence of hardware failure is isolated from the final system risk estimation. Final results are influenced only by the software model and the human decisions. The following profile is used for the human:

- The probability for a user to insert a right/wrong card is 0.55/0.45
- The probability for a user to insert a right/wrong PIN is 0.55/0.45
- The probability for a guard to accept/reject a user request to open the gate is 0.5/0.5

Assume PACS is used in a building with 10 employees with SSNs and PINs as follows:

Name	**SSN**	**PIN**
Jacob	212590000	0000
Michael	212590001	1111
Joshua	212590002	2222
Matthew	212590003	3333
Andrew	212590004	4444
Christopher	212590005	5555
Joseph	212590006	6666
Nicholas	212590007	7777
Daniel	212590008	8888
William	212590009	9999

Table 14. User records

The following assumptions apply:

- Only the first 5 people have the authorization to pass through the gate.
- All four numbers in a PIN are the same. There are only 10 different PINs available during simulation.
- All cards used during simulation belong to the 10 records in Table 14.

For each user, the probability of inserting the right/wrong card is 0.55/0.45. The first 5 cards in Table 14 are treated as right cards; the rest, as wrong cards. The right/wrong cards are uniformly distributed in the set of right/wrong cards. Once the user inserts the card, the probability of inputting a right PIN is 0.55. The probability of a user inputting a wrong PIN is 0.45. The wrong PINs are uniformly distributed in the set of wrong PINs.

Step 2: Inject software failures into PACS

A correct database should contain the first 5 records in Table 14. Now assume that the database is erroneous, and the following information is the information actually stored in the database.

SSN	Name	PIN
212590000	Jacob	0000
212590001	Michael	5555
212590002	Joshua	2222
212590003	Matthew	3333
212590004	Andrew	4444
212590005	Christopher	5555
212590006	Joseph	6666
212590001	Michael	1111

Table 15. Database used in PACS

The following errors are observed in the database:

1. There are two records for Michael in Table 15; the first record contains the wrong PIN
2. Christopher and Joseph are not supposed to be in the database

Because of those errors, the following different value-related failure modes exist in PACS:

1. A user with a correct card and correct PIN cannot enter the gate
2. A user with an unauthorized card and right PIN can enter the gate
3. A user with a correct card and wrong PIN can enter the gate

Those failures are typical in this type of system. The failure probability for each failure mode can be obtained through software testing.

Step 3: Test PACS.

A test environment is designed using visual C++. The software input is sampled from the database in Table 14. Assume that the analyst has no knowledge about the actual failures residing in the software; using the original design information, tests are performed at different software levels.

[High-level Testing]

The first testing is performed on the entire software. The following results are obtained after the indicated number of tests:

Number of Tests	10	100	1000	10000
Right Card, Right PIN, Success	6	58	542	5385
Right Card, Right PIN, Fail	***0***	***7***	***74***	***741***
Right Card, Wrong PIN, Success	***0***	***1***	***18***	***186***
Right Card, Wrong PIN, Fail	1	8	100	1060
Wrong Card, Right PIN, Success	***3***	***19***	***222***	***2196***
Wrong Card, Right PIN, Fail	0	0	0	0
Wrong Card, Wrong PIN, Success	***0***	***0***	***0***	***0***
Wrong Card, Wrong PIN, Fail	0	5	26	209
Wrong Card, Fail	0	2	18	225

Table 16. Test results for PACS

Based on the test results, the failure probabilities can be calculated for different inputs:

Input	Failure	Conditional Probability			
		10	100	1000	10000
Right Card, Right PIN	Fails to go through	0	0.108	0.120	0.121
Right Card, Wrong PIN	Goes through	0	0.111	0.153	0.149
Wrong Card, Right PIN	Goes through	1	1	1	1
Wrong Card, Wrong PIN	Goes through	N/A	0	0	0

Table 17. Failure probabilities for PACS (from high-level test results from Table 16)

From the results in Table 17, we observe that more software failures are detected after enough rounds of testing are performed. In this example, all software failures can be detected after a certain rounds of testing.

In this example, the high-level operational profile for PACS is influenced by software errors. Theoretically, a user with a wrong card shall not be able to go through the gate, and a user with a right card and the right PIN can always go through. The high-level human input profile can be calculated, based on the theoretical probabilities; but this method is inaccurate because of software failures. In this example, multiple software failures are observed after software testing. So the high-level operational profile should also be updated based on test results. The operational profile for the human can be calculated based on the test results in Table 16.

Input	Conditional Probability			
	10	100	1000	10000
Right Card, Right PIN	0.6	0.65	0.616	0.6126
Right Card, Wrong PIN	0.1	0.09	0.118	0.1246
Wrong Card, Right PIN	0.3	0.19	0.222	0.2196
Wrong Card, Wrong PIN	0	0.05	0.026	0.0209
Wrong Card, No PIN Input	0	0.02	0.018	0.0225

Table 18. Operational Profile for High-level PACS

[Low-level Testing]

The second test is performed at a detailed level. The testing is performed for sub-functions: Card validation and PIN validation. The following table shows the test results for card validation:

Total Tests	10	100	1000	10000
Right Card, PIN Entry Process can proceed	7	56	544	5500
Right Card, Fail	***0***	***0***	***0***	***0***
Wrong Card, PIN Entry Process can proceed	***1***	***20***	***192***	***1825***
Wrong Card, Fail	2	24	264	2675

Table 19. Testing results for card validation

Based on the test results, the failure probabilities can be calculated for different inputs:

Input	Failure	Conditional Probability			
		10	100	1000	10000
Right Card	Fails to go through	0	0	0	0
Wrong Card	Goes through	0.333	0.455	0.421	0.406

Table 20. Failure probability for card validation

A further test is performed for PIN validation. It is performed separately and conditioned on the types of card validation. Table 21 lists the PIN validation test results when the user has used a right card to pass the card validation stage. Table 22 lists the PIN validation test results when the user has used a wrong card to pass the card validation stage.

Total Tests	10	100	1000	10000
Right Card, Right PIN, pass	3	35	450	4345
Right Card, Right PIN, fail	***2***	***18***	***97***	***1038***
Right Card, Wrong PIN, pass	***0***	***0***	***7***	***100***
Right Card, Wrong PIN, fail	5	47	446	4517

Table 21. Testing results for PIN validation (right card)

Total Tests	10	100	1000	10000
Wrong Card, Right PIN, pass	***7***	***62***	***575***	***5624***
Wrong Card, Right PIN, fail	0	0	0	0
Wrong Card, Wrong PIN, pass	***0***	***0***	***0***	***0***
Wrong Card, Wrong PIN, fail	3	38	425	4376

Table 22. Testing results for PIN validation (wrong card)

The failure probabilities can be calculated from the test results:

Input	Failure	Conditional Probability			
		10	100	1000	10000
Right Card, Right PIN	Fails to go through	0.4	0.340	0.177	0.193
Right Card, Wrong PIN	Goes through	0	0	0.016	0.022

Table 23. Failure probabilities for PIN validation (right card)

Input	Failure	Conditional Probability

		10	100	1000	10000
Wrong Card, Right PIN	Goes through	1	1	1	1
Wrong Card, Wrong PIN	Goes through	0	0	0	0

Table 24. Failure probabilities for PIN validation (wrong card)

Step 4: Build a software model based on different levels of knowledge

The software model can be constructed from the test results. There are two different strategies. The first is to inject only those detected failures. The second, more conservative one, is to inject all possible failure modes using probability estimation.

