System Dynamics Modeling for Human Performance in Nuclear Power Plant Operation

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ABSTRACT

Perfect plant operation with high safety and economic performance is based on both good physical design and successful organization. However, in comparison with the affection that has been paid to technology research, the effort that has been exerted to enhance NPP management and organization, namely human performance, seems pale and insufficient. There is a need to identify and assess aspects of human performance that are predictive of plant safety and performance and to develop models and measures of these performance aspects that can be used for operation policy evaluation, problem diagnosis, and risk-informed regulation.

The challenge of this research is that: an NPP is a system that is comprised of human and physics subsystems. Every human department includes different functional workers, supervisors, and managers; while every physical component can be in normal status, failure status, or a being-repaired status. Thus, an NPP's situation can be expressed as a time-dependent function of the interactions among a large number of system elements. The interactions between these components are often non-linear and coupled, sometime there are direct or indirect, negative or positive feedbacks, and hence a small interference input either can be suppressed or can be amplified and may result in a severe accident finally.

This research expanded ORSIM (Nuclear Power Plant Operations and Risk Simulator) model, which is a quantitative computer model built by system dynamics methodology, on human reliability aspect and used it to predict the dynamic behavior of NPP human performance, analyze the contribution of a single operation activity to the plant performance under different circumstances, diagnose and prevent fault triggers from the operational point of view, and identify good experience and policies in the operation of NPPs.

Regarding the human reliability analysis function, the partial Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) method was applied. Performance Shaping Factors (PSFs) were employed to analyze the influence of human performance indicators already existing in ORSIM.

Based on the human performance model, an operation case study was investigated. A series of carefully chosen candidate policies were tested on a computerized model that represents the structure, processes, and interactions of the underlying target NPP systems. These candidates included: (1) New management system application; (2) Personnel population change, (3) Planning delay, and (4) Tolerance to surprise workload.

Thesis Supervisor: Michael W. Golay

Title: Professor of Nuclear Engineering

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CHAPTER 1 – INTRODUCTION

1.1 Research Background

1.1.1 Research Motivation

As of December 2005, there were 443 nuclear power reactors in operation around the world, and another 24 were under construction. These produce 16% of the world's electricity, the biggest share of clean, CO_2-free energy [1]. Also, in the future, nuclear energy may be used to generate hydrogen for use in petroleum refinement, to provide a fuel for transportation, and to desalinate seawater.

Figure1-1 shows the increasing consumption of electricity in the world from 2003 to 2030. It is noticed that the world's total net electricity consumption doubles, growing at an average rate of 2.7% per year, from 14,781 billion kilowatthours in 2003 to 21,699 billion kilowatthours in 2015 and 30,116 billion kilowatthours in 2030. The consumption of electricity generated from nuclear power worldwide increases from 2,523 billion kilowatthours in 2003 to 3,299 billion kilowatthours in 2030 in the IEO2006 reference case.

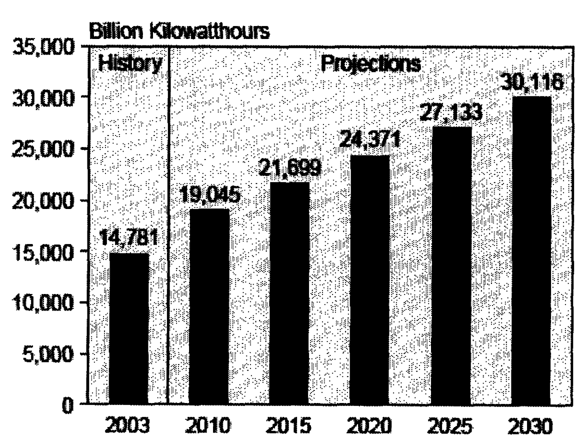


Figure 1-1 Growing World Electricity Consumption, (Source: 2003: Energy Information Administration (EIA), International Energy Annual 2003 (May-July 2005))

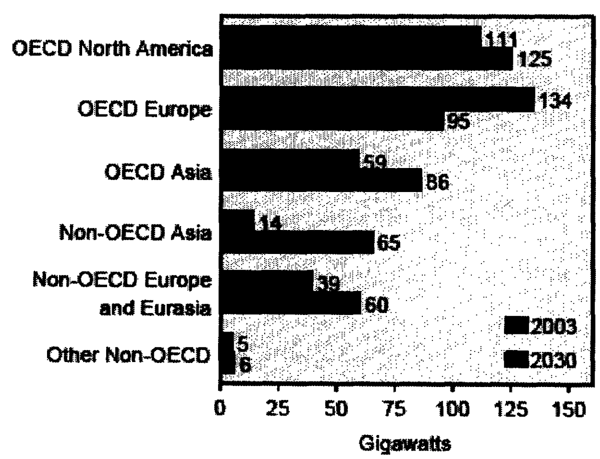


Figure 1-2 World Nuclear Generating Capacity by Region, 2003 and 2030 (Source: 2003: Energy Information Administration (EIA), International Energy Annual 2003 (May-July 2005))

Higher fossil fuel prices and concerns about security of energy supplies are expected to improve prospects for nuclear power capacity over this period, and many countries are expected to build new nuclear power plants. Global nuclear capacity is prognosed to rise from 361 gigawatts in 2003 to 438 gigawatts in 2030. Nuclear power generation in the non-OECD countries increases by 3.5% per year between 2003 and 2030. Non-OECD Asia, in particular, is expected to see the largest increment in installed nuclear generating capacity, accounting for 69 percent of the total increase in nuclear power capacity for the non-OECD countries (Figure 1-2). There is no doubt that in the coming several decades, the number of nuclear power plants (NPPs) will grow steadily around the world.

While nuclear energy has many promising opportunities, there are too. Safety issues are always the central concern for nuclear utilization. These issues are raised in terms of both physics and organization.

On the side of physics and technology, the existing nuclear power plants based on LWR technology are recognized as a safe, reliable, and competitive power source in many countries currently, and will be kept in use for a long time. It is recognized as Generation III nuclear reactor. In the near future (~2010), advanced LWRs will be developed and commercialized based on current LWRs, and it will be named as Generation III+ nuclear reactor. At the same time, a new spent fuel separation technology can be developed and implemented. Also, advanced fuel cycle technology is being investigated. In addition, the at-reactor and away-from-reactor storage facilities as well as a geological disposal site for high-level radioactive wastes from the reprocessing are being established. With technology developing, Generation IV nuclear reactor program has been proposed in the academic field. Its objective is to obtain more manageable nuclear waste, effective fuel utilization, increased environmental benefits, competitive economics, recognized safety performance, and safe nuclear energy systems. It is worthy to mention that the most appealing characteristics of Generation IV are full actinide recycle and hydrogen production. The commercialization of Generation IV is expected to be fulfilled by 2050.

On the other side, as another key factor for the safety and economic performance of an NPP, human performance [2], including optimization of the industrial operation, personnel organization and management policy, is still far from satisfactory.

1.1.2 Issues and Challenges

From the view of a global system, a perfect plant operation with both high safety and solid economic performance is based on good physical design, successful management, and sound organization. Whereas, in comparison with many efforts that have been put into the technology research, the strength exerted to enhance NPP management and organization seems relatively minor.

Currently, all NPPs can share management experience and operation policies smoothly with each other. Communications between NPPs are straightforward without any reservation. As a result, a set of long-tested strategies have been proved to meet the safety criteria and are accepted widely. However, NPP management strategy is relatively outdated, and attitudes toward new policies are conservative and rigid. This situation roots deeply in two aspects: one is the difficulty for decision makes to fully understand the intricate relationship between human beings and the physical system of NPP, and the other is the objection from the nuclear regulatory organizations for safety consideration on NPP operation.

First, the difficulty for decision makers can be analyzed in detail as below:

An NPP system can be thought of as been comprised of many sub-systems including administrative departments and the physical components. Each department holds different functional workers, supervisors, and managers; while every physical component could be in a normal status, failure status, or being repaired status. Theoretically, the state of an NPP can be described as a time-dependent function of a large number of system elements, including both humans and hardware. But this job is far from well down. The difficulty to analyze the system lies in the abstract description of human behavior and the complex interactions among these components.

It is acknowledged that human performance is difficult to model quantitatively. There are several reasons for this: [3]

- The understanding of organizational behavior is much less complete than for physical systems. The identification of relevant dependent and independent variables is unclear. Further, the "equations of motion" for such systems are unknown. As a consequence the state of model building is primitive and consists primarily of mental models that are intuitive to the modeler.

- Much of an organization's behavior is itself dependent upon individual and collective behavior of the humans that operate the system. However, this dependence is itself not well-known or modeled.

- The measures or indicators of human performance that are relevant to any systems behavior are themselves ill-defined and ill-understood.

In regard to the interactions in the system, they are often non-linear and coupled, sometimes presented in loops with direct or indirect, negative or positive feedbacks. Generally, a small input interference or noise either can be suppressed without damage, or it can be amplified and may result in a severe accident finally. Therefore, what we are facing is not a pure physics or social system, but a complicated composite system. When encountering a composite and complex system, most people make decisions according to "natural common sense" more than system thinking and behavior, that is, the decision is based on an empirical judgment rather than quantitative analysis. The general assumptions under above condition include: top event triggers bottom event linearly, continuously, and directly without coupling, delay, thresholds or dead-zones; feedback is accurate and timely; and the impact loops are straightforward and not intercrossed. As a result, some latent problems may not be given attention and removed until they emerge and do damage, or some policy aimed to improve one performance may degrade another system performance instead…

Second, considering the lack of a pilot simulator to provide reliable feasibility evidence, the nuclear regulation organizations make every effort to avoid the risk to implement any brand new management strategy directly. The regulatory agencies, for example, NRC, are always involved in the safety concerns and apply system Probabilistic Risk Assessment (PRA) tools to assess the system reliability. Without a set of systemic human performance measures and a quantitative analysis approach, it is difficult for them to evaluate the safety performance of the holistic system, or perform further risk-informed regulation activity.

It can be expected that there is still much space to improve the economic performance of NPPs through optimizing resources and refining operation. Also, it is a major safety concern to investigate the intrinsic interaction mechanism inside the human systems so as to make most operation predictable and controllable. Thus, a series of reasonable indicators and convincing standards are needed to judge the organization strategy for reactors in both the industry and the regulatory agencies.

1.1.3 Research Objectives

This research aims to build a qualitative framework for human system in NPPs, and, in addition, a quantitative computerized model, through which we can predict the dynamic trendline of the NPP performance, analyze the contribution of every human action to the plant operation under different circumstances, analyze the NPP safety performance, diagnose plant fault triggers, and identify good experience and policy in the organization of NPPs. For example, how big a workforce is optimal in every functional group so as to balance redundancy and economy, and how much training is required to maintain acceptable human reliability or quality?

In summary, the goals of this research can be stated as:

1. Create a simplified, user-friendly NPP operation simulator to support NPP training demo, policy making, safety performance evaluation, and failure diagnosis;

2. Develop a set of time-dependent performance indices to evaluate plant performances quantitatively in terms of human related stability, reliability, and economic criteria;

Based on the features of the research objectives, several criteria governing the modeling process are raised. They are addressed as following:

First, physical processes should be simplified to some degree in modeling. Rather than study the detailed physical circumstances of a reactor at each moment (such as the specific values of temperature, pressure, or neutron flux), our concern is focused on material condition degradation rates during operation and consequently the hardware defect generation rates. Also, we do not care how workers control, detect, and fix each instrument or valve. Instead, their work productivity, quality, error probability, and the operation process of the workflows are the objectives.

Second, major attention is paid to the dynamic interactions between organizational and physical systems as well as to those within organizational systems. To be systematic, the model is modularized and separated into several subsystems including reactor physics system, planning sector, maintenance sector, operations sector, engineering sector, and human resource sector, etc. In every sector, human behaviors, such as workflow, stability, and human error probability, are simulated concretely. Moreover, because collaborations widely exist among all the functional departments, the mutual influence between each two subsystems should be considered. .

Ultimately, it can be anticipated that the initiative and experiences in this stage will stimulate more and more administrators and decision makers in the nuclear power industry to employ and to spread this type of modeling more extensively and in greater detail. With the application broadened and deepened, the completeness and accuracy can get well established and more functions can be developed.

1.1.4 Survey on Human Performance Programs

The U.S. Nuclear Regulatory Commission (NRC) is increasingly paying attention to organizational system design and behavior, that is, human performance. The Reactor Oversight Process (ROP) that is conducted by NRC is focused on safety performance indicators, and it has recognized human factors as an important contributor for holistic system safety.

The U.S. nuclear power industry has also exerted considerable effort to improve human performance, through activities by INPO, NEI, and EPRI. In many ways, these efforts began in 1997 when INPO added human performance as an explicit area for review in INPO plant evaluations. This had the effect of bringing plant and utility senior management attention to bear directly on the level of human performance, because an adverse finding in this area would affect the overall rating of the facility that was being evaluated. In addition, INPO developed training courses and related materials to teach plant staff the basic issues of human performance and how they related to plant performance, both in relation to safety and to production. These included courses entitled "Human Performance Fundamentals" (1997) and "Principles for Effective Self-Assessment and Corrective Action Programs" (1999). As a result of these and other initiatives by INPO, most, if not all, of the plants began efforts to measure human performance in a variety of ways. In addition, the industry invested significant efforts in gathering human performance data for its own management uses, maintaining plant safety and increasing efficiency of operation. These programs, and especially the data they collect, are an excellent and needed resource not only for developing human performance measures, but also for validating modeling and simulation methodology and results.

With the concerns on human performance, the NRC's Office of Nuclear Regulatory Research (RES) and the Idaho National Laboratory (INL) conducted an industry workshop in Charleston, SC in December of 2005. This public meeting was attended by individuals from INPO, EPRI, and various utilities who work in human performance fields. In the workshop, participants showed their common practices and standard measures, such as human error rate, corrective work backlog, maintenance rework ratio, training time, etc. In a follow-on discussion, there were many concerns voiced regarding how the data could be used, and how these changes might impact the regulation of the industry.

Actually, the model to be developed here just provides such a simulation approach, through which nominal human performance data can be used as input and practical human performance indicators can be predicted in advance of the adoption of a new management policy. After comparing the calculated values with design-based data, we can conclude how safely the new system will perform and how the new policy will work.

1.2 Research Methodology

System dynamics is a methodology to study a complex system, especially a social system or a composite system. Just as an airline uses a flight simulator to help pilots learn, system dynamics is a method for developing management simulators which are often computer simulation models. System dynamics is grounded in control theory as well as in the modern theory of nonlinear dynamics in mathematics, physics, and engineering. Therefore, this tool can be applied to model both human and physics dynamic behaviors in a time dependent way.

1.2.1 System Dynamics on Business Policy

1.2.1.1 Systems Thinking

The system dynamics approach was proposed in 1950's by Jay Forrester. It is a unique method to help managers and public policy makers analyze systems and test new policy. In a comprehensive new treatment, John Sterman explains what system dynamics is and how it can be successfully applied to solve social and organizational problems. This approach requires re-observing isolated events as well as their causes, and treating an organization as a system made up of interacting parts. A system means an interactively interdependent group of entities. In the work presented in this thesis, the objective is to study management processes. The focus will be on systems of people and hardware that are involved in organizational interactions and work processes.

1.2.1.2 System Behavior [4]

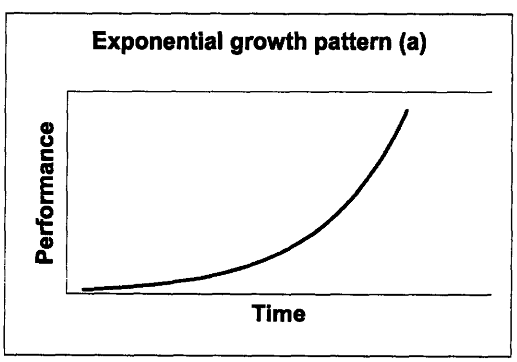
The four patterns of behavior shown in Figure 1-3 are the basic behavior modes of a simple system. They show up either individually or in combinations.

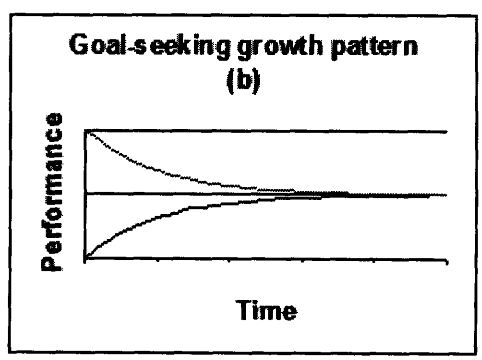
Figure 1-3(a) represents an exponential growth trend. In real work processes, the growth may not follow this pattern exactly, but the basic idea of accelerating growth is observed. When positive feedback exists in a system, the behavior often goes in the manner.

With goal-seeking behavior (Figure 1-3 (b)), the system starts either above or below a goal level and moves toward the goal over time. When a single negative feedback exists in the system, the behavior usually follows this trend.

With S-shaped growth (Figure 1-3(c)), initial exponential growth is followed by goal-seeking behavior, which results in the variable leveling off. A complex system with both positive and negative feedbacks could behave like this.

With oscillation (Figure 1-3(d)), the quantity of interest fluctuates around some level. Note that oscillation initially appears to be exponential growth, and then it appears to be s-shaped growth before reversing direction.





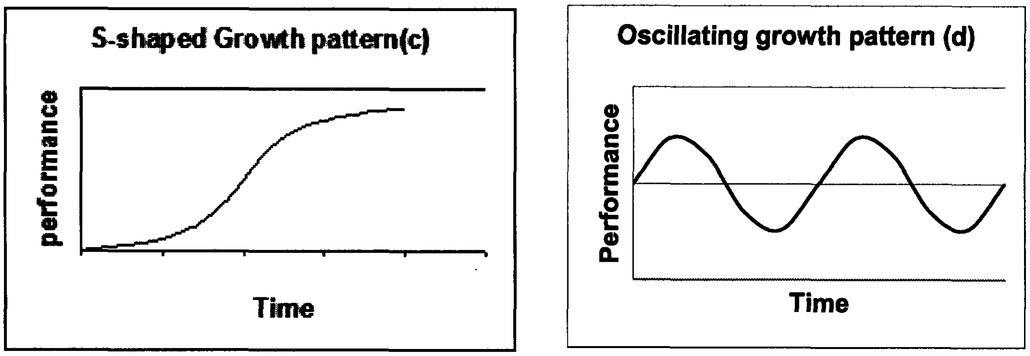


Figure 1-3 Characteristic patterns of system behavior

1.2.1.3 Framework of System Dynamics

In order to study system behavior, it is necessary to first represent the underlying system structure using some notation based upon our knowledge about the system. The notation used in system dynamics modeling is often called the 'causal loop diagram'. It visually defines the causal relationships between the system variables using loop diagrams.

Figure 1-4 shows an example of a causal loop diagram. It describes a simplified workflow in a generic work implementation process, a local workflow in some sector. The project will be finished when all the work moves from "Work to be Done" to "Work Completed". The rate of the flow, which is the "work completion rate", is determined by the "workforce" and "productivity". When the work lags behind schedule (work completed is less then scheduled work completed), the schedule pressure increases, requiring the hiring of more workers in order to catch up with the original schedule. However, a large workforce can produce a human resource redundancy, so that the production cost is increased and productivity actually goes down.

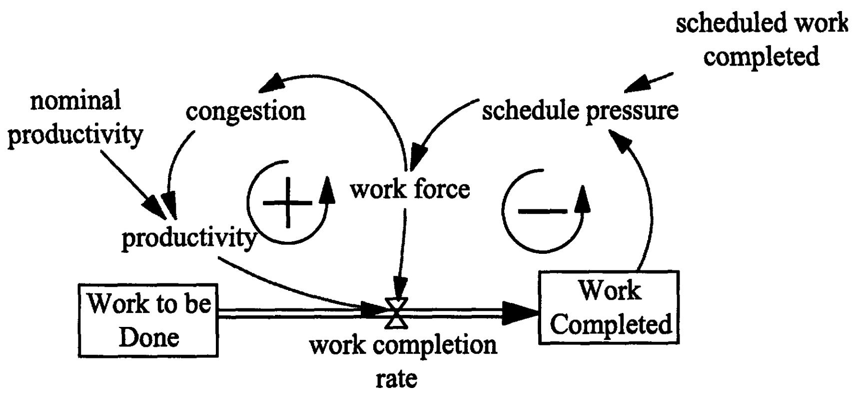


Figure 1-4 Casual loop diagram for a simplified work flow, (Source: [5])

This typical causal loop diagram can be taken as an example to illustrate the different types of variables used in system dynamics models: levels, rates, auxiliary variables, data, and constants.

Levels: Also can be termed as stocks, accumulations, and states. Levels describe the magnitudes of conserved entities. The values at some time depend on the historical integration of both the input rate and output rate, so they have memory for the history. The variables "Work to be Done" and "Work Completed" in Fig. 1-4 are Levels. Equation 1-1 shows how the Levels integrate or "accumulate" based upon the values themselves and other variables in the system. The magnitudes of the Level variables ultimately determine the dynamic behavior of a system as follows:

$$\begin{aligned}&\text{Work Completed}(t) = \int_0^t \text{work completion rate}(t)dt \\ &= \text{Work Completed}(t - dt) + \text{work completion rate}(t - dt) \times dt\end{aligned} \tag{1-1}$$

Rates: Rates are the variables that directly change the magnitude of the Levels. They determine the rate of change of the conserved quantities. The "work completion rate" in Figure 1-4 is a rate variable.

Auxiliary: Auxiliary variables provide the information needed to calculate the magnitude of the rate variables. They are computed from Levels, Constants, Data, and other Auxiliaries.

Auxiliary variables have no memory. The "schedule pressure" in Figure 1-4, for example, is an Auxiliary variable. The equation for it is:

$$\text{schedule pressure}(t) = \frac{\text{schedule work completed}(t)}{\text{Work Completed}(t)} \tag{1-2}$$

Data: These are also called exogenous variable. Data are input variables and their values at any time are already known. The "scheduled work completed" is a Data variable. Its values as a function of time are specified before the simulation.

Constants: These are variables that do not change with time. For example, the "nominal productivity" in Figure 1-4 is a Constant variable.

One of the most important features of system thinking is that of feedback. Feedback is defined as the transmission and return of information. Actually, feedback is no more than a set of causal relationships between some variables, yet as a whole they form a 'loop', meaning that the information returns to where it originated. Depending upon the relationships between variables, the returning information can amplify or attenuate the initial information more by forming either a "reinforcing" or a "balancing" feedback.

The system structure can be constructed with such causal loop diagrams, which link together all the variables involved in the system to indicate the network of their relationships. At the same time, the relationship among the variables is governed by quantitative equations, which is called "quantification". Equations 1-1 and 1-2 are examples of quantification.

When the model is built and quantified, it can then be used to simulate the system that is represented. Based upon inputs entered into the model and the knowledge already built about the system, the model can provide a dynamic activity of each system variable based on initial conditions.

1.2.1.4 System Dynamics Software

The methods of system dynamics are generic, but their implementation requires the use of specific computer software. A number of different software packages such as Ithink/Stella®, DYNAMO®, PowerSim®, and Vensim® are available to build system dynamics models. Vensim® are used in the work presented here because:

(1) It supports a compact, but informative, graphical notation;

(2) Vensim equation notation is compact and complete;

(3) Vensim provides powerful tools for quickly constructing and analyzing process models;

(4) Vensim provides a full Dynamic Link Library of functions (Dlls), making it very easy for a third-party development platform to integrate its features and to develop customized applications, which is part of the work in this thesis.

1.2.2 ORSIM Model

The model that we are going to use is ORSIM (Nuclear Power Plant Operations and Risk Simulator). The operational component of ORSIM is derived and modified from a HGK Associates product called OPSIM (Nuclear Power Plant Operations Management Simulator), which was originally proposed by Professors Michael Golay and Kent Hansen in the Nuclear Science and Engineering Department at M.I.T. [6]. As a continued and supplemental work, the risk evaluation function and performance matrix was developed by Dr. Haibo Chen, also from M.I.T, who mainly proposed that hardware risk be treated as dependent upon plant material condition. To specify the function of HRA as well as the holistic system PRA in this model, the consideration of human error rate analysis is integrated into ORSIM, which will be demonstrated in chapter 3.

The modeling methodology applied in ORSIM is System Dynamics. With the System Dynamics technique, ORSIM quantifies the effects of mutual feedback relationships in the coupling of the teams who perform nuclear power plant operations, planning, maintenance, engineering, and management, etc.

CHAPTER 2 –ORSIM MODEL

2.1 Introduction

The ORSIM model replicates the organizational structure of a typical utility and the activities carried on in the course of plant operation. The organizational structure is divided into small units representing different administrative sectors that include management, operations, engineering, maintenance, human resources and planning. All of them interact with each other as well as with the plant's physical systems.

The basic structure of the model is, in all sectors, the work flow which can be described by the relevant work input rate, output rate, and work inventory. Generally, within a typical sector, the work generation rate is governed by a series of specific mechanisms such as the physical system condition. The inventory or backlog of work to be done is the net accumulation of the input and output rate. The work accomplishment rate is fixed by the productivity of the workforce, and so on. The basic framework of the work flow is shown as Fig. 2-1.

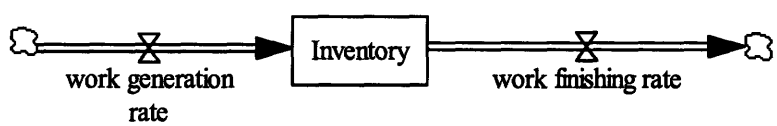


Figure 2-1 Basic work flow

The workforce in each sector is composed of sector managers and supervisors, sector professional staff, and sector support staff. The model contains a central management sector that represents the key policy makers in the plant. Workers are allocated to different tasks based upon work priority algorithms. These priorities can be modified to simulate different workforce allocation policies.

The logic of the model can be described in some details. The plant physics performance indicators, such as defect generation rate and material condition, and human performance indicators, such as workforce productivity and quality, are set up and represented as dynamic variables that change continuously throughout the simulations. These variables jointly determine the plant general operation conditions in terms of availability, stability, and reliability. Through building the relationship between performance indicators and plant operation condition, a matrix of time–dependent general performance indices is developed to measure plant safety as a function of continuous operation. The matrix includes a reliability index, an economic performance index, and plant stability indices.

All model variables are named according to the following convention:

- 'y': Variables starting with 'y' are lookup variables that define nonlinear functions with numerical parameters (where the parameters are the x- and y-axis values). Example: "y defect generation rate due to old equipment effect"
- 'D': Variables starting with 'D' are constant variables. Example: "D number of reactors"
- 'i': Variables starting with 'i' are constants that represent initial values. Example: "i old equipment" represents the quantity of old equipment in the beginning of the simulation.
- 'x': Variables ending with 'x' are one-dimensional vectors that have several elements. Example: "D equipment x", which represents the quantity of equipment covered under different programs. It has three elements: STP, PMP, and OTHER (the definition will be introduced later).
- 'xx': Variables ending with 'xx' are two-dimensional vectors that have several elements in both dimensions. Example: "D supervisor time distribution xx", which represents how the supervisors in different departments allocate their time to different responsibilities.

Now, the subsystem models will be introduced separately.

2.2 Subsystem Modeling

2.2.1 Physical System Sector

A nuclear power plant has a large number of structures, systems, and components (SSCs). They function together in order to produce electricity in a safe and reliable manner. Because the physical system is treated as an abstract individual interacting with humans, the average status of SSCs, such as the defect generation rate, should be addressed instead of the specific physical features.

Thus, the general aging and degradation behavior of SSCs needs to be modeled. The defect generation rate increases as SSCs age or as the inventory of defects grows. Also, as symptoms of the physical systems, transients and trips are modeled to reflect the working conditions of the physical systems.

In the ORSIM model, the maintenance of SSCs are separated into three programs: Surveillance Testing Program (STP) covers safety-critical SSCs that, by NRC regulation, are required to be tested periodically; Preventive Maintenance Program (PMP) covers safety-important SSCs, and Other (OTHER) Program covers all SSCs not covered in either STP or PMP. It is assumed that SSCs covered under the same program share the same characteristics.

Figure 2-2 shows the defect creation mechanism for the physical system. Defects flow into the backlog of 'Undiscovered Defects' with a 'defect growth rate x', which is determined by the total quantity of equipment ('D Equipment x'), probability for a piece of equipment to develop a defect in a unit time ('hazard rate defect generation x'), and the time span ('time step'). Here we assume that defects only occur during plant operation (when 'plant state' equals unity, which indicates the 'on' state).

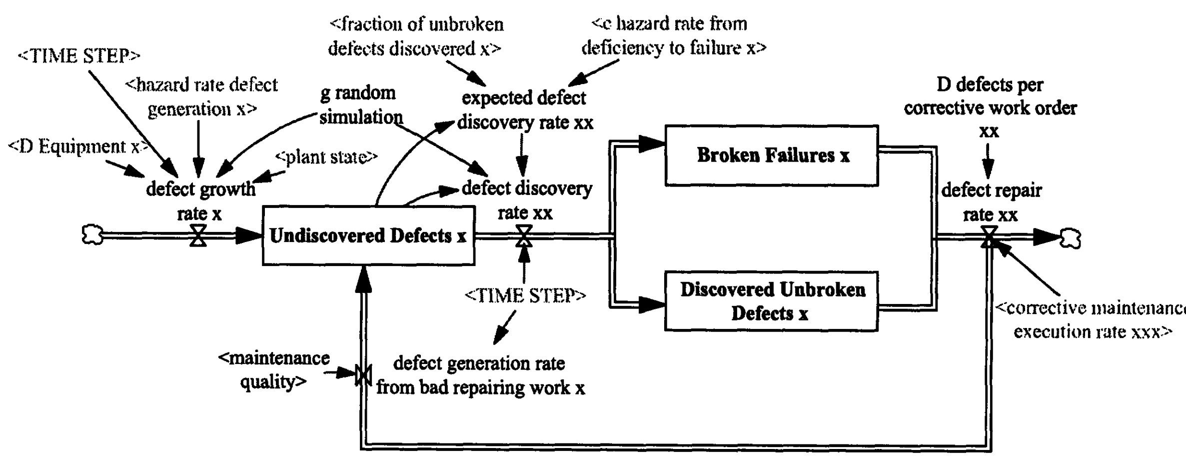


Figure 2-2: Flow diagram of physical system defect generation, identification, and restoration

These undiscovered deficiencies are identified at 'defect discovery rate xx' either after they break, or before they break through inspections, preventive maintenance, and plant walk-downs. This rate is therefore determined by the likelihood that a defect breaks down a SSC ('c hazard rate from deficiency to failure x'), and the likelihood that a defect is identified during inspection, preventive maintenance, and plant walk-downs ('fraction of unbroken defects discovered x').

Once identified, defects flow into 'Broken Failures x' or 'Discovered Unbroken Failures x' and consequently, work is generated in the maintenance sector. Based upon the priority of the work, it will be performed either immediately or after some time delay. The repair activity brings equipment with defects back to a normal state at 'defect repair rate xx'. Because of the imperfect quality of repairing work, a repaired defect may flow back into the "Undiscovered Defects" if the defect is not repaired properly or if some deficiency is introduced in the course of the repair.