[Results of Strategy 1]

A high-level software model is constructed using the test results in Table 16. The observed software failures are injected into SimPRA. (See Figure 47)

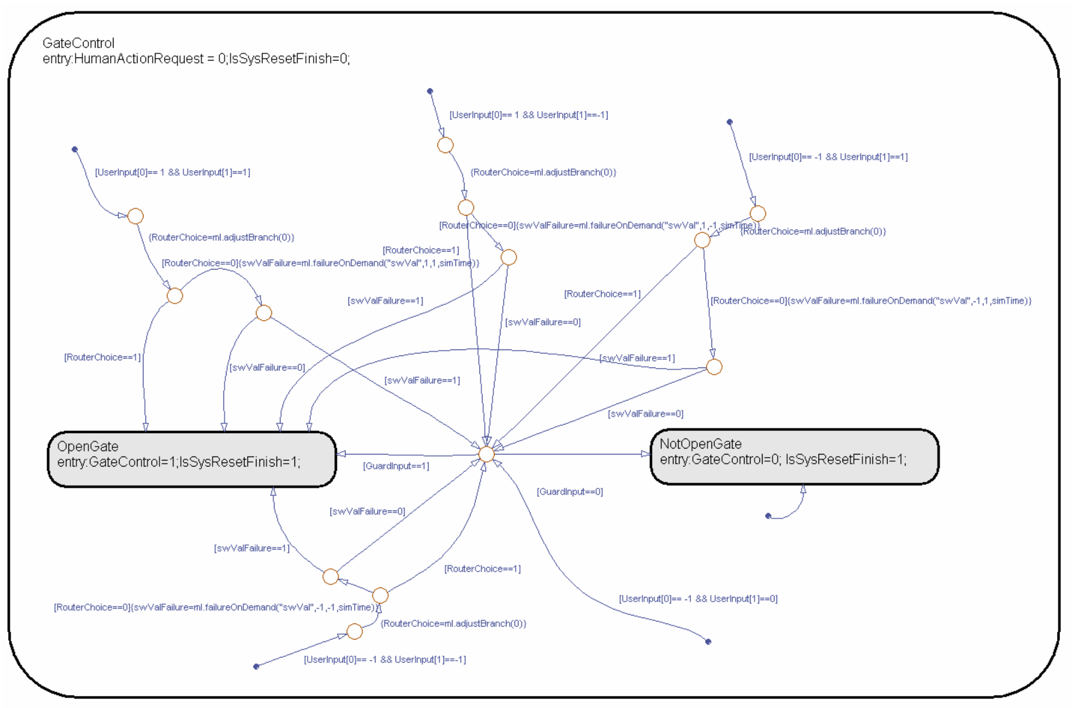

GateControl
entry:HumanActionRequest = 0;IsSysResetFinish=0;
[UserInput[0]== 1 && UserInput[1]==-1]
[UserInput[0]== -1 && UserInput[1]==1]
[UserInput[0]== 1 && UserInput[1]==1]
{RouterChoice=ml.adjustBranch(0)}
{RouterChoice=ml.adjustBranch(0)}
[RouterChoice==0]{swValFailure=ml.failureOnDemand("swVal",1,-1,simTime)}
{RouterChoice=ml.adjustBranch(0)}
[RouterChoice==1]
[RouterChoice==0]{swValFailure=ml.failureOnDemand("swVal",1,1,simTime)}
[swValFailure==1]
[RouterChoice==1]
[swValFailure==0]
[RouterChoice==0]{swValFailure=ml.failureOnDemand("swVal",-1,1,simTime)}
[RouterChoice==1]
[swValFailure==0]
[swValFailure==1]
[swValFailure==1]
[swValFailure==0]
OpenGate
entry:GateControl=1;IsSysResetFinish=1;
[GuardInput==1]
NotOpenGate
entry:GateControl=0; IsSysResetFinish=1;
[GuardInput==0]
[swValFailure==0]
[swValFailure==1]
[RouterChoice==1]
[UserInput[0]== -1 && UserInput[1]==0]
[RouterChoice==0]{swValFailure=ml.failureOnDemand("swVal",-1,-1,simTime)}
{RouterChoice=ml.adjustBranch(0)}
[UserInput[0]== -1 && UserInput[1]==-1]

Figure 47. Software model with failure injected (gate control module)

The failure probabilities are stored in FIKB. The probability is obtained from different test results:

- Case 1: 10 tests
- Case 2: 100 tests
- Case 3: 1000 tests
- Case 4: 10000 tests

The system is modeled at the highest level. The operational profile is based on the test results in Table 18. The following results are obtained after 500 runs:

Test Case	**Escape Success**	**LossOfOccupant**	**Time**
Case 1	0.658	0.342	244.08
Case 2	0.877	0.123	252.20
Case 3	0.929	0.071	260.92
Case 4	0.895	0.105	269.88

Table 25. Simulation results for high-level PACS model

A detailed-level software model is constructed using the test results in Table 19, Table 21, and Table 22. The observed software failures are injected into the Software model. (See Figure 48 and Figure 49)

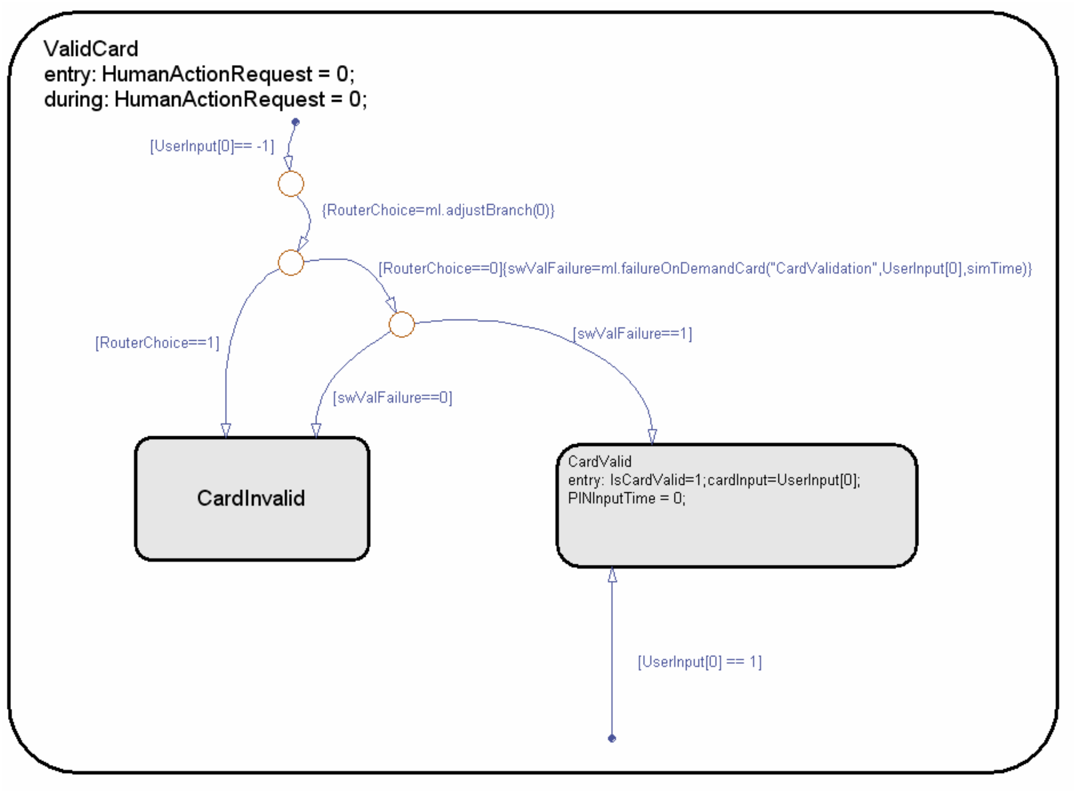

ValidCard
entry: HumanActionRequest = 0;
during: HumanActionRequest = 0;
[UserInput[0]== -1]
{RouterChoice=ml.adjustBranch(0)}
[RouterChoice==0]{swValFailure=ml.failureOnDemandCard("CardValidation",UserInput[0],simTime)}
[RouterChoice==1]
[swValFailure==1]
[swValFailure==0]
CardInvalid
CardValid
entry: IsCardValid=1;cardInput=UserInput[0];
PINInputTime = 0;
[UserInput[0] == 1]

Figure 48. Software model for PACS (card validation module)