Another key point is how defects are generated, or, how to compute the hazard rate, which is the likelihood that a piece of equipment develops a defect within a unit time. In ORSIM, it is assumed that the arrival of defects follows a non-homogeneous Poisson process that is influenced by wear and tear, poor-quality parts installed during repairs, workmanship errors caused by maintenance staff when performing their work, and the material condition of the plant. The latter has relevance because poor material conditions may place undue stress on components and lead to premature defect generation.

As time goes on, equipments grow older and older. However, it is assumed that the age of equipment is reset to zero every time after it successfully undergoes surveillance test or is preventively maintained. At such time, it flows out of existing 'Equipment x' and re-enters immediately as new equipment.

2.2.2 Maintenance Sector

Maintenance begins with identification of deficiencies in SSCs. The existence of deficiencies is discovered by several mechanisms, i.e., inspections, preventative maintenance, observations, or breakdowns. To some extent, the defect and broken discovery rate is influenced by the organizational structure and operational procedures.

To remove a defect systematically, it is required to sort the defect according to its safety significance. Defects in each category may generate additional work. For example, planning and scheduling of the repair is necessary. The repair also creates coordination work with other sectors, e.g. engineering and operations. Finally, it may be necessary to inspect and approve the repair. This review may lead to rework which is a form of feedback.

The types of work in the maintenance sector include surveillance testing, preventative maintenance, planning and scheduling, and four kinds of priority level repair work. Priority 1 repair work is focused upon acute safety problems, priority 2 repair work is focused upon keeping the plant operating, priority 3 repair work is focused upon corrective maintenance work orders, and "Quick-fix" or tool pouch repair work is focused upon simple maintenance work. Priority 1 work is the highest priority and represents problems that might affect plant safety. In most plants, such work is rare and therefore does not go into the ORSIM model. Priority 2 work is the second most important and corresponds to problems that affect operation severely, an example of which is a coolant pump failure. This type of event occurs occasionally in each operation cycle. Priority 3 work is routine corrective work. The work is sufficiently complex so that it requires planning, scheduling, and coordination with other sectors. The lowest priority work is quick-fix, or 'tool pouch' (many call it 'FIN' for 'fix it now'), which represents the simplest repairs that can be done without planning and scheduling. From past operating data, the fractions of each category can be obtained.

In ORSIM, surveillance testing and preventative maintenance are assumed to require a constant level of effort. Priority 2 (P2) and 3 (P3) repair work's generation rates are determined by defect discovery rate, and varies as a function of time, as does the quick-fix work. To be convenient, we unify priority 2, 3, and quick-fix work to the category of corrective maintenance work.

Work flow in a maintenance system is shown in Figures 2-3 and 2-4. After each defect is identified, the work then flows into stocks of different categories and is recorded as work orders. Scheduling and planning, if necessary, will be performed before the execution of these work orders. The execution of the repair work requires allocation of manpower to the tasks. The number of workers assigned is determined by the task's priority and worker availability. Only workers that are idling or those that are finishing up their work orders can be allocated to perform incoming work orders. The time to finish a work order is random, governed by a distribution with the expected value determined by average worker productivity. Once a work order is performed, it leaves the system.

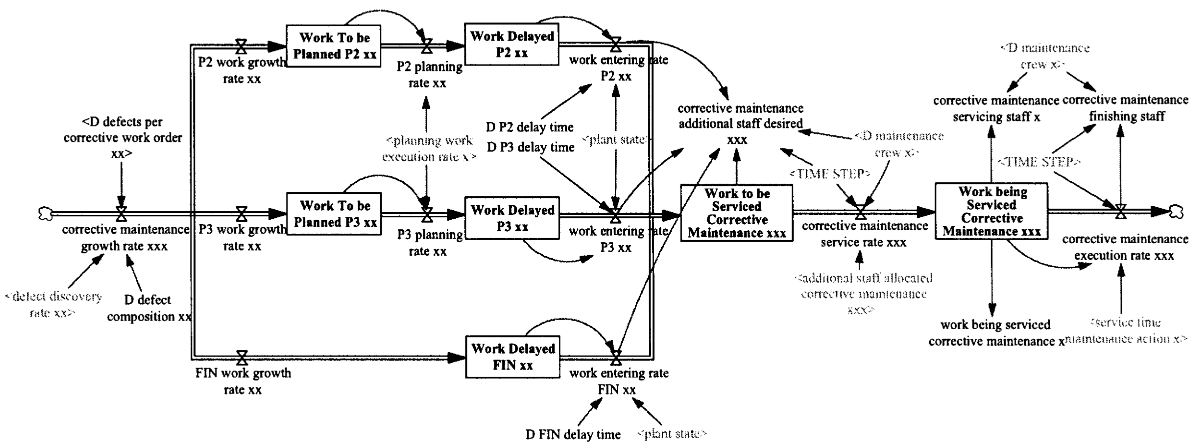


Figure 2-3: Corrective maintenance work includes 3 types: priority 2, priority 3, and tool pouch

Surveillance testing (ST) and preventive maintenance (PM) work orders are known in advance. ORSIM sets the amount of work to be done at the beginning of each refueling cycle. Before execution, some planning effort is required. The planned work orders then wait in line to be serviced, and leave the system once they are completed.

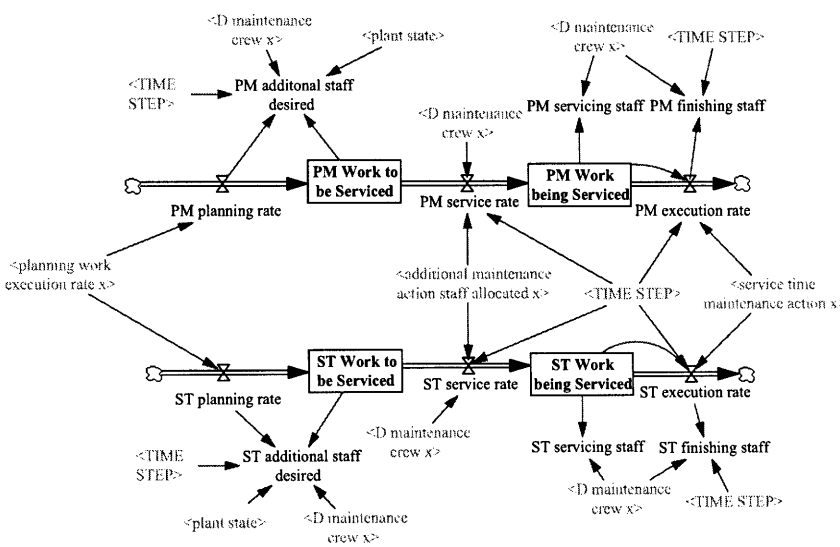


Figure 2-4: Surveillance testing and preventive maintenance work flows

The allocation of maintenance workers is worthy of mention. Priority rules function here when the number of workers is less than that which is desired for all tasks. One typical rule applied in NPPs is P2>PM> ST>P3>FIN. Certainly, training is the most important task and is ranked above others, which is required for the workers. For the same category of work, broken defects are fixed first, then unbroken defects. For same-category-work coming from different programs, workforce is assigned to work orders from a different program. One example is STP>PMP>OTHER.

All sector staff is classified into journeymen and apprentices to represent varying degrees of technical or management skill, which impacts the values of productivity and the quality of the work that they perform. Productivity and quality of maintenance should be paid considerable attention because they are indicators of human performance and directly dominate plant safety. In ORSIM, productivity and quality of maintenance staff work are represented by a set of time-dependent variables.

Productivity is determined as shown in Figure 2-5. Starting with a nominal productivity, ORSIM adjusts it up or down by multiplying influence factors associated with human performance indicators, including worker skills, management efficiency/availability, supervisor availability, workforce training, and support and coordination from the operation sector and engineering sector, etc. The data regarding the look up function between the influence factors and the human performance indicators are needed here. They could be obtained either from the databases from previous studies or the surveys from technicians, operators and other experts involved in NPP operation.

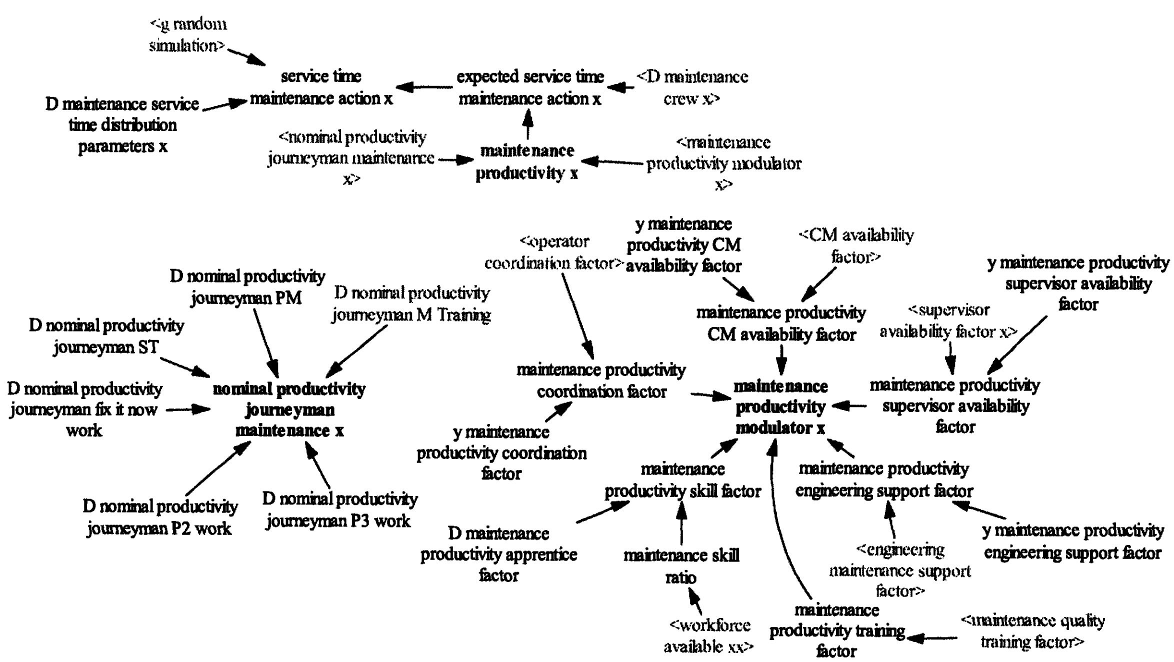


Figure 2-5: Maintenance productivity

Also, maintenance quality, which is a measure of what fraction of the work is done correctly the first time and will not require re-work, is explored. The logic of maintenance quality is similar to maintenance productivity.

2.2.3 Operation Sector

Each nuclear unit has a supervisor, control room operators, and auxiliary operators who operate the equipment. At multi-unit stations there may be a shift manager responsible for the entire site. While the unit is operating, some activities that the operators perform include testing safety-significant emergency equipment, supporting maintenance activities, performing minor maintenance, and processing radioactive liquids and gases. During a refueling outage (conducted every one to two years), the operators manipulate the fuel and transfer new fuel into the reactor while removing old fuel from the reactor.

Figure 2-6 shows work flows in the operation department. The tasks include operating, coordination, and training. The number of operators desired for each task is decided by how much work is created per week and how much work an operator can perform in a week. Operators then are assigned to different tasks. When the number of available operators is less than desired, priority rules are applied.

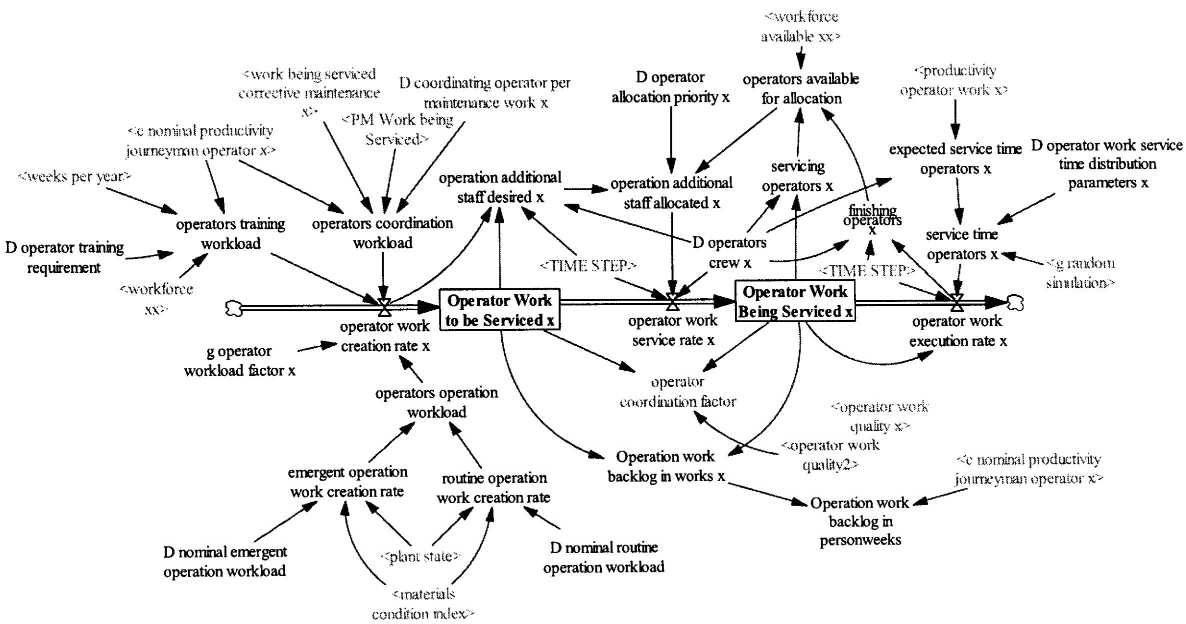


Figure 2-6: Operation sector work flows

The "operator coordination index" is described as the ratio of the actual number of operators assigned to do coordination work to the number of operators needed to do coordination work. It reflects the degree to which the maintenance workers can effectively obtain coordination from operators when needed.

The knowledge, skills, and ability requirements for reactor operators are specified by the NRC. Licensed operations personnel must go through ongoing re-qualification training throughout the year to demonstrate their competence. Included in this training is periodic emergency drill training on a full scope simulator of the control room. Training, as well as operator skills and management availability affect the quality and productivity of operation work in the same manner as in the maintenance sector.

2.2.4 Engineering Sector

Functions that the engineering sector performs include unexpected workloads (surprises), plant modification, licensing, maintenance support, and information selection that includes googling, reading, attending seminars and conferences, etc. Training work always stays in the first priority rank.

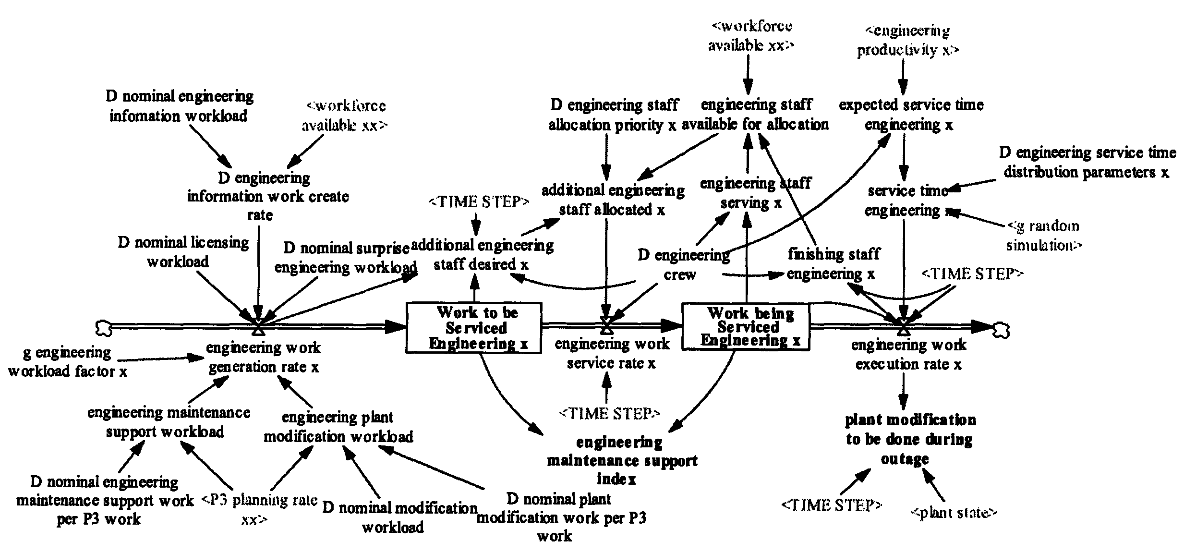


Figure 2-7: Work creation and execution in the engineering sector

Figure 2-7 represents the work creation, engineer allocation, and work execution in the engineering sector, which follows a procedure similar to the operation sector. From past operating data, we can derive, on average, how much licensing and information work needs to be performed in a given time period. Maintenance support and plant modification workloads here are produced from priority 3 maintenance work. It means that the maintenance work on major components deserve engineering support and engineering modifications work from engineers. While all types of work mentioned previously are generated internally, the exogenous part of the work is reflected by the surprise work.