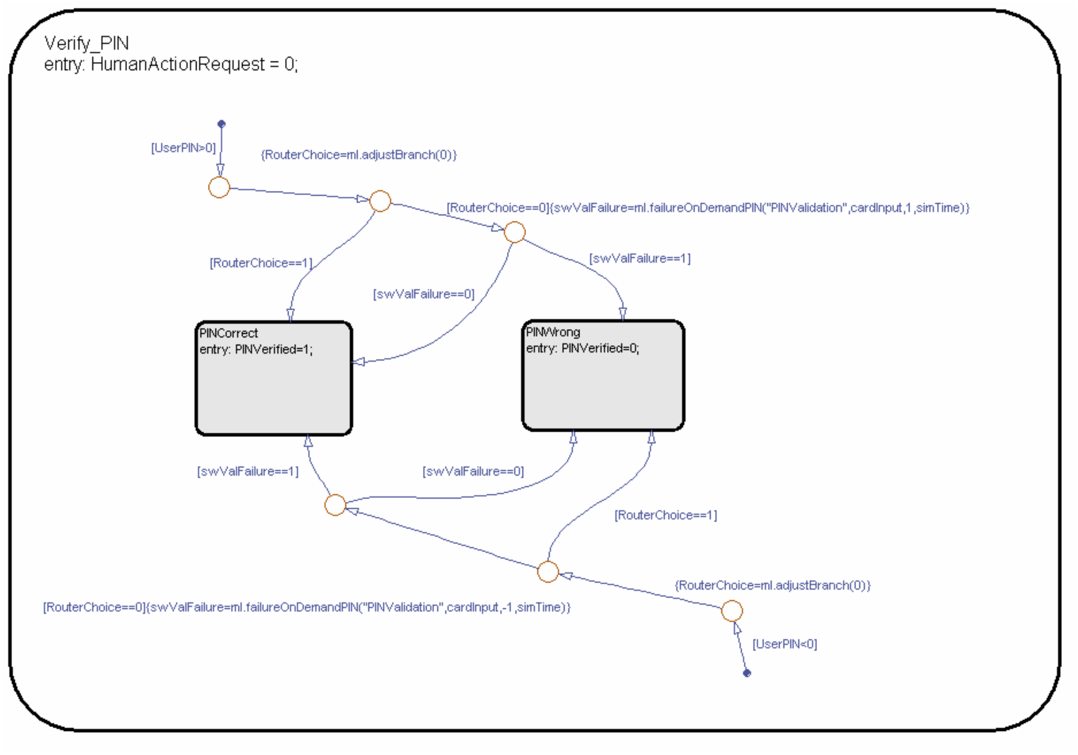

Verify_PIN
entry: HumanActionRequest = 0;
[UserPIN>0]
{RouterChoice=ml.adjustBranch(0)}
[RouterChoice==0]{swValFailure=ml.failureOnDemandPIN("PINValidation",cardInput,1,simTime)}
[RouterChoice==1]
[swValFailure==1]
[swValFailure==0]
PINCorrect
entry: PINVerified=1;
PINWrong
entry: PINVerified=0;
[swValFailure==1]
[swValFailure==0]
[RouterChoice==1]
{RouterChoice=ml.adjustBranch(0)}
[RouterChoice==0]{swValFailure=ml.failureOnDemandPIN("PINValidation",cardInput,-1,simTime)}
[UserPIN<0]

Figure 49. Software model for PACS (PIN validation module)

The failure probability is determined from the test results in Table 19, Table 21, and Table 22. The following is obtained after 500 runs:

Test Case	Escape Success	LossOfOccupant	Time
Case 1	0.823	0.177	304.52
Case 2	0.873	0.127	317.23
Case 3	0.858	0.142	327.75
Case 4	0.893	0.107	346.05

Table 26. Simulation results for low-level PACS model

[Results of Strategy 2]

For the second strategy, all possible failure modes are injected into the software model, including failure modes not detected after several rounds of testing.

There are 8 different types of failures defined for the software model:

amount, value, range, type, time, rate, duration, and load

Rate is defined as the frequency at which the input is sent or the output is received. Duration is defined as the time period during which the input or the output lasts. Load is defined as the quantity that can be carried at one time by a specified input or output medium. These types of failure modes are typical in real time system with heavy loads, for instance, a server which processes requests from large amounts of clients simultaneously. PACS is a gate control system running on a single computer. The time interval between two human inputs is usually several seconds. The process time for every input is less than 0.001 second. Rate, duration, and load are not applicable for PACS.

Amount, range, and type are the inputs from the human model. The human inputs are limited to a fixed amount of inputs in step 1. The testing is performed based on the input profile. There are no range, amount, or type failures existing in the profile. Assuming that the tester has a perfect knowledge about the inputs from the human, amount, range, and type failure modes are not considered in this experiment.

The remaining failure modes value and time need to be explored. Three types of software failures are injected and detected in PACS. There are some other failures based on the logic of the software.

1. A user with a correct card and a correct PIN cannot enter the gate (included)
2. A user with an unauthorized card and a right PIN can enter the gate (included)
3. A user with a correct card and a wrong PIN can enter the gate (included)
4. A user with an unauthorized card and a wrong PIN can enter the gate

If a specific software failure mode is not detected, the Bayesian approach with non-informative priors is used to estimate the failure probability. One common used non-informative priors is Beta(0.5, 0.5) [60]. The beta distribution is used to model the probability of the failure modes.

$$\pi(q) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} q^{\alpha-1}(1-q)^{\beta-1} \tag{7.1}$$

Binomial distribution is used as the likelihood function:

$$\Pr(0 \mid N, q) = \binom{N}{0} q^{0}(1-q)^{N} \tag{7.2}$$

Since Beta distribution is conjugate with the Binomial distribution used as a likelihood function, the posterior function is a beta distribution Beta(0.5, 0.5+N).

The mean value of the posterior distribution is used as the estimation of the undetected software failure probability.

$$q = \frac{\alpha}{\alpha+\beta} = \frac{0.5}{1+N} \tag{7.3}$$

Based on that, the failure probabilities are recalculated for Table 17, Table 20, Table 23 and Table 24.

Input	Failure	Conditional Probability			
		10	100	1000	10000
Right Card, Right PIN	Fails to go through	0.071	0.108	0.120	0.121
Right Card, Wrong PIN	Goes through	0.25	0.111	0.153	0.149
Wrong Card, Right PIN	Goes through	0.5	1	1	1
Wrong Card, Wrong PIN	Goes through	0.5	0.083	0.019	0.002

Table 27. Failure probabilities for high-level testing – strategy 2 (Bayesian approach)

Input	Failure	Conditional Probability			
		10	100	1000	10000
Right Card	Fails to go through	0.063	0.009	9.2e-4	9.1e-5
Wrong Card	Goes through	0.333	0.455	0.421	0.406

Table 28. Failure probabilities for card validation – strategy 2 (Bayesian approach)

Input	Failure	Conditional Probability			
		10	100	1000	10000
Right Card, Right PIN	Fails to go through	0.4	0.340	0.177	0.193
Right Card, Wrong PIN	Goes through	0.083	0.010	0.016	0.022

Table 29. Failure probabilities for PIN validation (right Card) - strategy 2 (Bayesian approach)

Input	Failure	Conditional Probability			
		10	100	1000	10000
Wrong Card, Right PIN	Goes through	1	1	1	1
Wrong Card, Wrong PIN	Goes through	0.125	0.013	0.001	1.1e-4

Table 30. Failure probabilities for PIN validation (wrong card) - strategy 2 (Bayesian approach)

Time-related failure mode is another type of failure mode to be considered. In the performance requirements section in PACS Software Requirements Specification (SRS), it states that the data validation should take less than 1 second. The testing time is collected for different rounds of testing.

Total Number of Tests	10	100	1000	10000
Total Time Used (second)	NO[9]	NO	1	4
Average Time for each validation	NO	NO	0.001	0.0004

Table 31. Testing time for PACS

No time delay is observed in Table 31. The same equation is used to estimate the probability for time delay failures.

Total Number of Tests	10	100	1000	10000
Failure Probability	0.045	4.95e-3	4.995e-4	5e-5

Table 32. Failure probabilities for time-delay failure (Bayesian approach)

[9] Not Observable (i.e. < 1s)

The time delay failure is injected in the software model in addition to all other failure modes. Applying the results in Table 27, Table 28, Table 29, Table 30, and Table 32 to the software model, the following results are obtained after 500 runs:

Test Case	Escape Success	LossOfOccupant	Time
Case 1	0.755	0.245	234.094
Case 2	0.881	0.119	232.844
Case 3	0.894	0.106	242.172
Case 4	0.907	0.093	262.703

Table 33. Simulation results for high-level software model – strategy 2 (Bayesian approach)

Test Case	Escape Success	LossOfOccupant	Time
Case 1	0.891	0.109	316.132
Case 2	0.867	0.133	314.428
Case 3	0.900	0.100	327.354
Case 4	0.895	0.105	351.953

Table 34. Simulation results for low-level software model – strategy 2 (Bayesian approach)

[Further discussion]

In the two strategies discussed before, the model is built based on the assumption that the tester has a perfect knowledge of the operational profile. In reality, this may not be true. If system analysts find out that some specific inputs are not tested, the failure probabilities need to be adjusted by either doing more testing or adjusting the probabilities based on conservative estimations for zero events.