2.2.5 Planning Sector

The planning sector performs maintenance scheduling as well as outage planning tasks. The types of work therefore include planning for surveillance testing, preventive maintenance, corrective maintenance, and outages. When resources are not enough to meet demands, priority rules are applied to allocate resources to different tasks. (Figure 2-8)

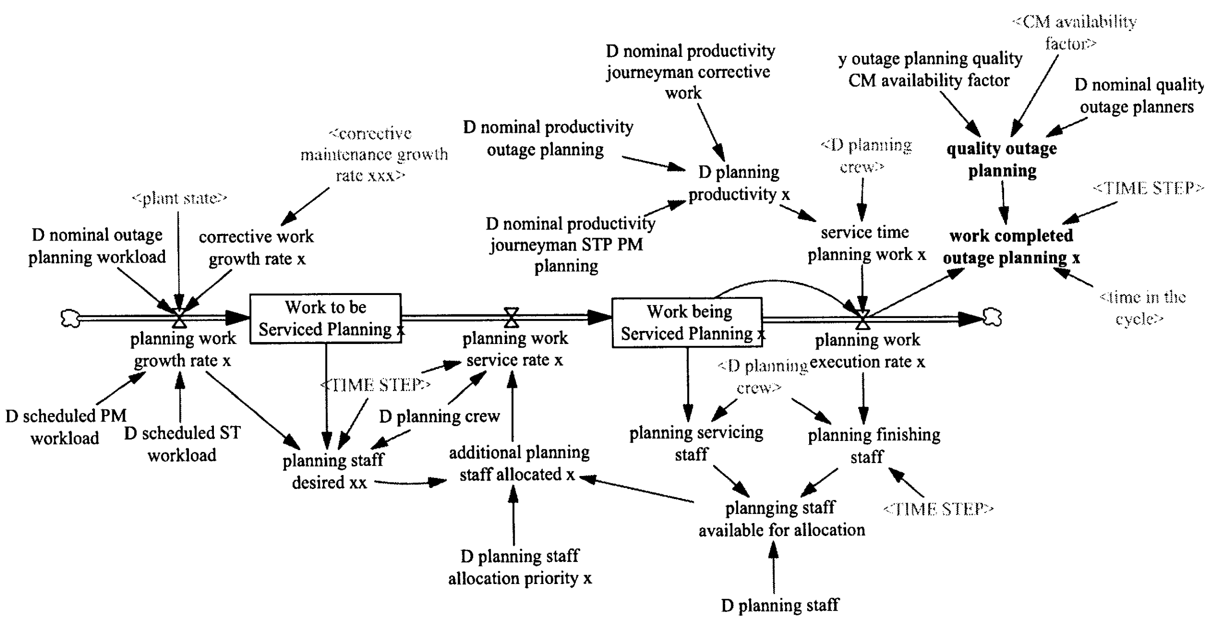


Figure 2-8: Planning work creation and execution

In the planning sector, outage planning is often at the lowest priority. However, it is quite important because good outage planning can shorten the real outage periods so that economic performance is maintained. In order to smooth and shorten an outage period, outage planning starts long before a planned outage takes place. ORSIM does not model activities during an outage period, but instead models the planning of outages and estimates the length of outage periods in the normal operation period. Once an outage begins, ORSIM assumes that the outage goes smoothly and is finished within the scheduled time. It is also assumed that the NPP and relevant maintenance, operations, engineering, and other functions and activities restart after the outage period.

2.2.6 Management Sector

Central management is defined as the set of senior managers who have oversight for the entire plant. Figure 2-9 is a causal loop diagram of the work creation and accomplishment for the central management of an NPP.

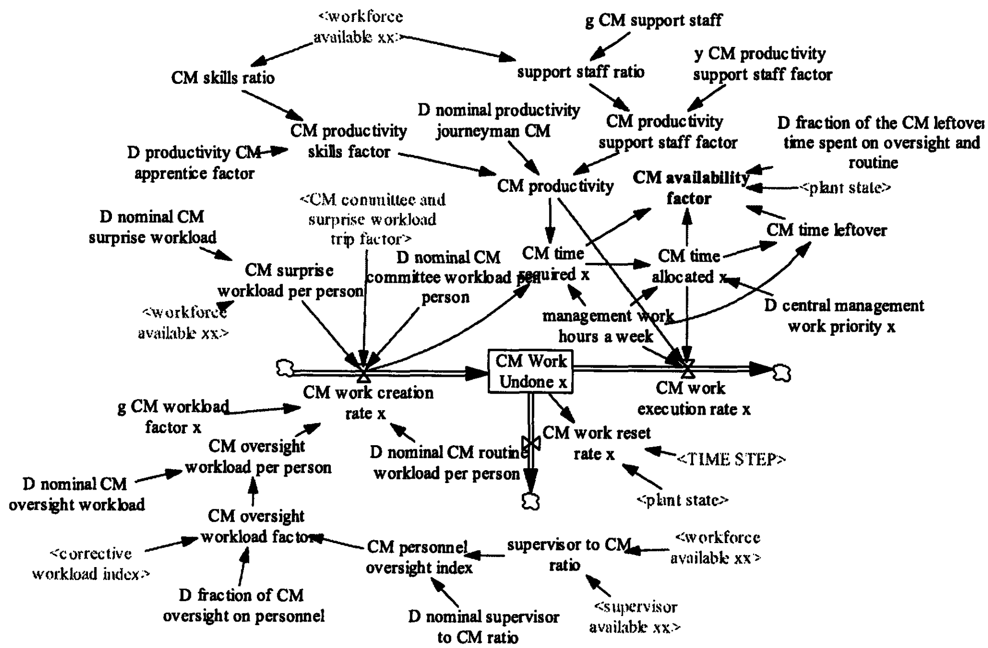


Figure 2-9: Central management work flows

Managers are required to attend many committee meetings where information about the plant, personnel, and the rest of the utilities' activities is updated. In addition, management is involved in dealing with unscheduled and/or unanticipated work that can be designated as "surprises". Finally, managers must deal with issues that emerge from other sectors of the plant organization, i.e. service and maintenance, operations, engineering, etc. The work created is termed "oversight" because of central management's role in overseeing the organization. Finally, "routine" work represents the routine daily work for managers, such as paperwork, replying to emails, reading reports, etc.

Central management availability for oversight is the point where central management interacts with other sectors. It is described as the ratio of the actual number of managers allocated to oversight and routine work to that desired for oversight and routine workloads. Managers are allocated to different tasks according to specified priority rules.

The work flows for the supervisory staff are similar to those for the central management staff.

2.2.7 Human Resource Sector

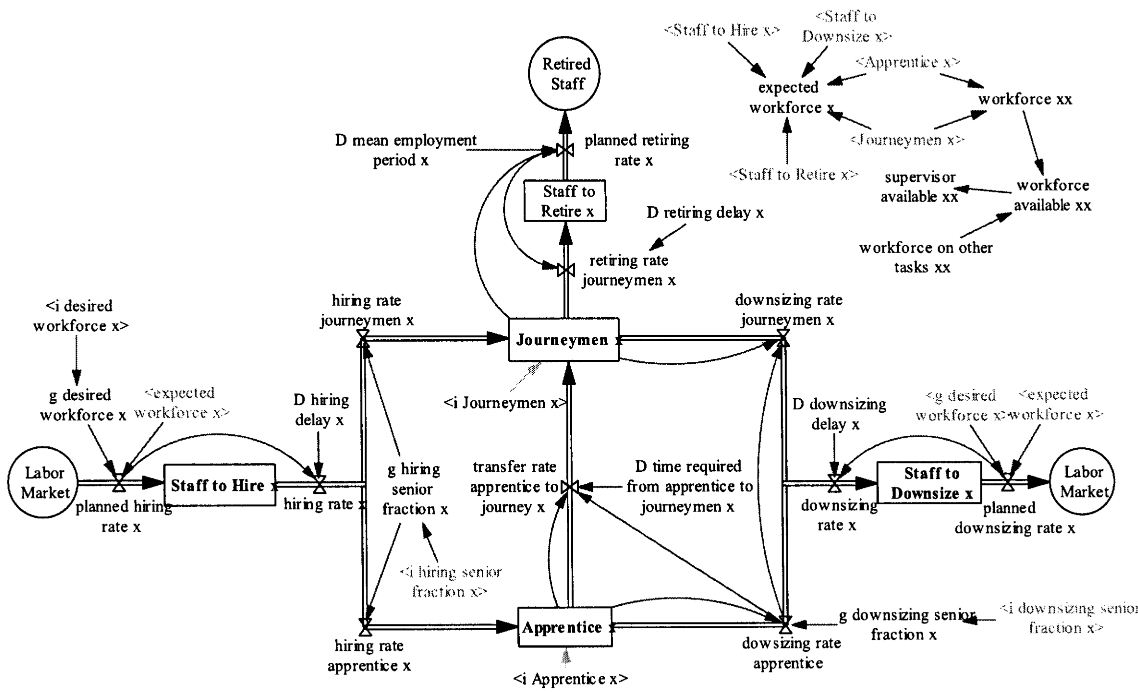


Figure 2-10: Manpower flow

All sector staff can be sorted into journeymen and apprentices to represent varying degrees of efficiency/skill. The evolving process of manpower is represented in Figure 2-10. The population of journeymen increases because of hires or promotions. It decreases because of downsizings, retirements, and departures. The ratio of worker population in different skill levels is emphasized because it influences the productivity and the quality of the work.

Once staff is hired, an inflow to 'Journeymen' or 'Apprentice' will occur dependent upon individual skills and experience. Apprentices are promoted to Journeymen after a number of years, and journeymen, if not downsized during their stay, will ultimately retire from their jobs after the "mean employment period". Of course, it is possible for both journeymen and apprentices to be downsized at any point in time, in which case they go back into the labor market.

2.2.8 Performance Evaluation Function

A matrix of variables is used to reflect plant performance as a function of continuous operation. This matrix includes reliability, economic, and stability.

2.2.8.1 Reliability Performance

In the ORSIM model, the conditional core damage probability (CDF) index is modeled to quantify operational risk. The CDF index is a ratio of the conditional CDF to the nominal CDF. The nominal CDF is defined with the assumptions that (1) no failure occurred and (2) a nominal human failure probability condition; the conditional CDF considers (1) broken failures and (2) an actual human failure probability condition. The quantitative relation between the situation how much broken failures occur in the system and the CDF index can be referred to reference [5]. Actually, the CDF index is determined by both hardware conditions and human actions. Human error probability is a significant issue in NPP operation. Also, its inclusion is a significant improvement in the updated model, which will be discussed in detail in chapter 3.

In addition, transient and trip events are used to represent the reliability aspect of NPP operations here.

The conditional transient frequency is proportional to the designed or base transient frequency with the same coefficient as CDF, that is the CDF index. After a conditional transient frequency is calculated, we can perform a random draw based on this expected value to determine whether or not a transient event will occur within time period (t, t+ dt).

The same strategy is applied in trip event modeling except for one difference. The probability of a trip given a transient event can be estimated from historical operation data. Hence, we only need to obtain the transient frequency (*TF*) in order to calculate the reactor trip frequency:

$$Trip\ Frequency = P(Trip \mid Transient) \times TF \qquad (2\text{-}1)$$

Figure 2-11 shows the logic of transients and trips in ORSIM:

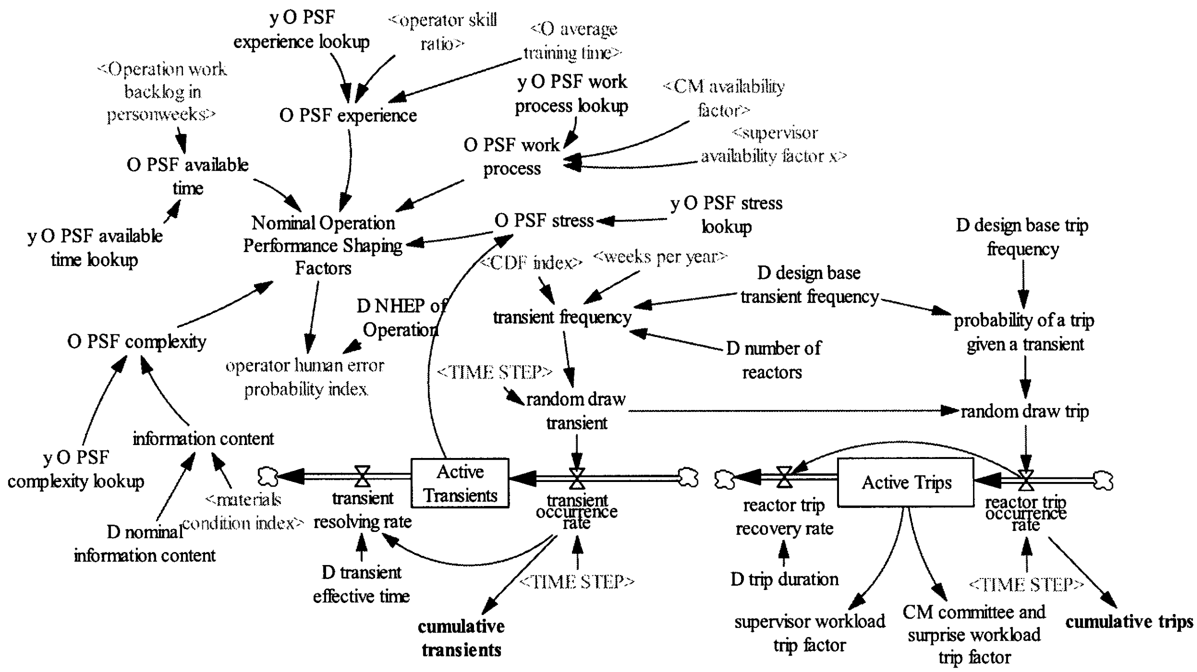


Figure 2-11: Transient and trip event frequencies

2.2.8.2 Economic Performance

Outages, whether expected or unexpected, will shut down NPPs and incur economic losses because of the inability to produce revenues from electricity production. This is represented in Figure 2-12, where two components of economic losses are shown. One is electricity loss from scheduled outages. Another loss is from unexpected trips. The losses per unit time depend on the capacity of the NPP.