For instance, if the analyst finds out that there is an out-of-range failure in the user PIN input, the failure probability needs to be adjusted for this situation since there is no testing for out-of-range failure. Assuming that the probability for the user to input an out-of-range PIN is 1%, the software failure mode probabilities in Table 29 and Table 30 can be recalculated by doing more testing. The probabilities can also be recalculated using a conservative assumption. The extreme case is to assume the failure always happens once the user inputs an out-of-range value. In this case, if the failure mode is related with invalid PIN input, the probability can be adjusted using the following equation:

$$p_{new} = p_{old} * 0.99 + 0.01 \tag{7.4}$$

This is an extremely conservative assumption. But it is normally enough for low probability events at the beginning of the simulation. If the simulation results indicate that this part of the system is important, the model can be refined using more testing results if needed.

Step 5: Inject the software code into the simulation environment and compare the results

The real code is injected into the PACS model. The IO part is reconstructed to fit into the simulation environment. In that way, the input/output is processed in the simulation environment. The human model is modified to generate the real input from the input space (Table 14) for the software. The detailed card information and the PIN information are selected and sent to the software model. The card/PIN data are validated using the real code.

The total number of lines of code (LOC) for PACS is 553, for the IO process part, 185. So the code coverage for this analysis is 66.55%. It can be increased when the human model is refined to incorporate the details of IO processes.

A coverage related criterion is added to the simulation environment to ensure that all software input can be covered during simulation. The following results are obtained after 500 runs:

Total Simulation Runs	Escape Success	LossOfOccupant	Time
500	0.883	0.117	414.91

Table 35. PACS simulation results (software code without coverage guidance)

Step 6: Quantitative coverage results

A post-simulation tool is designed to analyze the scenarios generated during simulation. The first guard action and the sequence of events prior to it are used to categorize the system level scenarios. See Figure 50 for the area studied inside the scenario. A quantitative coverage is assessed for the system level scenarios by comparing the results obtained from the code and from the software model simulation.

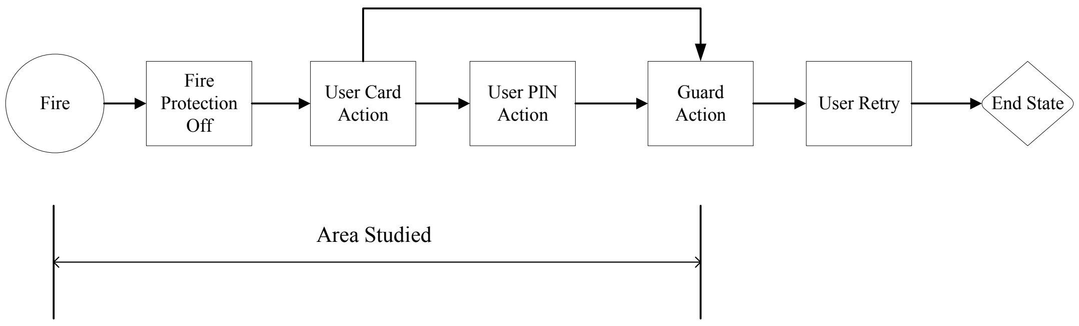


Figure 50. Area studied for coverage analysis

[Code simulation]

The simulation results produce 74 different scenarios if one uses the real software code.

[Low-Level Simulation]

The following coverage information is obtained after studying the low-level simulation results for 500 runs:

Test Case	Valid Scenario	Invalid Scenario	Coverage
Case 1	41	8	0.554
Case 2	44	7	0.595
Case 3	49	7	0.662
Case 4	50	6	0.677

Table 36. Coverage information for PACs low-level simulation

As shown in Table 36, a reasonable number of scenarios are covered in the low-level simulation. The uncovered scenarios are not simulated after 500 runs because the probabilities for those scenarios are low and their impact on the final system end states is not high. Those scenarios can be covered eventually after enough rounds of simulation have been run. Meanwhile, because of the abstraction in the software modeling, some invalid scenarios appear in the simulation results; for instance, the scenarios previously mentioned:

UserCard_f, UserCard_s, UserPIN_s, UserPIN_s, E-1,

That is because the failures are dependent on a specific input. A conservative assumption is used when the model is constructed. Several inputs are grouped together in the model which introduces these invalid scenarios.

For instance, in PACS, the first 5 users in Table 14 are treated as authorized users. Comparing the information in Table 14 and Table 15, one can find out that all authorized users are in the software database used, which means all authorized users could pass the card validation. Within the authorized users, Michael is the only person who can not pass PIN validation using his correct PIN. The conditional probability of PIN validation software failure for authorized users is 0.2, which means

20% of the users with correct card can not pass through the PIN validation using the correct PIN. That is the conditional failure probability used if all users with correct card are grouped as one input: correct card. Based on the probability, the following scenario becomes possible.

UserCard_f, UserCard_s, UserPIN_s, UserPIN_s, E-1,

But in reality, Michael is the only authorized user who can not pass PIN validation using his correct PIN. All other authorized users could pass the PIN validation using the correct PIN. Checking the scenario above, a user uses the correct card to pass card validation but fails to pass the PIN validation using his correct PIN at the first try. This indicates that the user could only be Michael. In the scenario, the user uses his correct PIN again and goes through the gate successfully. In reality, this is not the case since Michael will never be able to go through the gate using his correct PIN.

This can be solved by either using the real code in the simulation or by building all detailed inputs into the software model.

Checking the results in Table 26 and Table 36 reveals that even with the uncovered scenarios and invalid scenarios, the software model still captures the major scenarios during simulation and produces reasonably accurate results.

[High-level Simulation]

The scenarios generated for the high-level simulation contain basic events different from the low-level simulation and the code simulation. The card input event and the PIN input event are grouped as:

- RCRP: Right Card, Right PIN
- RCWP: Right Card, Wrong PIN

- WCRP: Wrong Card, Right PIN
- WCWP: Wrong Card, Wrong PIN
- WCNP: Wrong Card, No PIN input anymore

The detailed input events for low-level simulation are grouped together. For instance, the following combinations of basic events all belong to RCRP:

- UserCard_s, UserPIN_s
- UserCard_f, UserCard_s, UserPIN_f, UserPIN_s
- UserCard_f, UserCard_f, UserCard_s, UserPIN_f, UserPIN_s

The relationship between high-level scenarios and low-level scenarios is a one-to-many relationship. There is a mapping among simulation results at different levels. Table 37 presents one example scenario from each level. Scenario 15 in the code simulation corresponds to Scenario 95 in level 1 simulation and Scenario 2 in level 0 simulation.

Level	**Example scenarios**
Code	`15 : { FireProtection_Off@0 , UserCard_f(Christopher,1,5555)@7 , UserPIN_f(3333,5555)@17 , UserPIN_f(1111,5555)@30 , UserPIN_s(5555,5555)@44 , E-1@48 ,  } [ES-1 , 9.01`^{E}`-1 , 48.0]`
Level 1	`95 : { FireProtection_Off@0 , UserCard_f@8 , CardValidation@9 , UserPIN_f@16 , UserPIN_f@28 , UserPIN_s@41 , E-1@47 ,  } [ES-1 , 3.63`^{E}`-1 , 47.0]`
Level 0	`2 : { FireProtection_Off@0 , WCRP@34 , swVal@35, E-1@36 ,  } [ES-1 , 3.58`^{E}`0 , 36.0]`

Table 37. Example scenarios for different levels

7.6 Discussion

Comparing the results from different strategies and code simulation, the following figure is obtained.

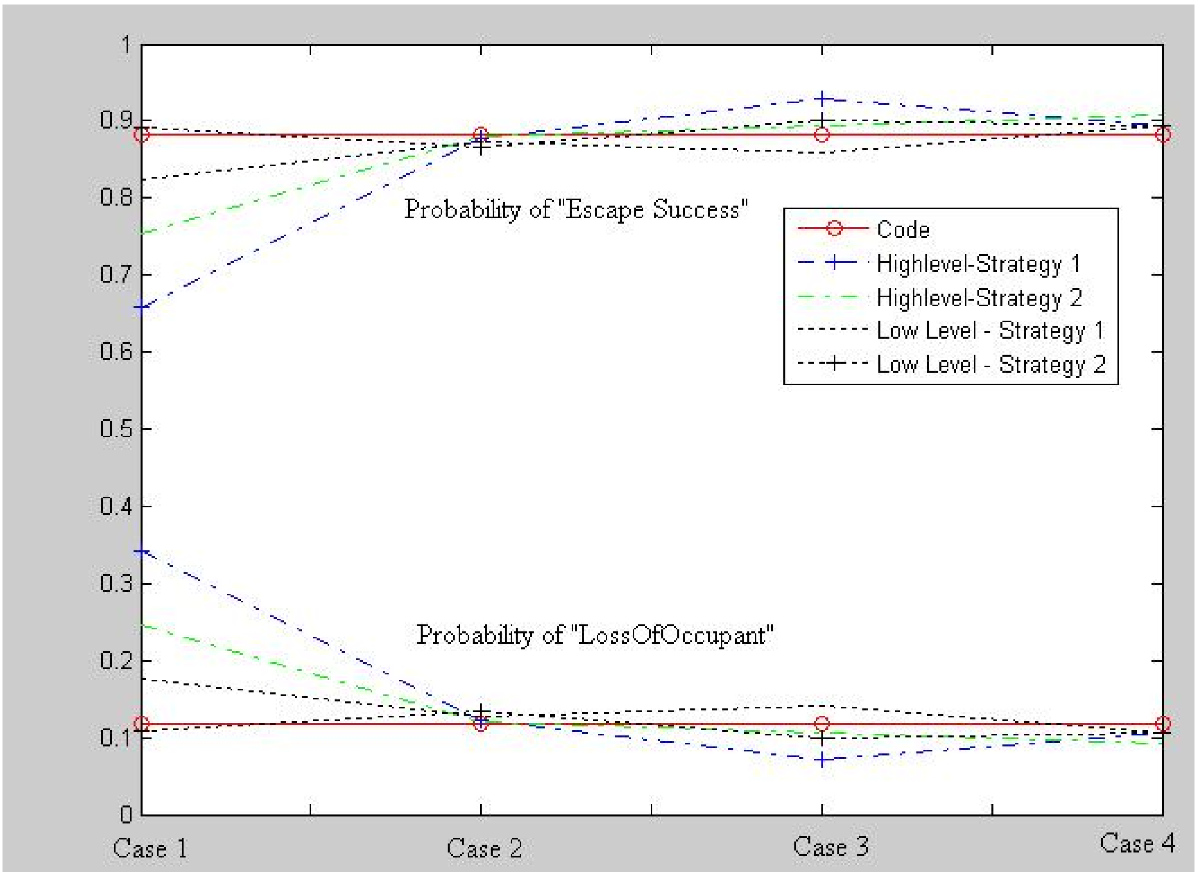


Figure 51. Simulation results from different strategies

From Figure 51, the following phenomena are observed:

1 The low level model simulation generates a better result compared with the high level model simulation as expected.

2 When the number of tests is small, the conservative strategy increases the result performance dramatically for the high-level simulation. The reason for this is that most of the software failures are not detected after a small amount of tests. Using a conservative strategy, the impacts of the undetected failures are effectively

represented.

3 When the number of tests is sufficient, the difference between the result from strategy 1 and conservative strategy 2 becomes small.

4 Enough testing can ensure a good estimation of risk

7.7 Summary

This chapter introduces the gate-control system (PACS), and the whole modeling process is studied using our methodology. The experimental-validation results show that:

1. Using a software model in the simulation environment leads to a reasonably accurate estimate for the end-state probability.
2. The software model can be refined after the analyst obtains more test results; the accuracy of end-state probabilities increases when the model improves.
3. High-level simulation is less time-consuming, but this comes at the expense of lower scenario resolution.
4. A smart adaptive simulation captures the benefits from both low-level simulation and high-level simulation; the simulation is less time consuming and produces sufficient details.

Chapter 8: Procedure to Develop the Software Model in Case of Objective Data

The integration approach is discussed in Chapter 5. This chapter provides further guidance on how to establish an accurate software representation when code is available and objective test data can be obtained. The procedure presented is based on lessons learnt from our experimental demonstration in Chapter 7. This approach can be used in addition to the integration approach discussed in Chapter 5.

8.1 Approach

Step 1: Build the executable low-level model for the software.

In the first step, the analyst needs to decide how to abstract the real software. The lowest level abstraction for the software needs to be defined. The following constrains restrict the analyst's modeling alternative to specific low-level models:

- Inputs/outputs resolution from other models (human, hardware, software): the software model can not go beyond the level of resolution that other models can understand/produce.
- Limits imposed by the code: the lowest level of abstraction can not go beyond the code resolution as expected.
- Limits of the characteristic of the input/output variables: the software model can not go beyond the natural resolution of the input/output variables.

- The lowest level software model should not break the dependences between input variables.

An executable software model needs to be built using SFSM based on the abstraction. (Section 4.3)

In the case of PACS, the input/output resolution of the human model stays at the level of correct card, wrong card, correct PIN and wrong PIN. This limits the lowest level of the PACS software model. The detailed card inputs and PIN inputs are grouped together as *correct card* and *wrong card*, *correct PIN* and *wrong PIN*. This is used as lowest input unit in the software model.

Step 2: Define a multi-level structure for the software model.

In this step, the analyst first needs to choose the functions to be abstracted, then define the abstraction methods and build the multi-level abstraction model for the software. The abstraction technique includes *functional abstraction* and *continuous abstraction*, which were introduced in section 4.2.

Functional abstraction leads to the omission of details related to sub-functions. Continuous abstraction focuses on input-output transformations resulting from functional computations. Errors are introduced during the abstraction process. These errors fall into two groups, which are explained below.

The scenarios generated in the DPRA environment contain a sequence of stochastic events resulting from model execution, and timing of occurrence. In between the points of occurrence of these random events, the behavior of the system is typically modeled using deterministic models describing the physical and other processes taking place in the system.

The first group of errors modifies the deterministic behavior. Both abstraction techniques change the input/output relationship, i.e. if the expected behavior is $f(i)$, the modified behavior is $f(i)+\varepsilon(i)$. $\varepsilon(i)$ is the error introduced into the deterministic behavior. This group of errors can be quantified before the simulation. It is usually small at the component level.

For instance, $f(x)=\sin(x) \qquad 0 \le x \le \pi$

Assume the abstraction function is

$$\tilde{f}(x) = 1 - abs(\frac{2x}{\pi} - 1)$$

The error introduced is represented by the shaded area in Figure 52.

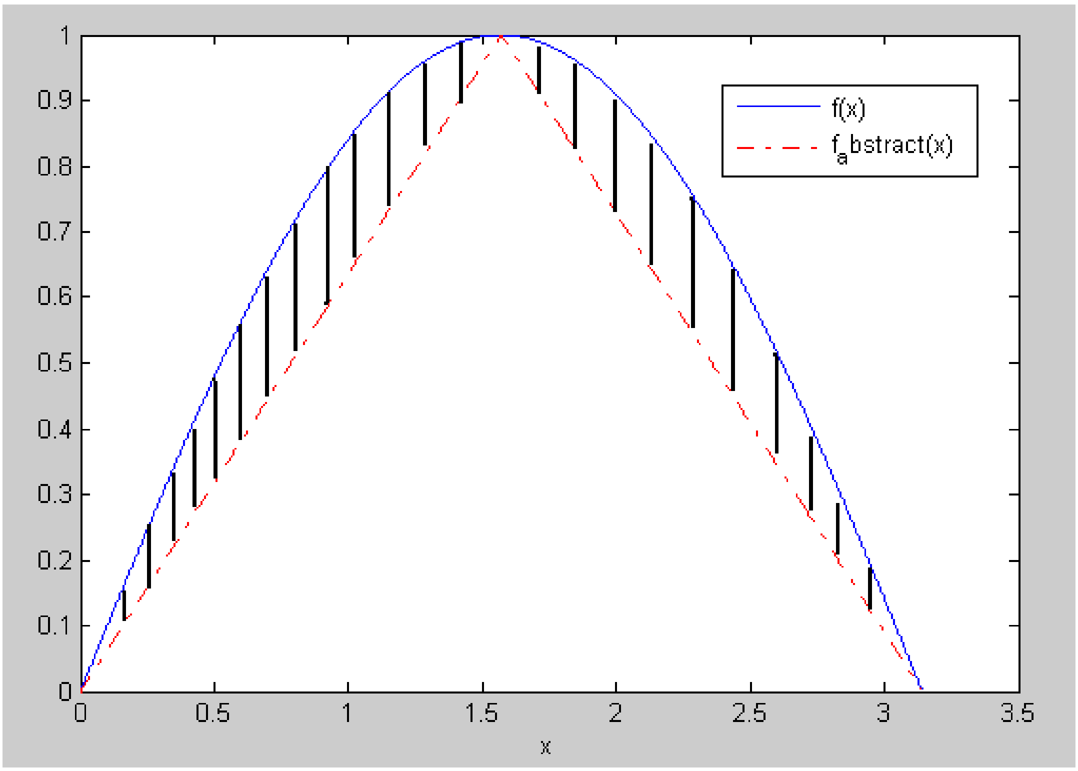


Figure 52. Error introduced in the deterministic behavior

The second group of errors modifies the stochastic events, such as software failures. There are three types of errors in this group:

- ***Event error***: the high-level events are usually a combination of low-level stochastic events. This thus introduces the event error. Normally the event error is acceptable if it does not influence the global behavior of the event.
- ***Time error***: the time of occurrence of the event is different since the details of the low-level events are not modeled in the high-level abstraction
- ***Probability error***: the probability of the event changes due to abstraction. The probability needs to be quantified using testing results. Probability error is introduced when the value of the probability used is not accurate.