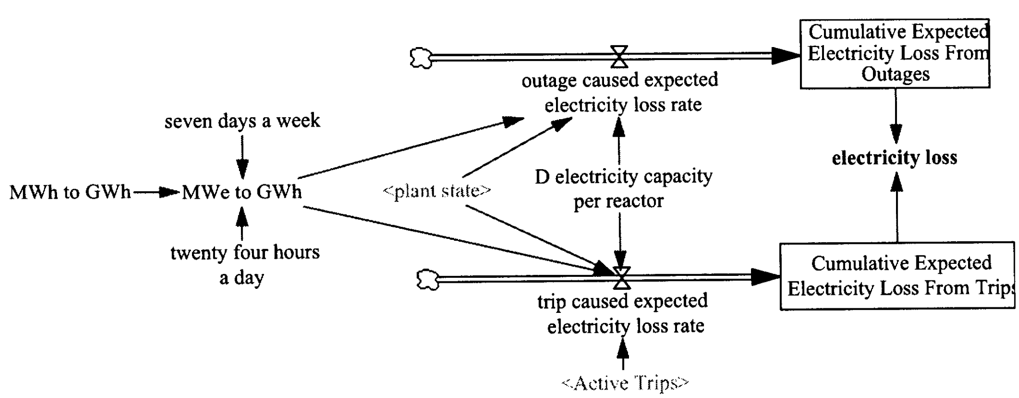


Figure 2-12: Electricity loss can be caused by either a planned outage or an unexpected outage (trip)

2.2.8.3 Stability Performance

Stability performance measures the stability of the system. A system is called stable when the work creation rate is less than the maximum work execution rate.

Work backlog can act as an indicator for this item. A smaller backlog is always preferred in a system. Further more, when the backlog converges to a steady state value, we say the plant is able to maintain stable operation.

In addition, a series of stability indices was developed to fulfill the same function from the workforce point of view (Figure 2-13). They measure the workforce margin in every sector and are a function of the expected work arrival rate, average work execution time, and number of workers available.

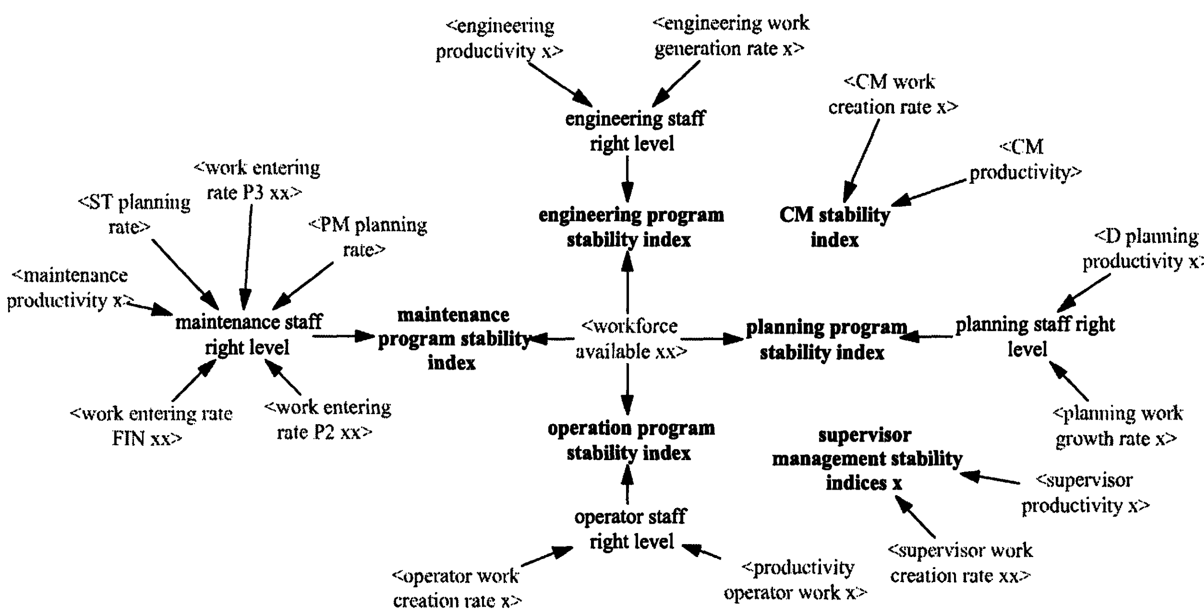


Figure 2-13: Maintenance program stability index

CHAPTER 3 – THE APPLICATION OF HUMAN RELIABILITY ANALYSIS IN ORSIM

3.1 Introduction

Human performance study of NPPs involves many research areas ranging from individual to organizational performance, as well as from human resource optimization to safety issues. The previous version of the ORSIM model, as introduced in Chapter 2, exhibits a global layout of NPP operating systems, tracks aspects of organization and management policy, and depicts a macroscopic workflow chart. Regarding the evaluation of personal performance, work quality and productivity associated with each sector are employed as the indicators to measure human performance from the perspective of work efficiency. As a critical objective, safety and reliability performance of the NPP has been emphasized. However, most work is focused on the physical part, and much attention is paid to determining the relationships between the system's material conditions and the system's hardware reliability. On the contrary, human reliability is often treated in a superficial manner.

Human error probability (HEP), which is an important human performance measure directly linked to NPP safety, is studied in the fields of human reliability analysis (HRA) as well as in probabilistic risk analysis (PRA). As a necessary supplement and enhancement, the in-depth investigation of HEP in ORSIM is considered a major work in this thesis, and will be elaborated open in this chapter. Within the complex ORSIM networks, the relationship between the existing human performance indicators and the holistic NPP reliability index is explored and established. Through the system dynamics modeling technique, the HRA module is modeled and then integrated into the previous ORSIM. The time-dependent HEP index is obtained as a result.

The Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) was set up in 1999, and became the up-to-date and prevailing HRA method for NRC when performing risk-informed regulatory activities. As a simplified approach, SPAR-H does have inherent modeling and analysis limitations compared with other more sophisticated methods, e.g. ATHEANA, in situations that require detailed analysis from the human performance perspective for an event.

However, the positive features of SPAR-H include: (1) consistency with other former HRA approaches in error types, base error rates, effects of performance shaping factors (PSFs) and dependency factors; (2) simplification in that it is applied only by completing a straightforward worksheet [7]. ORSIM is concerned more with the dynamic safety performance of a team in a statistical average than with the failure rates of specific elements or the evolvement process of a single post-initiator human failure event. Hence, SPAR-H is qualified to perform the analysis in this context. During the course of analysis, the thinking of PSFs is employed. PSFs, defined as influence factors related to human actions in the HRA frameworks, are connected with the existing human performance indicators in ORSIM, so that the HEP can be described dynamically as a function of the existing variables in the system.

3.2 HRA Orientation

Swain and Guttmann (1988) defined human reliability as the probability that a person (1) correctly performs an action required by the system in a required time and (2) that he does not perform any extraneous activity that can degrade the system. Any method by which human reliability is assessed may be called a human reliability analysis (Swain, 1990). HRA is performed as both a qualitative and quantitative analysis. It helps the analyst to study human system actions and to understand the impact of those actions on system performance and reliability. The analysis process typically includes the following steps: (1) identification of human actions, (2) modeling of important actions, and (3) assessment of probabilities of human actions. PRA, in conjunction with HRA, gives analysts the tools to deal with a series of parallel pathways with potential vulnerabilities, with consideration of the human contribution to that risk.

HRA study was initiated after the Second World War, when a considerable acceleration occurred in military technology. The first HRA study was carried out in 1952 for weapon systems feasibility of Sandia National Lab, USA. Development of the HRA was related to an increased use of general safety and availability analysis methods. The first probabilistic study for an NPP sitting program was presented in the 1960s. In the mid 1970s, a large probabilistic safety assessment that included human reliability analysis, WASH-1400, was published by the NRC. The majority of HRA methods were developed in the mid 1980s, mainly as a consequence of the concern caused by the accident of the Three Mile Island NPP. Partly because of the conditions under which it was developed, HRA methods initially followed procedures similar to those employed in conventional reliability analysis. The major difference was that human activities were substituted for equipment failures and that modifications were made to account for the greater variability and interdependence of human performance as compared with that of equipment.

Many different HRA approaches were developed in the last thirty years. HRA approaches can be classified according to (1) detail level of modeling, (2) treatment of black box and cognitive mechanisms, (3) treatment of time dependence, (4) treatment of contextual factors, and (5) the data used [8].

The detail level of modeling may be used to sort HRA methods into holistic, such as expert judgment approaches, and into decomposition ones, such as THERP (Swain & Guttmann, 1983) and ATHEANA (Cooper, 1996). The reason for selecting different decomposition levels is related to data availability (available on human actions as a whole or for different decomposed sub-actions), and also related to risk management, because more refined modeling could offer a larger space to reduce hazards. The black box model for HRA aims to assess the effect of human actions on system safety and reliability, while the cognitive model intends to explain human internal failure mechanisms, such as CREAM (Hollnagel, 1998). A time independent model, represented by THERP, is applicable well to human actions before an initiation event (IE) because the available time is not an important contributor to the success of maintenance and testing actions comparably. The TRC (time reliability correlation) model is applied to actions after IE, especially when the available time is limited. Another solution for modeling time dependence is to treat time as one PSF, such as SLIM-MAUD (Embrey, 1984). Performance shaping factors (PSFs) represent the effect of contextual factors on human failure probability. The number and types of PSFs in various methodologies vary significantly. Examples of PSFs are working conditions, stress levels, feedback from MMI, availability and quality of procedures, time, training and experience, etc. The applicability of PSFs is also related to HRA data. Either generic human reliability data are used directly in estimation and modified by using PSFs, e.g. the data in THERP, or plant specific data is directly utilized.

In support of the Accident Sequence Precursor Program (ASP), the U.S. Nuclear Regulatory Commission (NRC), in collaboration with the Idaho National Laboratory (INL), in 1994 developed the Accident Sequence Precursor Standardized Plant Analysis Risk Model (ASP/SPAR) for human reliability analysis method. Based on experience gained in field testing, this method was updated in 1999 and renamed as the Standardized Plant Analysis Risk-Human Reliability Analysis method (SPAR-H). Since that time, NRC staff analysts have been using this method to perform their risk-informed regulatory activities, such as determining the risk significance of inspection findings in Phase 3 of the Significance Determination Process, developing an integrated risk-informed performance measure in support of the reactor oversight process, and systematically screening and analyzing operating experience data in order to identify events that are precursors of severe accident sequences. As a result of implementation by staff analysts, and from other experience gained at the INL in applying the method to human reliability analysis, a number of improvements needed for definitions, terms, and concepts were identified. In the updated version of Year 2004, an approach to uncertainty representation was outlined based on the beta distribution. Additional details regarding human error probability (HEP) dependency assignment were also made available.

The SPAR-H method differs from less detailed HRA methods in that it requires analysts to consider dependency and a defined set of PSFs when performing quantification. For example, analysts using techniques such as the Failure Likelihood Index Method (FLIM) or the Success Likelihood Index Method (SLIM) are free to include any number of PSFs that they think might apply. The SPAR-H method also differs from some of the earlier time reliability curve (TRC) methods in that the SPARH method does not overly rely on time as the primary determinant of crew performance, but rather treats time as one of a number of important shaping factors that influence human performance. The SPAR-H method is straightforward and easy to apply. This simplified HRA approach contains a number of significant features including the calibration of its base failure probability and quantification of PSFs' influence based on other HRA methods. SPAR-H has been refined as a result of experience gained during its use in the development of over 70 SPAR PRA plant models for the NRC, in limited HRA applications for dry cask spent-fuel storage, in the implementation of risk-informed plant inspection notebooks, and through third party applications to other domains such as aerospace.

The method does not differentiate between active and latent failures. It is thought that the same PSFs and base failure probabilities are applicable to each type of error. The base error probability contained in the worksheets for actions and diagnosis includes omission and commission types of errors. This is in contrast to other more in-depth methods, such as ATHEANA which focuses on the identification and quantification of errors of commission. This feature satisfies the requirement and criteria of ORSIM modeling.

The range of effects used in SPAR-H reflects the treatment of the work process PSF in other HRA methods. For example, the range of effect for work processes in SPAR-H is bounded by identification of a range of effect for work process PSF in two methods, CREAM and HEART (Williams, 1992). Also the ORE/CBDT approach (EPRI TR-100259, 1992) provides the reference bounds for the effective range of available time PSF in SPAR-H. Thus, this approach is consistent with most other previous HRA methods.

Traditionally, the influence of multiple shaping factors with multiple levels generally requires imposing a high degree of expert consensus judgment on the HRA process. SPAR-H attempts to make the assignment of human error probability a more repeatable task and a less complex function that only an expert can perform. Given that a series of basic HEP and influence correct levels for PSFs are already set up, the HRA process is simplified so that the analyst only needs to discover the appropriate error and assign the correct level of influence factors (i.e., multiplier for the HEP). The HRA search process for determining unsafe actions given a particular context still remains a challenging task for the PRA/HRA analyst, but this is the information brought to SPAR-H for quantification. Generally, in the ORSIM context where all specific events and evolving sequences are ignored, the SPAR-H approach as well as the relevant PSF elements can be a qualified candidate for HRA modeling [8].

3.3 SPAR-H Method and Application Analysis

The basic SPAR-H framework can be described as the following:

• Decomposing probability into contributions from diagnosis failures and action failures;

• Accounting for the context associated with human failure events (HFEs) by using performance shaping factors (PSFs) and dependency assignment to adjust the base HEP;

• Using pre-defined base HEPs and PSFs together with guidance on how to assign the appropriate value of the PSF;

• Employing a beta distribution for uncertainty analysis;

• Using designated worksheets to ensure analyst consistency.

3.3.1 Task Type

The SPAR-H method classifies human activity into two general task categories: action or diagnosis. For instance, action tasks include operating equipment, performing line-ups, starting pumps, conducting calibration or testing, and other activities performed during the course of NPP operation. Diagnostic tasks require knowledge and experience to judge existing conditions, plan and prioritize activities, and determine appropriate courses of actions. Base error rates for the two task types associated with the SPAR-H method were calibrated to match other HRA approaches. This means that SPAR-H human error rates fall within the range of rates predicted by other HRA methods. Specifically, this method takes 0.01 for the basic HEP of diagnosis, and 0.001 for action.

If the SPAR-H method is being used to evaluate a single basic event consisting of multiple actions and decisions, this type of failure event typically produces a higher HEP than diagnosis or action alone because these two activities can be treated as two independent elements in a series system. In the case of a typical NPP, an integrated task assigned to one person/team can be assumed to comprise 10 steps in a series, a combination of diagnosis and actions. The first step should be diagnosis, where the human is required to check the origin of the problem and ascertain a feasible solution. The following steps describe actions and a set of routine activities that are executed. Thus, the entire HEP for a task should be the sum of 0.011 and 9 times 0.001, that is 0.02.

3.3.2 Performance Shaping Factors (PSFs)

Historically, the first use of PSFs in HRA to adjust nominal or base failure rates was addressed in THERP. The current version of the HRA method also uses PSF information in one form or another when calculating HEPs. The SPAR-H method is built on an explicit information-processing model of human performance derived from the behavioral sciences theory that was implemented in studying activities at NPPs (Blackman and Byers 1994). Eight PSFs were identified in SPAR-H: available time, stress and stressors, experience and training, complexity, ergonomics or human machine interface (HMI), procedures, fitness for duty, and work processes.

Additionally, comparison matrices were created (one for the diagnosis error type and the other one for the action error type) that compared PSFs and their weight multipliers in the SPAR-H method with those in other contemporary HRA methods. For the comparison of the PSF context for each HRA method, refer to Appendix A. The detailed multiplier values of PSFs for SPAR-H as well as other peers are presented in Appendix B. PSFs for action and diagnosis can be found in Appendix C. When applied in ORSIM, because the average performance of a team in a sector is concerned, the classifications and values of PSFs sometimes deserve appropriate modification depending on the department and responsibility.

While many popular methods only address the PSF influence from a negative perspective, the SPAR-H method is one of the few that recognizes that a number of PSFs may have both a positive and negative effect on performance. That is, positive influences of PSFs can operate in some instances to reduce nominal failure rates. For example, superior experience and improved training can enhance the operator's understanding of the system status beyond the average or nominal case, whereas insufficient training always results in a higher error possibility. In other HRA methods, positive effects on PSFs are typically limited to the influence of time on task performance reliability.

The SPAR-H method assumes that positive effects may often be a reflection of the function of the negative effects of the PSF on performance. Error probability increases as the negative influence of the PSF increases. In contrast, error probabilities decrease as the positive influence of the PSF increases until some lower boundary is reached. Figure 3-1 describes this analytic relation and the influence of the PSF (x-axis) on mean human error probability (HEP) values (y-axis).

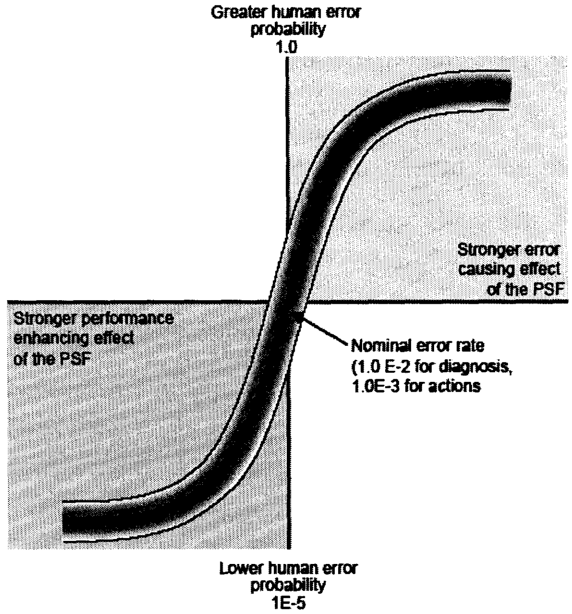


Figure 3-1 Ideal mean HEP as a function of the influence of performance shaping factors (Source: NUREG/CR-6883, INL/EXT-05-00509, "The SPAR-H Human Reliability Analysis Method", 2005)

To simplify, the effect of each PSF on the HEP for diagnosis or action task used in the SPAR-H method is evaluated through multiplication. Each PSF influence is treated independently, as is the convention in HRA.

The detailed description of PSFs is introduced as below:

• Available time

Available time refers to the amount of time that an operator or a crew is assigned to diagnose and act upon an event. A shortage of time can lower the operator's ability to respond or make a correct decision by considering alternatives. In the ORSIM model, there is no variable directly indicating the available time assigned to a task. However, an indirect indicator could be found to fulfill this function, such as work backlog per person per week. When the work backlog density is higher, workers are required to hurry. The quantitative relationship between work backlog density and available time in each sector relies on expert judgment.

• Stress and stressors

Stress has been broadly defined and used to describe negative as well as positive motivating forces for human performance. Stress used in SPAR-H means the level of undesirable conditions and circumstances that impede the operator from completing a task normally. Stress can include excessive workload, physical stress, or mental stress, which is expressed by muscular tension and general apprehension or nervousness associated with the importance of an event. Environmental factors are referred to as stressors, such as excessive heat, noise, poor ventilation, or radiation, which can affect the operator's mental or physical performance. It is important to note that the effect of stress on performance is curvilinear — some small amount of stress can enhance performance, and should be considered nominal, while high and extreme levels of stress will negatively affect human performance. In the operation sector of an NPP, stress usually comes from abnormal reactor activity: when transients happen, operators are inclined to suffer more intensive stresses. The stress factor in maintenance and engineering sectors is relatively moderate and unchangeable.

- Experience and training

This PSF refers to the experience and training of the operators involved in the task. Considerations related to this item include the skill or experience level of the individual or crew and training time during the past specified period. Fortunately, the ORSIM model already contains the related variables and they can be directly connected to this item.

- Complexity

Complexity refers to how difficult the task is to perform in the given context. Complexity considers both the task and the environment in which it is to be performed. The more difficult the task is to perform, the greater the chance for human error. Complexity also considers the mental effort required, such as performing mental calculations, memory requirements, and relying on knowledge instead of training or practice. Complexity can also refer to the physical effort required, such as physical actions that are difficult because of complicated patterns of movement. From the view of information theory, when the material condition degrades, or the hardware failure probability rises, the system information content will increase. Consequently, the task complexity will also be increased. This logic has been adopted in ORSIM.

- Ergonomics (including the human-machine interface)

Ergonomics refers to the equipment, displays and controls, layout, quality and quantity of information available from instrumentation, as well as to the interaction of the operator/crew with the equipment to perform tasks. Aspects of human machine interaction (HMI) are included in this category. The adequacy or inadequacy of computer software is also included in this PSF. Because all physical equipment is set up before the NPP started operation, the situation of ergonomics is a time independent factor in ORSIM unless specially mentioned. This element will not be considered in the HEP index study.

• Procedures

This PSF refers to the existence and use of formal operating procedures for the underlying tasks. Common problems for procedures include situations where procedures give wrong or inadequate direction regarding a particular control sequence. Another common problem is the ambiguity of steps. Similar to the ergonomics factor, procedures always follow a set of routine steps, and the influence is comparably stable. This element does not have an effect on the ORSIM HEP index.

• Fitness for duty

Fitness for duty refers to whether or not the individual performing the task is physically and mentally fit to perform the task at the time. Things that may affect fitness include fatigue, sickness, drug use (legal or illegal), overconfidence, personal problems, and distractions. ORSIM uses the average performance of the crew, so this factor should be kept at an unchangeable level and exert little influence on HEP variability.

• Work processes

Work processes refer to aspects of doing work, including inter-organizational activity, safety culture, work planning, communication, and management support and policies. If planning and communication are poor, individuals may not fully understand the work requirements. Work processes include consideration of coordination, command, and control. Work processes also include any managerial, organizational, or supervisory factors that may affect performance. Measures could include the amount of rework, risk worthiness of items in the utility corrective action program backlog, enforcement actions, turnover, performance efficiencies, etc. In the ORSIM model, supervisor availability, central management availability, and collaboration between sectors all bear an influence over the work process.

3.3.3 Application of Multiple PSFs

Reer (in OECD NEA 1998) and others noted that the application of multiplicative models when employing PSFs for calculating HEP is only approximately correct. The issue lies in the possibility that the calculated conditional HEP is greater than 1 when given multiple negative PSFs. A simple modification method is adopted here for the nominal error probability. It has been proved to meet mathematical requirements. The formula applicable to the adjustment of the nominal human error probability is:

$$HEP = \frac{NHEP \cdot PSF_{composite}}{NHEP \cdot (PSF_{composite} - 1) + 1} \qquad (3\text{-}1)$$

where NHEP is the nominal HEP. NHEP equals 0.01 for diagnosis, 0.001 for action, and 0.011 for the combination of diagnosis and action. This adjustment factor was used when three or more PSFs were assigned negative ratings. Thus, in situations where a strong negative context is present, we feel that it is possible to obtain sufficiently high HEPs.

3.4 Issue Analysis

3.4.1 PSFs Modeling in ORSIM

Based on the above discussion, the PSFs or HEP indices are employed in ORSIM to measure the practical HEP as contrasted with the nominal design-based HEP. The relationship between PSFs and human performance indicators in each specific sector are shown in Table 3-1:

Table 3-1 ORSIM variables used as PSFs for HEPs

Sector	Available Time	Stress	Complexity	Experience/ Training	Work Process
Operation	Operation work backlog	Active Transients	Information content	Operator skill ratio, Operator average training time	CM availability factor, Supervisor availability factor.

Engineering	Engineering work backlog	/	Information Content	Engineers skill ratio, Engineer average training time	CM availability factor, Supervisor availability factor.
Maintenance	Corrective maintenance work backlog	/	Information Content	Maintenance skill factor, Maintainer average training time	CM availability factor, Supervisor availability factor, Engineering- maintenance support factor, Operator coordination factor.

In comparison with the above modification to ORSIM, the previous version of ORSIM treated human reliability in a simplified way. The HRA was thought to be affected only by information content and work quality. As a comparison, the operator HEP indices from the two versions are shown in Figure 3-2:

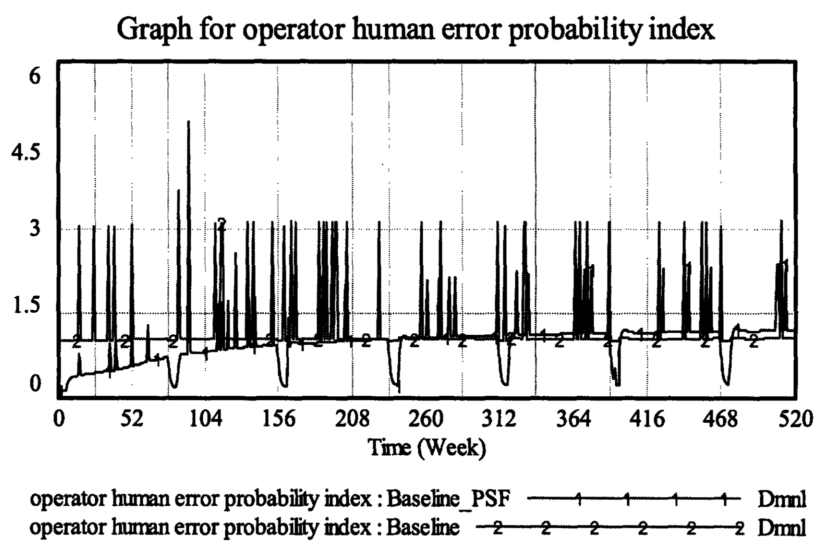


Figure 3-2: HEP index in operation sector

In the above figure, curve 1 represents the updated version and curve 2 is for the previous version. It is obvious that both profiles have the same level in the second half of the period shown. Because the simulation results of the previous version have been proven to match the operation data selected discretely from the actual NPP during normal operation, this new model can be verified to some extent. Differences exist at the beginning because, when equipment is brand new, any work with hardware will be easier and the stress imposed on humans will be at a lower level. Another difference lies in the influence amplitude of the transient. The occurrence of a transient mainly increases stress on operators, and therefore they are more likely to commit errors. However, according to HRA theory, the increment is not so high.

Also, only the HEP in the operation sector was taken into account to describe the human influence toward the CCDF index in the old model. Actually, maintenance and engineering work also impact the severity of an incident by recovering lost systems or by erroneously disabling safety related equipment [9]. This is known as a common cause of failure, affecting several safety systems, and may have a significant contribution to the reactor CDF. Additionally, human maintenance is a common cause of failure. Therefore, it is necessary to include the HEP indices for maintenance and engineering sectors in the model.

3.4.2 Relation between HEP and Quality

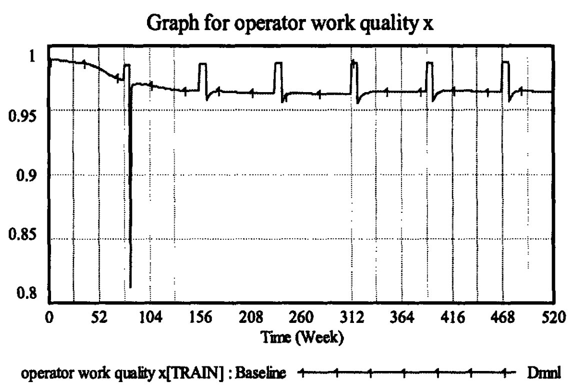
With the introduction of HEP, a confusing nomenclature about human quality has been set forth.

The original definition of human quality used in ORSIM is depicted as: the fraction of work that can be performed correctly. The term of human quality is widely referred to in the industry as a measure of personnel performance. However, NPPs are distinct from generic industries on the safety level, and here human quality represents not only economic efficiency but also the public safety. So PRA and HRA are proposed to study the system and the human failure rate quantitatively in this sensitive field. Traced back to the definitions, quality has the same scope as human reliability, and it is the ratio of correct actions to total actions. Moreover, these two variables stem from similar sources. Although in ORSIM, the quality model is quantified based on each specific NPP database as well as on expert opinions when concerned with such human factors as skill, training, supervision, collaboration, and so on, it is not acknowledged and not universal for all NPPs. Under this condition, it is expected that quality can be deduced from HEP which has been widely accepted as a quantitative analysis approach. Thus, a uniform modeling system can be established in the human performance field.

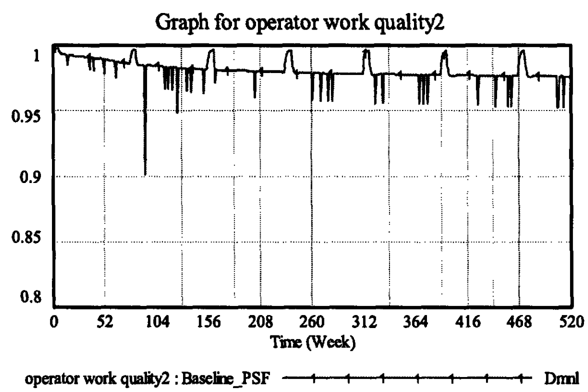
Actually, quality and HEP have a mutually supplemental relationship, so that quality can be described by the formula: *Quality= 1- HEP.* For multiple step activities,

$$Quality = \Pr ob(success) = \prod_{i=1}^{N} P_i = \prod_{i=1}^{N}(1-HEP_i) \cong 1-\sum_{i=1}^{N} HEP_i = 1-(\sum_{i=1}^{N} NHEP_i)\prod PSF \quad (3\text{-}2)$$

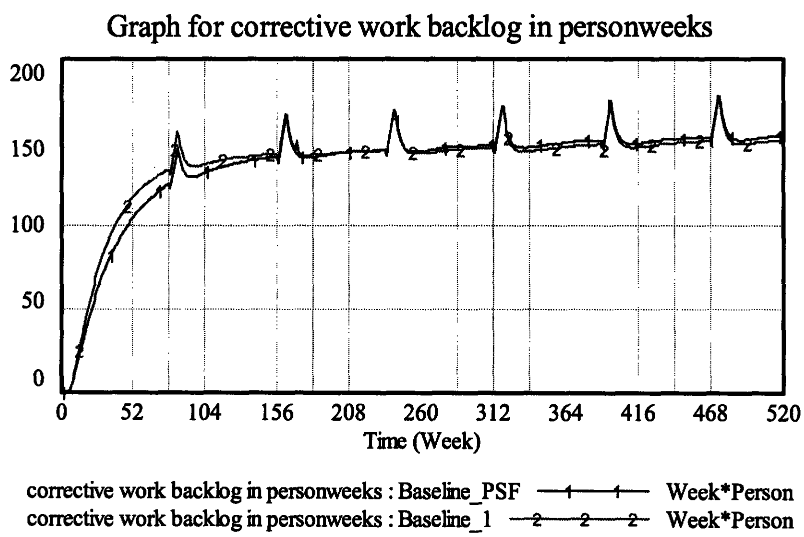
N is a step amount and is assumed as 10 in a generic task. Generally, the first step of a task is diagnosis, and the following steps are actions. Therefore, the base HEP for a whole task should be the sum of a 0.011 and 9 times 0.001, that is 0.02. When these data are employed in the ORSIM model, the corresponding results are described in Figure 3-3:



(a) Operator quality from previous model



(b) Operator quality calculated from HEP



(c) Corrective work backlog comparison in two cases

Figure 3-3 Quality calculated from HEP

Similar operator quality trends are present in (a) and (b), except that the updated model introduces the effects of transients upon operator actions as indicated by the frequent spikes. Also, when the new qualities are employed in the model, a similar corrective work backlog occurs. It can be concluded that the new method satisfies the data from NPP operation. Traditionally, quality was always mentioned in a qualitative way. With this approach, it can be connected with HEP and can also be quantitatively calculated.

CHAPTER 4 – CASE STUDY OF AN NPP

4.1 Introduction

After the model is structurally tuned and parameters are set up and validated, ORSIM is then ready to be used.