If the functional abstraction groups multiple stochastic events together, the event error will be introduced and the time error will be introduced also. The probability of the high-level event can be quantified using the high-level test result. The probability error is introduced if the test result is not accurate.

Figure 53 a) presents a high-level event RCRP. The high-level event presents the combination of the low-level events in Figure 53 b). At the high level, based on the test results in Table 18 (10000 test cases), the characteristics of this event can be defined as:

Probability p = 0.6126

The time needed for this event is uniformly distributed between 14 seconds and 52 seconds.

At the low level, based on the test results in Table 19, Table 21, and Table 22 (10000 test cases), the characteristics of the low level events can be defined as:

$$\begin{aligned}&p(card\_validation, success) = p(right\_card) * p(success \mid right\_card)\\&+ p(wrong\_card) * p(success \mid wrong\_card)\\&= 0.55 + 0.45 * 0.406 = 0.7327\end{aligned}$$

$$p(card\_validation, fail) = 1 - p(card\_validation, success) = 1 - 0.7327 = 0.2673$$

The time needed for card validation is uniformly distributed between 6 seconds and 8 seconds.

$$\begin{aligned}&p(PIN\_validation, success)\\&= p(right\_PIN, right\_card) * p(success \mid right\_PIN, right\_card)\\&+ p(right\_PIN, wrong\_card) * p(success \mid right\_PIN, wrong\_card)\\&+ p(wrong\_PIN, right\_card) * p(success \mid wrong\_PIN, right\_card)\\&+ p(wrong\_PIN, wrong\_card) * p(success \mid wrong\_PIN, wrong\_card)\\&= 0.55 * \frac{0.55}{0.7327} * 0.807 + 0.55 * \frac{0.1827}{0.7327} * 1 + 0.45 * \frac{0.55}{0.7327} * 0.022 = 0.4777\end{aligned}$$

$$p(PIN\_validation, fail) = 1 - p(PIN\_validation, success) = 1 - 0.4777 = 0.5223$$

The time needed for PIN validation is uniformly distributed between 6 seconds and 8 seconds.

Comparing the high-level event RCRP, the low-level events are card_validation and PIN_validation. The high-level event is a combination of the low-level events. The event is different thus event error exists in this situation. The time occurrence of the high-level event RCRP should map to the last event in the low-level sequence, time error is introduced if the occurrence of the event is not modeled correctly. Probability error will be introduced also if the probability used at the high-level is not accurate.

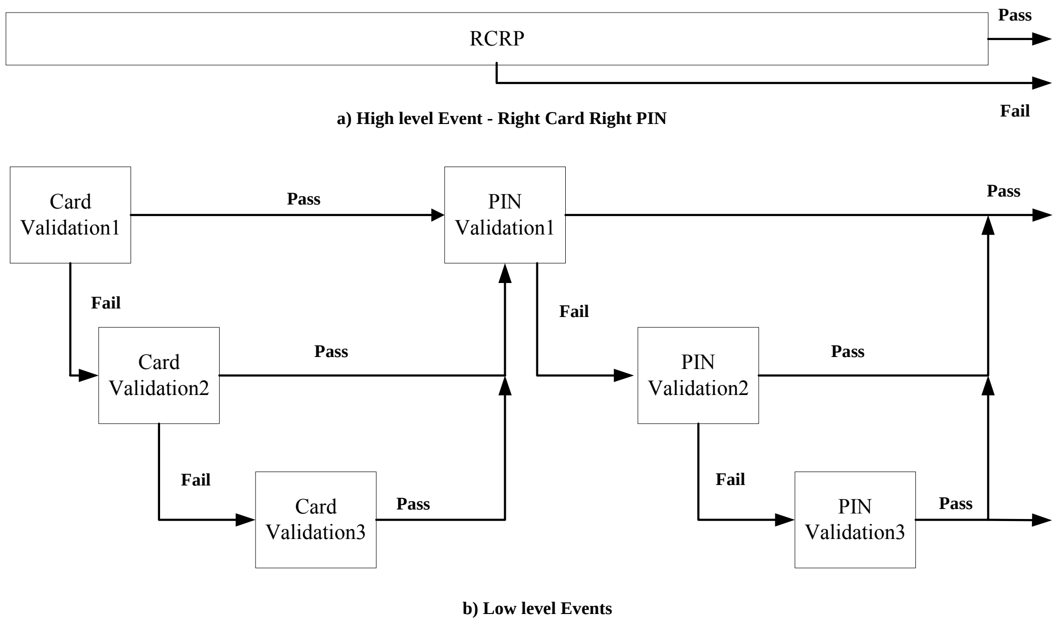


Figure 53. High-level event vs. low-level events

The continuous abstraction does not deal with the combination of multiple stochastic events. But the accumulation of the errors, introduced in the deterministic behavior, over a chain of events may exceed a threshold which will lead to the occurrence of a different stochastic event.

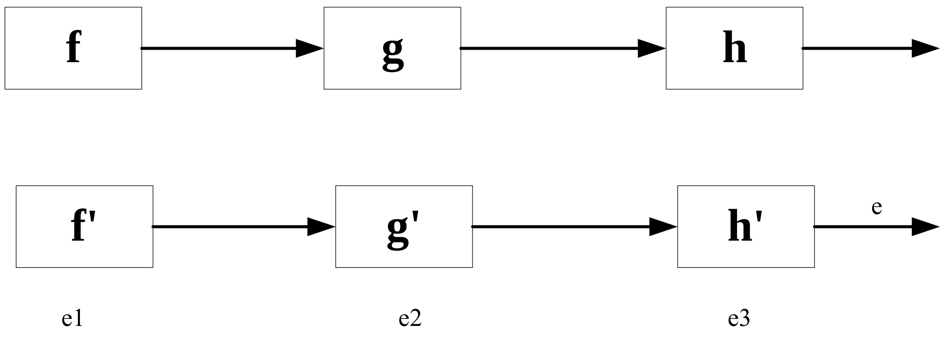


Figure 54. A chain of events

For instance, considering the chain of events in Figure 54, errors are introduced in the abstraction of function f, g, and h. The propagation of the errors leads to an accumulated error ϵ. If the error is large enough, it may influence the execution of the stochastic events following, such as the possible occurrence of a software failure. In this way, the event error and the probability error are introduced. If the continuous abstraction changes the software execution time, the time error is introduced also.

The abstraction is recommended for the functions with the following characteristics:

- The execution of the function is time-consuming. The abstraction can be a functional abstraction to reduce the complexity of the software function. It can also be a continuous abstraction to simplify the calculation process.
- The function interacts with other models multiple times sequentially in one run. The functional abstraction should be used to group several interactions in one single time step if applicable. The sequential inputs from the interactions need to be combined together.

  Assuming the sequential inputs to the software function are f_1 to f_n, it needs to be combined as one single input:

  $$I_i = (f_{11}, \cdots, f_{n1}) \qquad I = \{I_1, \cdots, I_m\} \qquad \sum_m p(I_m) = 1 \qquad (8.1)$$

  m represents the number of different combinations for sequential inputs f_1 to f_n.

  Other models need to be updated to be able to understand and produce this type of inputs.

The improvement brought to the computational complexity includes two components:

1. The computation time decreases due to abstraction

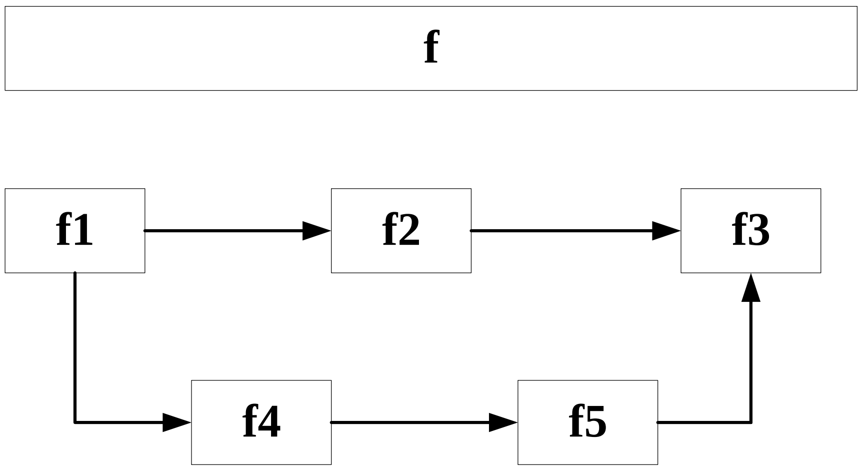


Figure 55. High-level function f vs. low-level function f

Figure 55 presents a high-level abstraction model for function f and the low-level model for function f. Assume that the execution of each function block takes 1 time cycle. The execution of the high-level model only takes one time step. The low-level model contains two paths: Path1 (f1, f2, f3), Path2 (f1, f4, f5, f3).

The average execution time is

$$t_{LL} = p(Path1) * 3 + p(path2) * 4 \tag{8.2}$$

Generally, the average execution time can be represented as:

$$t_{LL} = \sum_{i=1}^{n} p(Path\_i) * t(Path\_i) \tag{8.3}$$

The time decreases by the factor of $\frac{1}{t_{LL}}$.

2. The number of branches generated decreases due to the grouping of multiple stochastic events.

Assume n different sequences of low-level stochastic events are grouped into 1 event in the high-level model. The branches generated decrease by the factor of 1/n.

In Figure 53, the high-level event includes six low-level stochastic events sequences. The branches generated will decrease by the factor of 1/6.

The analyst needs to make a balance between the errors introduced during abstraction and the improvement brought to the computational complexity.

Step 3: Obtain the operational profile for the software

In this step, the analyst needs to obtain the operational profile [19] for the software from the software requirements and the system requirements. The test is conducted based on this profile. The profile is an external input profile from other models (hardware, software, human).

If unexpected inputs to the software model are observed during the simulation, the profile needs to be updated. More testing needs to be conducted or the conservative estimation can be used to adjust the test results (See section 7.5 step 4). The conservative estimation can be obtained through the following equation:

$$p_{new} = p_{old} * (1 - q) + q \qquad (8.4)$$

P_{new} is the new failure probability estimation

P_{old} is the original failure probability obtained through testing.

q represents the probability of the unexpected input detected

In the case of PACS, for each user, the probability of inserting the right/wrong card is 0.55/0.45. The right/wrong cards are uniformly distributed in the set of right/wrong cards. Once the user inserts the card, the probability of inputting a right PIN is 0.55.

Step 4: Define the possible software failure modes

Based on the logic of the software, all possible software failure modes are defined in this step. There are eight types of failure modes defined for the software model. These are value, range, amount, type, time, rate, duration, and rate. The definition of the failure modes can be found in [2]. The analyst needs to study the applicability of each failure mode.

In the case of PACS, amount, range, value, load, duration, and rate failure are not applicable. All possible value failures and time failures are defined and studied for PACS.

Step 5: Test the software using the operational profile

In this step, the software is tested using the operational profile defined in step 3. The test is performed at different levels.

Assume that the external profile defined in step 3 is represented as:

$$I = \{I_i, p(i)\} \qquad i = 1, \cdots, n_i \tag{8.5}$$

The profile for the software function to be tested is presented as:

$$I_f = \{I_i, p(i)\} \qquad i = 1, \cdots, n_f \tag{8.6}$$

The output is represented as

$$O_f = \{O_i, p(i)\} \qquad i = 1, \cdots, n_o \tag{8.7}$$

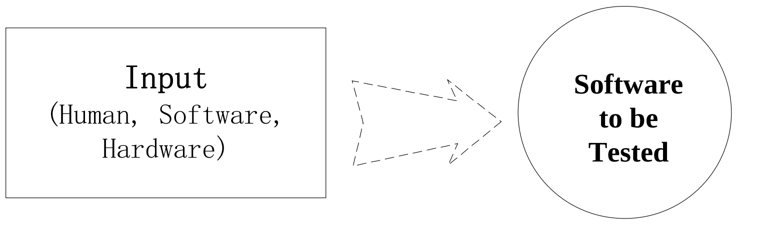
If $I_f \subseteq I$, which means that the software function to be tested is only related with the external profile, the software can be tested directly. (case a in Figure 56)

If $I_f = I_{f1} \bigcup I_{f2}$, $I_{f1} \subseteq I$, $I_{f2} \subseteq O_{sw1}$ (8.8)

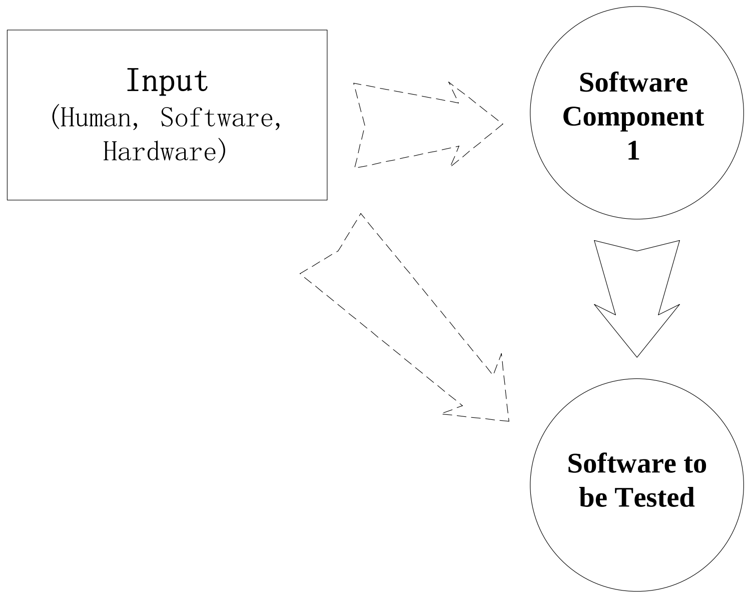
which means the inputs of the software to be tested are not only from the external profile, but also dependent on the outputs of the other software to be tested (software component 1) (case b in Figure 56), the software profile needs to be updated in the following condition.

If unexpected software failures are observed in the test result for software component 1, and the software failures detected introduce some unexpected outputs, the profile for software function f needs to be updated to reflect the new inputs from software component 1.

$O' \notin O_{sw1}$ $\qquad I_f' = I_f \cup O'$ (8.9)



a) Software inputs are from external models



b) Software inputs are from external models and the execution of other software to be tested

Figure 56. Different conditions for software testing

The probability of the software failure is calculated using the following equation:

$$p = \frac{number\ of\ test\ cases\ with\ failures}{number\ of\ total\ test\ cases} \tag{8.10}$$

In the case of PACS, the test is performed at the high level and the low level. The input profile of the high level test is only influenced by the human model. Thus it can be tested directly using the operation profile. The low-level test includes the tests for card validation and PIN validation. The inputs of card validation are only from the human model. It can be tested directly using the profile obtained from the human model. Based on the design document, the perfect card validation should have the following results:

- A user with a right card can pass the card validation
- A user with a wrong card can not pass the card validation

The following software failures are detected during testing of card validation:

- A user with a right card can not pass the card validation
- A user with a wrong card can pass the card validation

Since the input profile of PIN validation is dependent on the human input and the results from card validation, it needs to be updated based on the software failure detected. The initial input profile for PIN validation only includes:

- PIN profile for the user with a correct card

Based on software failures observed in the implementation of the function card validation, the following profile should be added to the original profile:

- PIN profile for the user with a wrong card that passes the card validation

The PIN validation function needs to be tested for both conditions.