Originally, the basic version of ORSIM was built based on the generic characteristics of a typical light water reactor NPP in the U.S., and we call this the "Vanilla Model". However, when applied to a specific NPP, a set of necessary modifications on the model are needed because of the NPP's special features, especially the features in the organizational structures and management procedures, and also because of the data that is different from one plant to another.

As discussed in Chapter 1, a major application of the ORSIM model is to analyze the feasibility of management policies. The impact of human performance probably occurs in unpredictable ways and after considerable delays in time. It may be difficult for decision makers to develop a deep understanding without years of experience. However, with a simulator such as ORSIM, it becomes possible to simulate the effects in a reliable and nondestructive manner and to explore system responses. Through the tracking-back function of the model, the root cause of any perplexing consequence can be identified even in a complicated NPP system.

The target NPP in this study is a 1000 MWe boiling water reactor (BWR) in the U.S. This NPP has operated in a normal condition and much exemplary experience in organizational processes has been accumulated. However, like other NPPs, in order to improve the safety and economic level as well as to correct inadequacy in policies, many constructive proposals are considered by the decision makers in the areas of operation, radiation protection, configuration management, maintenance strategies, industrial safety, and organizational effectiveness, etc. The impacts of these measures and changes need to be demonstrated by theoretical deduction or simulation before actual implementation.

This chapter mainly focuses on the customization process of ORSIM for the selected NPP, and the feasibility analysis of organization policy alternatives.

4.2 Scenario 1: Configuration Management Backlogs

4.2.1 Problem Description

According to the proposed item of "Areas where some improvement is needed" in the target NPP document "Station Comments on Configuration Management", it can be concluded that "Engineering backlogs have remained high and have increased in some key areas" because "planned engineering resource shifts to security modifications" in Year 1, and "additional resources have been reallocated" in Year 2 "to partially address this improvement area". In addition, "Process efficiencies are planned for Year 3 in parallel with implementation of new corporate document management processes". Therefore, the underlying issue focuses on the reason why engineering work backlogs have increased and the method to solve this problem.

Based on this information, the original ORSIM model can be adjusted. It is assumed that the engineering sector employs 50 people and a 520-week simulation period is considered. This is the scenario: in the 260th week some workers leave for other safety work assignments and in the week 312 (1 year later) some of them return. When a different amount of the workforce population leaves or returns the effects on the engineering sector and other sectors are totally different. Thus, a series of simulations are carried out with different shift numbers and return numbers. At the same time, the engineering productivity has increased by 20% because a new document system was adopted. So, we consider two changes: a shift in workforce and an improved document system.

As mentioned in Chapter 2, the functions of the engineering sector are sorted into six types: Training, Surprise work, Modification work, Licensing work, Engineering support work, and Information work, which are listed by the order of priorities from top to bottom. The workforce allocation is based on the priority rule that the workforce requirement of the higher priority work should be fully satisfied first. The workload generation rate data assumes that this is a surprise workload: 6 work/week, licensing workload: 9 work/week; support and modification workload are decided by maintenance workload; information workload is decided by the workforce population. The last three input values are set as 5, 6, 1.5 work / week respectively.

According to the problem description, the parameter "engineering backlogs" is built to depict the operational performance in the engineering sector. The engineering work backlogs are equal to the sum of "work to be serviced" and "work being serviced" in engineering sector.

4.2.2 Simulation Analysis

A. Effect of workforce shift population

After exploring all potential situations, we choose two typical cases to be illustrated here. E_shift_22_15 means 22 workers are shifted in week 260 and 15 of them return in week 312; E_shift_21_15 is expressed in the same manner except that 21 persons left; baseline means the normal case.

Figure 4-1 shows that the training work always can achieve clearance because a sufficient workforce is assigned for they have the highest priority. However, when the workforce decreases below a critical point, the surprise work, which ranks second in importance, only can satisfy a part of its demand for workers. Thus the engineering backlog increases as a result (Curve 6). Figure 4-2 shows that the lowest priority job, information work, begins to pile up dramatically after workers have shifted away because nobody is doing it. It is notable that after week 312 when part of the workforce is relocated, and the DTE document system is actualized so that the engineering work productivity increases, then the simulated work backlog is cleared, and drops back almost to its original level.

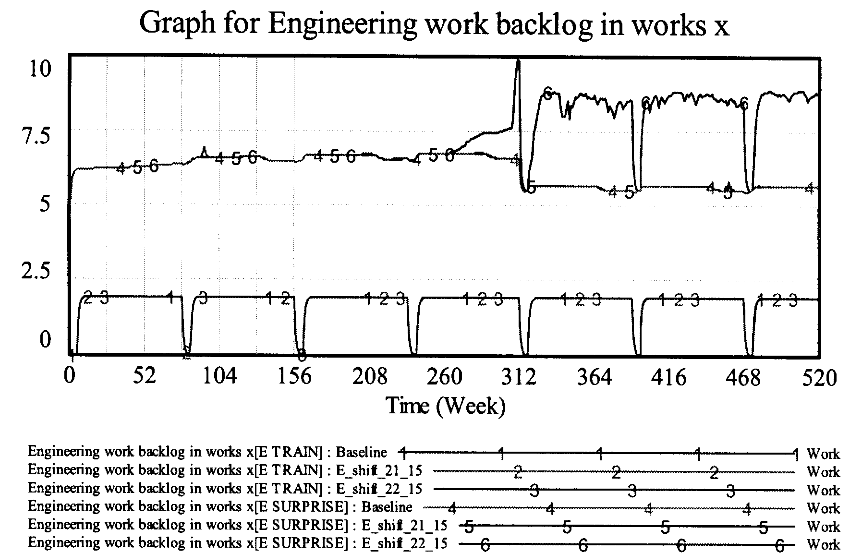


Figure 4-1 Training and surprise engineering work backlog

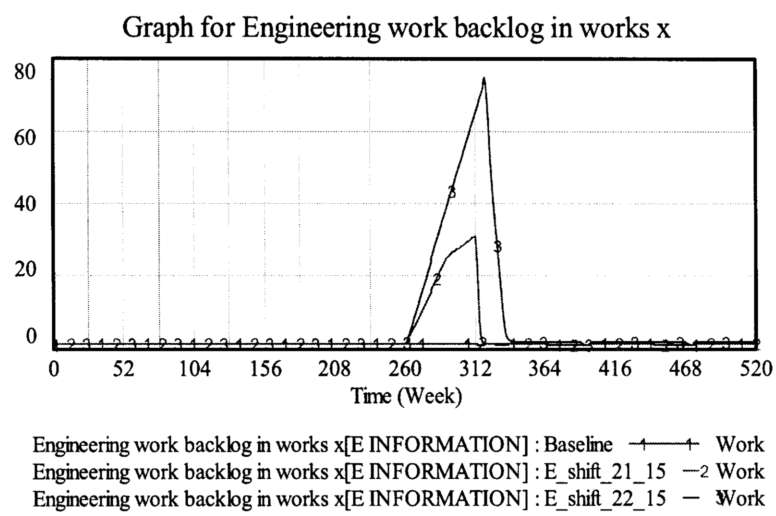


Figure 4-2 Modification work backlog

So far, the ripple effect has spread to the maintenance sector and that sector passes its endurance limit; the entire system is going to collapse unless some relief strategy is provided. Actually, the case of a 21 worker-shift is a critical point where the available workers for the shift arrive at the top value and the maintenance corrective work backlog can not be held at a stable level if one more person leaves (22 leave totally, which is shown in Figure 4-3). The impact continues because the chain reactions are triggered regarding the HEP in the operation sector as well as in the active transient situation. Figures 4-4 and 4-5 reflect this change. This example also demonstrates that changes in one part of a system always influence other parts and affect the behavior of the whole system.

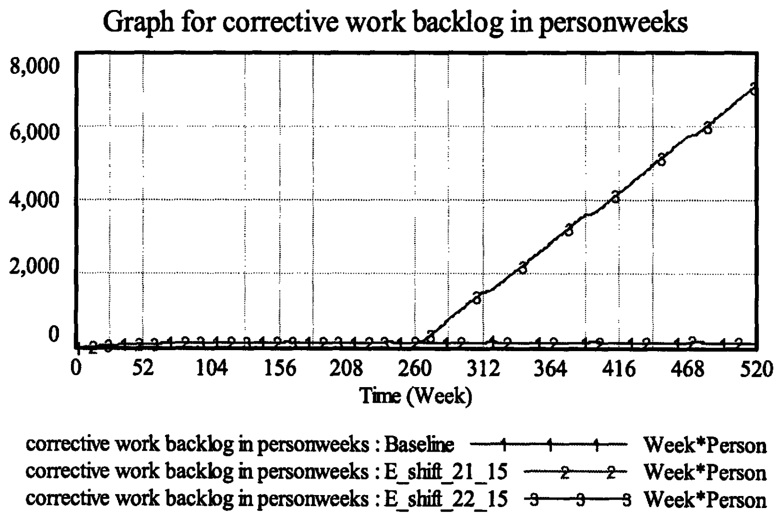


Figure 4-3 Corrective work backlog when engineering workforce shift

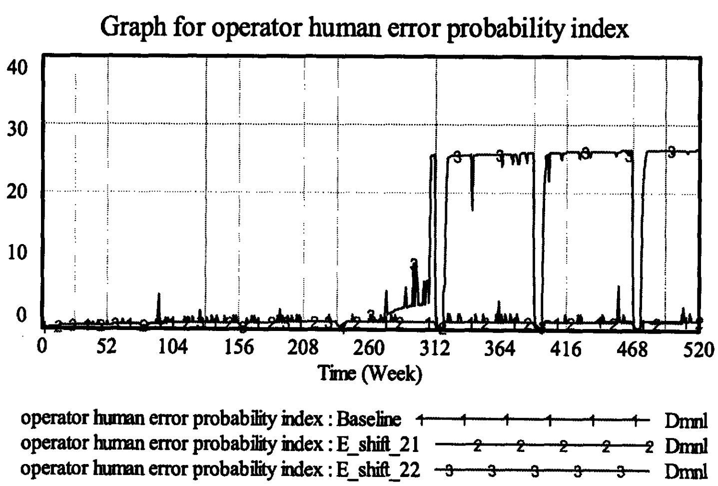


Figure 4-4 Operator HEP index

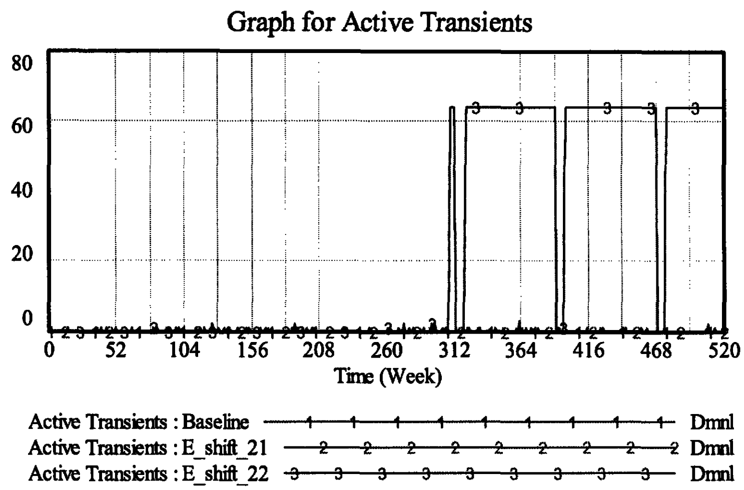


Figure 4-5 Active transients

The perturbation exerted from engineering to maintenance originates with the engineering support work, which is assigned a lower priority and sometimes is ignored when there is a workforce shortage. The engineering support factor is equal to the ratio of support being serviced to the total support work entering the engineering stack discounted by engineering (shown is Figure 4-6). After one year, engineering performance recovers so that the support factor returns to its normal value. However, the maintenance work is beyond recovery.

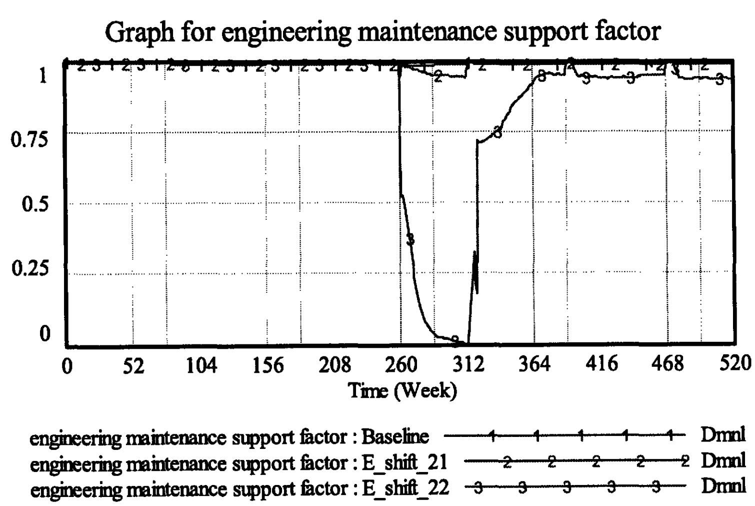


Figure 4-6 Engineering maintenance support factor

Recalling Figure 4-1, we can find the spike phenomena in curve 6 are attributed to the frequent reactor trips that happen when uncontrollable high backlog in the system degrades the reactor material condition. The graph for reactor trips is shown is Figure 4-7.

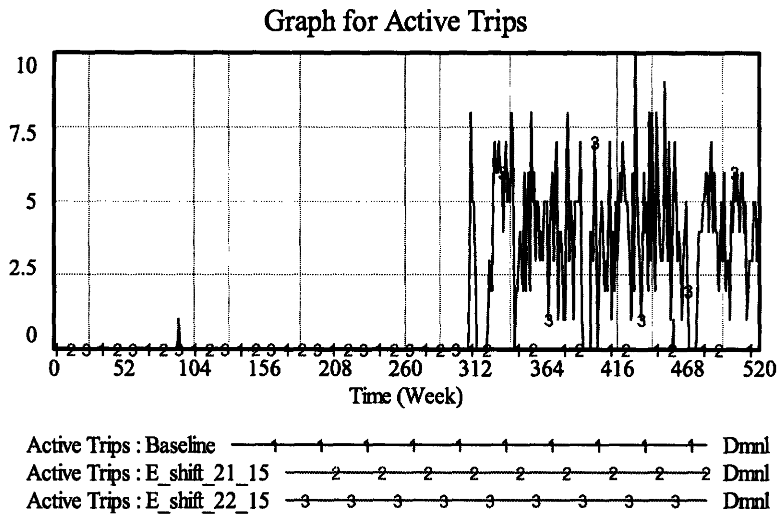


Figure 4-7 Reactor active trips

By adding all the different kinds of engineering work together and then dividing by the productivity, this study can get "engineering work backlog in person weeks", which is shown in Figure 4-8. Because information work represents a major aspect of the total backlog, the "engineering work backlog in person weeks" presents a similar profile to the information work backlog in Figure 4-2, except for a higher returned level during the last period in the worst case scenario (curve 3) where a decreased engineering productivity is introduced in the last period because supervisors and central managers spend much more time to take care the reactor trips under such a degraded condition.