Step 6: Analyze the test results

The test results are analyzed in this step. The software failure modes need to be quantified using the test results. The test results are first categorized based on the type of inputs and outputs. The conditional probability for each failure mode is calculated if the failure mode is observed.

If the software failure introduces unexpected output, and the output serves as an input to next sequential component, it may introduce a new combination of sequential inputs. If the high-level abstraction model combines the sequential inputs during abstraction, and the newly discovered sequence does not belong to the original combination set, the new sequence combination needs to be added as a new input to the high level model.

$$I_{m+1} = \{(f_1^{'}, \cdots, f_n^{'})\} \qquad I_{m+1} \notin I \qquad I = I \cup I_{m+1} \qquad (8.11)$$

Also the probability profile for each input to the high-level model needs to be replaced based on the profile observed in the test results.

For instance, in the case of PACS, Table 16 lists the high-level test results for PACS. The results are categorized based on the inputs (right card, wrong card, right PIN, wrong PIN) and output (success, fail). The probability for each failure mode is calculated and presented in Table 17. In this case, the high-level operation profile is influenced by software errors. Thus the profile is updated as in Table 18.

Step 7: Estimate the probability for undetected software failures

If some software failures defined in step 5 are not discovered in the simulation results, the conservative estimation should be used to estimate the failure probability. The estimation can be done using the Bayesian Approach defined in Chapter 6. The probability for the failure after N tests can be calculated using the following equation:

$$q = \frac{0.5}{1+N} \qquad (8.12)$$

In the case of PACS, some failure modes are not detected after a small amount of testing. The probability of the undetected failure modes are estimated using the conservative estimation. The simulation results indicate that the undetected software failures are effectively represented using the conservative estimation.

Step 8: Inject the software failures in the executable software model

The software failures are injected in the multi-level software model defined in step 2. AKB and FIKB needs to be constructed based on the testing results

8.2 Discussion

The approach defined in this chapter is applicable to the case when the real software is available. If the real software is not available, the software failures need to be quantified using expert judgment or statistical data from similar projects. The basic steps for this case are:

Step 1: Build the executable low-level model for the software.

Step 2: Define multi-level structure for the software model.

Step 3: Define the possible software failure modes.

Step 4: Quantify the probabilities of software failure modes using expert judgment or statistical data.

Step 5: Inject the software failures in the executable software model.

Chapter 9: Conclusion and Future Work

9.1 Conclusion

DPRA is a methodology to assess the probability of failure or success of a mission. The current DPRA environments do not allow modeling of software risk contribution. This dissertation describes a framework and a set of techniques to extend the DPRA approach to allow consideration of the software contributions on system risk. The framework includes a software representation, an approach to incorporate the software representation into the DPRA environment SimPRA, and an experimental demonstration of the methodology.

Here are the major contributions:

- Systematically identify the software modeling requirements for simulation-based DPRA environments
- Assess the existing software representations with respect to the DPRA modeling requirements
- Extend the concept of FSM to SFSM and apply it to the area of software modeling DPRA environments
- Establish a software representation framework including a software behavior model and a software guidance model
- Build a multi-level software representation using functional abstraction and continuous abstraction techniques

- Integrate the failure mode taxonomy developed by Li [2] in the software representation
- Develop the mechanism to separate the software-related knowledge with the system-related knowledge
- Define the structure for AKB, FIKB, SKB
- Propose a framework to simulate the multi-level objects in the simulation-based DPRA environment
- Enhance the current single-level SimPRA to support multi-level objects in the modeling framework
- Apply the concept of entropy to dynamically control the simulation level of detail for the multi-level objects
- Implement the entire methodology in the SimPRA software
- Develop an easy to use tool to help the analyst develop the software model
- Conduct an experimental demonstration to study the quantification aspects of the software model when objective test data is available
    - Develop a consistently quantified software representation
    - Embed software profile information in the software model
    - Cover the failure mode taxonomy developed by Li
    - Obtain data from testing
    - Account for the dependencies between model components
    - Compare the software model simulation results with the simulation using the real code

- Formalize a procedure to establish a consistently quantified software model when code is available and objective test data can be obtained

9.2 Future Work

This dissertation describes a framework for integrating software into Dynamic PRA. It is the first study of its kind. More research is needed. Below are some possible avenues for future research:

9.2.1 Large scale validation

Although a case study has been provided, which demonstrates the applicability of this framework and of the set of techniques developed, the methodology should be applied to a large system. Problems that arise in that process need to be identified, and their solutions should be provided.

9.2.2 Software-related knowledge

Different types of prior software-related knowledge may exist. In this dissertation, the time-factor information was added to SKB and supported by the multi-level scheduler and planner. In future research, different types of software-related information could be defined and added to SKB. For instance, different software-abstraction levels could be associated with different levels of accuracy in the results. The accuracy-related factor could then be added to SKB.. The current multi-level simulation environment provides an open interface which easily allows the introduction of new types of knowledge.

9.2.3 Software-testing knowledge

SimPRA uses two types of information to guide the simulation: prior knowledge and knowledge obtained during the simulation.

In this dissertation, the knowledge obtained during simulation is mainly entropy-based information. Knowledge about the relationship between branch selection and end-state probabilities is summarized after simulation. The information gain is dynamically updated to adjust the simulated branch selection process.

Other types of information can also be used to adaptively adjust the simulation, for instance, the software test coverage information. Various software coverage indices (i.e. statement coverage, branch coverage, etc) can be calculated after simulation. In subsequent simulations an uncovered statement, branch could receive additional weighting compared with statement, branches already covered.

In the current SimPRA environment, when the system simulator proposes transitions to the scheduler, the scheduler retrieves the information for the proposed transitions and decides which branch to explore, based on the previous simulation results. The new framework can be upgraded to include the instruction from sub-component guidance model. (See Figure 57)

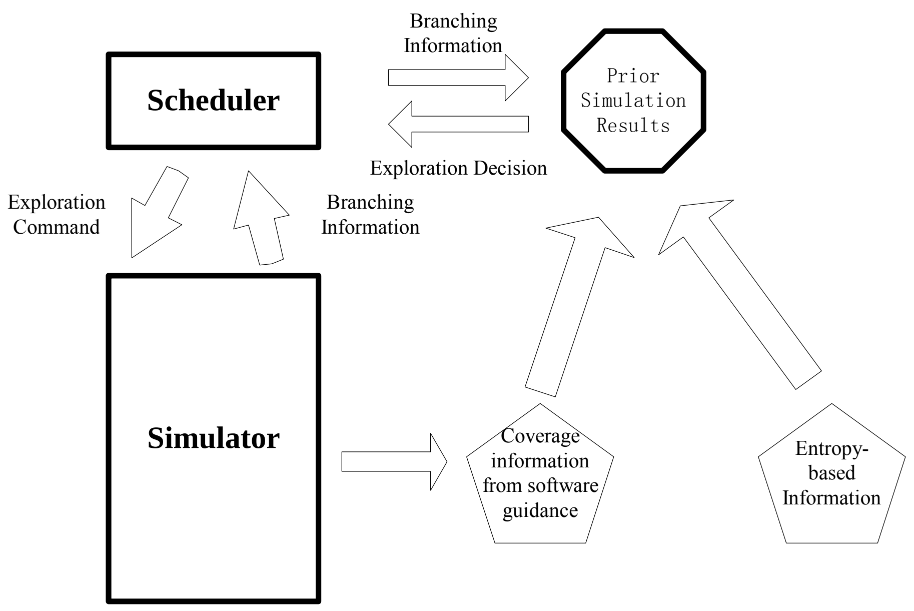


Figure 57. New framework for branch exploration

The coverage information is a different type of information for branch decisions. The system scheduler needs to combine its current entropy-based decision and the decision generated by the software-guidance model and based on the software coverage results. Different strategies can be defined to combine the two decisions.

Strategy 1:

Different weights can be assigned to the entropy-based information on the one hand and software coverage on the other, depending on the simulation goal. The analyst decides the weights, based on the simulation requirements. If a complete software branch exploration is expected as a result of the simulation, the software-coverage weight should be assigned a higher value. If the simulation focuses on final system risk, the entropy-based information should receive more weight.

Strategy 2:

An adaptive-selection strategy can be defined, based on the simulation process. If the entropy-based information is insufficient initially because of a lack of simulation results, the system scheduler may base its decision on the coverage information received from the software-guidance model. If entropy-based uncertainty is low after many rounds of simulation, the system scheduler can select branches based mainly on entropy-based information.

9.3 Acknowledgement

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