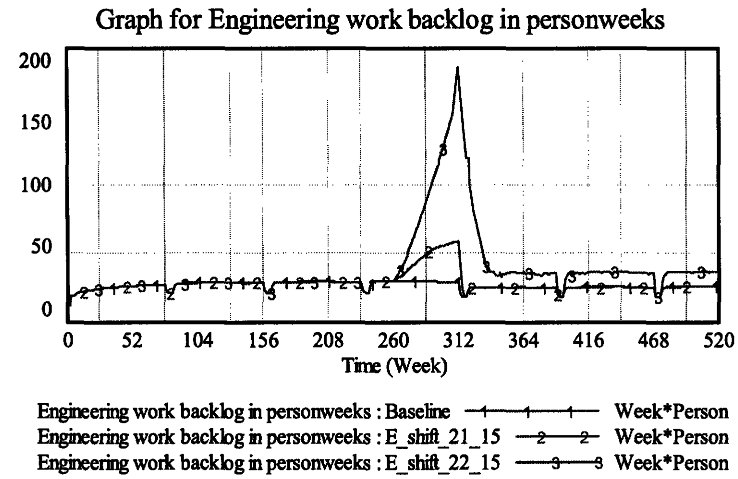


Figure 4-8 Engineering work backlog in person weeks

B. Effect of Productivity

Engineering productivity exerts an obvious influence on the engineering work backlog: in the 21 worker shift case, a higher engineering productivity is achieved by installation of a new document system, and a lower engineering work backlog level is reached in the final state. This has been shown in Figure 4-9.

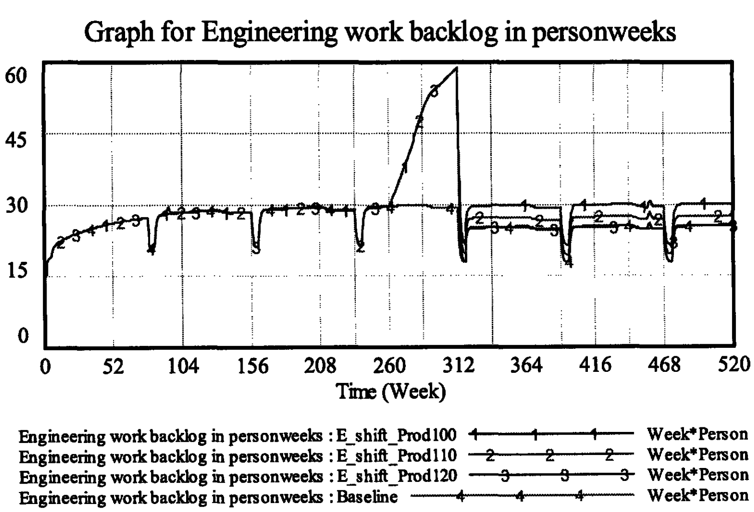


Figure 4-9 Engineering work backlog when different DTE2 productivity applied

4.2.3 Conclusion and Advice

Based on the above analysis for simulation results, several conclusions can be made:

1. Despite a relocation of workforce, an increase of productivity can eliminate a high work backlog. However, the amount of workforce shift in the engineering sector should be kept within limits. If not, the engineering work backlog will increase, and the performance in other sectors will also get worse, and finally a severe accident may occur.

2. Compared with the engineering sector, the maintenance sector is a weaker part because when a disturbance happens to the system, the maintenance sector is the first sector to go over beyond its tolerance limit and collapses. The probable strategy is to assign more workforces there, or to adopt an electronic detection tool for predictive maintenance to mitigate the burden on maintenance workers.

3. In the case that any activity taken in the engineering sector produces a disturbance in the work backlog in the maintenance sector, the priority rule that assigns a low status to "engineering support work" should be reconsidered, and the collaboration work between engineering sector and maintenance sector deserves more attention.

4. A highly efficient system for document management can improve the operation in all sectors.

4.3 Scenario 2: Planning Delay

Delay is usual in the organizational process between two steps or two functional departments. In the NPP in this study, delay basically exists within the planning department, or between planning work and the maintenance work. The latter factors have been considered in the vanilla model. Here, the former case will be introduced in detail.

The baseline delay time is 0.0325 weeks. In comparison, the cases with delay time 0.325, 0.65, 1.625 and 3.25 weeks (say 10, 20 50 and 100 times of original value) are simulated separately. It can be found that with the increase of delay time, the corrective work backlog also increases, because the delay causes work to pile up in the queue. The results are shown in Figure 4-10. Figure 4-11 represents the growing operator HEP index. The spikes account for the more and more intensive transients. Therefore, delay is an unmanageable issue not only influencing production efficiency but also adding the possibility of greater risks.

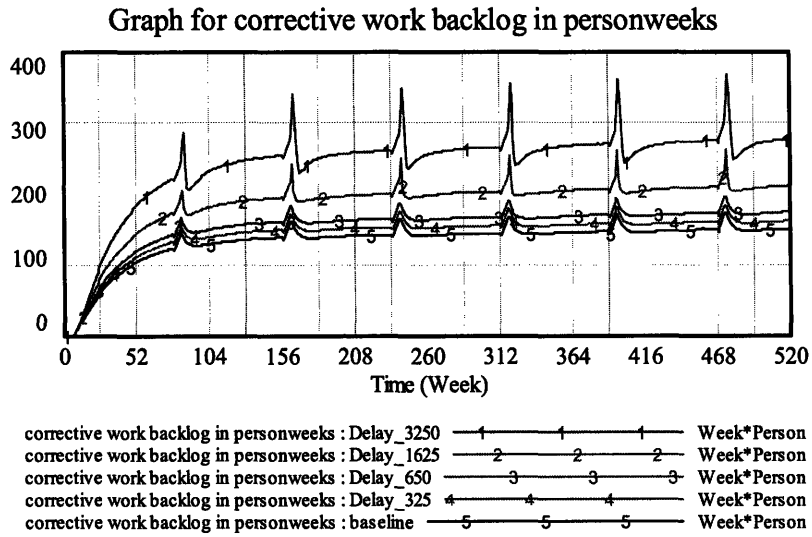


Figure 4-10 Corrective work backlog when planning delay is used

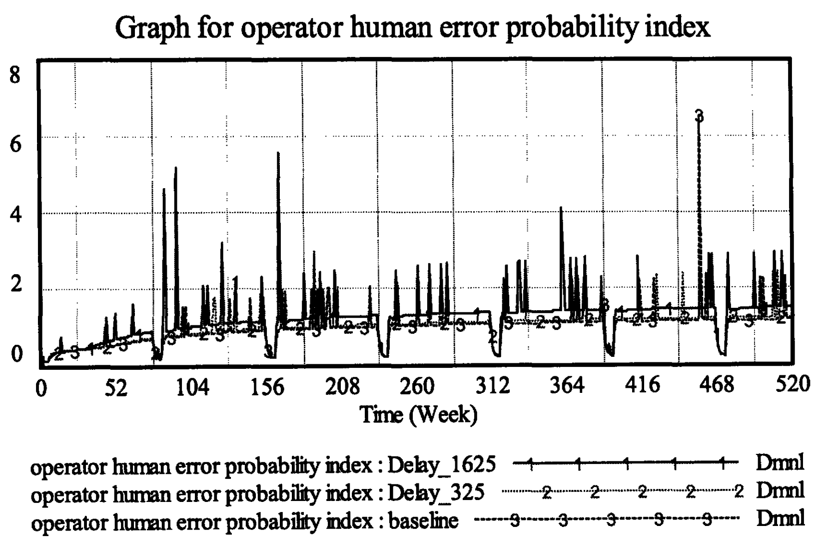


Figure 4-11 Operator HEP index

4.4 Case Study 3: Surprise Tolerance

Surprise or unexpected workloads account for a big share of the routine work in a NPP. It mainly occurs in engineering, central management, and supervisor departments. In order to understand the ability for system to bear an unexpected emergency, it is meaningful to study the system condition when surprise workloads happen.

The normal engineering surprise workload is 6 pieces of work per week. The fictitious cases of an extra 18, 27 and 36 surprise workloads lasting 20 weeks are simulated here. Figures 4-12, 4-13, 4-14 depict the relevant engineering work backlog, corrective work backlog, and operator HEP index respectively. It is found that when extra workload is added, engineering work backlog always increases. This tremendously high workload can be removed gradually after the extra workload source disappears. Besides, the roubustness of engineering sector is strong, which means the subsystem has the ability to tolerate a big surprise workload disturbance. However, another kind of situation happens in maintenance. When the forced extra workload is unremarkable, there is no indication in corrective work backlog. If the impact from engineering exceeds the limit the maintenance sector can handle, the corrective work backlog will increase. At the same time, the operator HEP as well as the CDF is also influenced, which roughly follows the same trends of corrective work backlog. The mechanism of interactions among all the sectors has been explained in section 4.2.

Graph for Engineering work backlog in personweeks

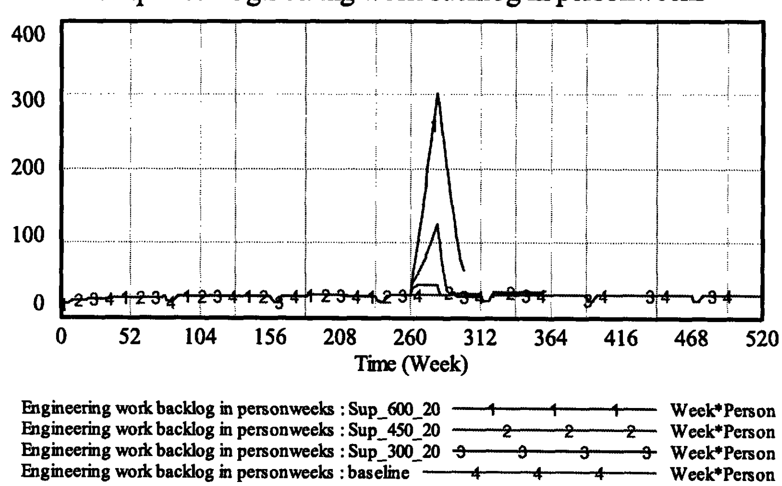


Figure 4-12 Engineering work backlog in the case of surprise workload

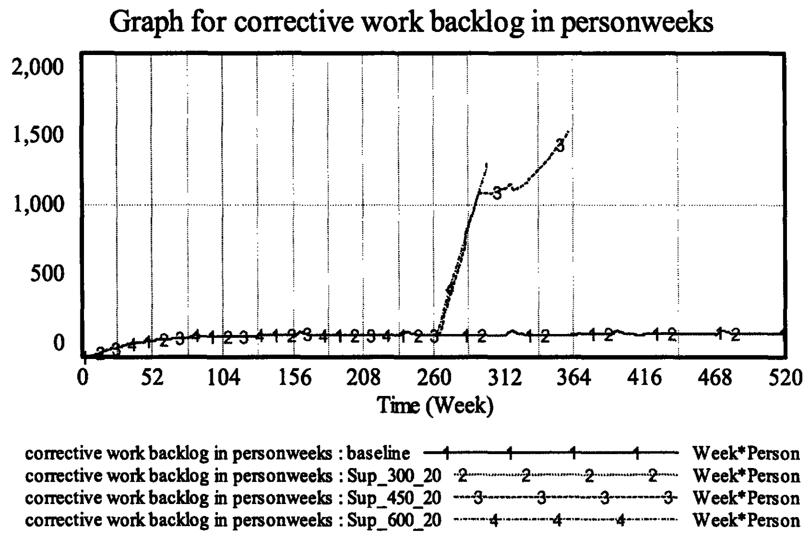


Figure 4-13 Corrective work backlog in case of engineering surprise workload

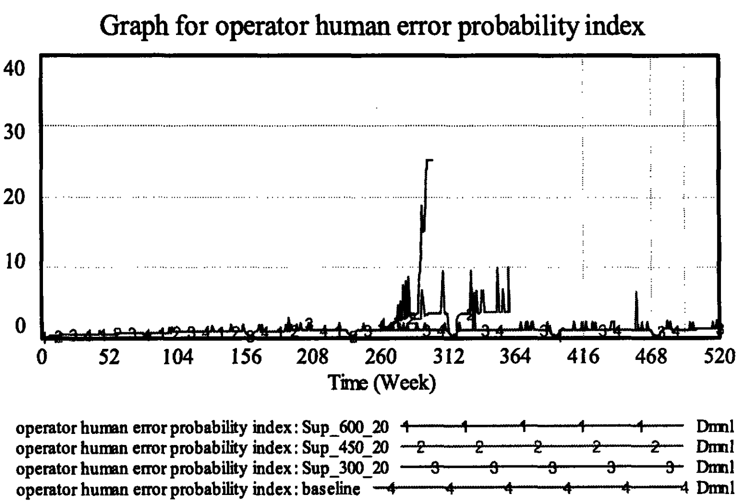


Figure 4-14 Operator HEP index in the case of engineering surprise workload

4.5 Summary

In this project, ORSIM is customized and applied to the target NPP. ORSIM is a scalable and user-friendly tool because of the simple process for tuning. During the application, ORSIM presents a strong function to identify existing problems and investigate practices as well as policy changes (for example, what is the limit of shifting workers that can sustain the system's stability; how long of a planning delay is acceptable; what is the influence on the whole NPP; and what is the system's tolerance to unexpected workloads). Through the tracking function, the channels of interaction within the system can be explored. And finally, the root cause of any abnormal behaviors can be discovered.

CHAPTER 5 – CONCLUSION

5.1 Conclusions

This thesis introduces an approach to study and model human performance in the operation of nuclear power plants (NPPs). It uses ORSIM, a computerized model based on the system dynamics method. The ORSIM model focuses on how humans process workflow and how interactions occur between every organizational part of an NPP system time-dependently.

There are two objectives for this thesis:

- Development of a human reliability model in the ORSIM environment;

With regard to the significance of human reliability in a NPP, the partial Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) approach is applied to conduct HRA. In detail, eight Performance Shaping Factors (PSFs) are treated as direct indicators influencing the human error rate. These factors include: available time, stress and stressors, experience and training, complexity, ergonomics (including the human-machine interface), procedures, fitness for duty, and work processes. The relationships between these indicators and the existing human performance indicators are also investigated in this thesis.

- Work with utilities to demonstrate how ORSIM is applied in practice.

It should be noted that both the structural details and input data of the underlying model need to be adjusted for any specific plant. Actually, ORSIM is a scalable tool that can be upgraded to a customized version. As an example, the operation case study for a selected NPP is investigated. Meanwhile, policy alternatives are examined and corresponding problems are diagnosed. The scenarios involved include but are not limited to: (1) Workforce shift, (2) New management system, (3) Delay in planning department, and (4) Tolerance to surprise workload.

This thesis concludes that ORSIM is a good tool for nuclear plant managers and nuclear regulators to understand the reactor status and human performance in the plant from a holistic view, as well as to make risk-informed decisions regarding policy changes. The matrix of performance indices developed in this thesis is able to measure stability, reliability and economic performance in a concise and clear manner. Together with the tracking capability built into ORSIM, it is rather easy to locate root causes for problems and to identify circumstances in which organizational improvements can be implemented.

5.2 Remaining Issues

5.2.1 Model Parameter

When the ORSIM model is used, an important fine-tuning procedure is data selection. Many of the variables in the model are easy to represent. Thus, manpower levels can be obtained from historical records. Each sector has records that can be used to create a picture of the distribution of manpower throughout the system. Similarly, the flow of most types of work can be obtained from existing sector records. Given the time-dependent values of work levels and schedules, it is usually easy to find the flow rates into and out of inventories. Nevertheless, some generation rates can not be obtained directly. For example, the amount of coordination work for a work order may have to be calculated by averaging many examples.

However, compared to work flow data, it is much more complex to obtain the data for factors influencing human productivity and reliability. Much of the data will have to be inferred from real experience. Thus, if plants have data on work output as a function of time, it may be possible to relate changes in productivity to other conditions in the plant. The most likely pathway to obtain the factors is to interview plant staff and management via a Delphic process. Experience with models suggests that certain factors will emerge as the most significant ones in overall performance and one can concentrate extra effort on representing these factors.

5.2.2 Validation of the Model

Simply speaking, model validation means the comparison between model prediction and actual observation. In many instances of quantitative model validation, a "graphical validation" approach is used, i.e., by visually comparing graphs of prediction and observation. That is what we have done in ORSIM in current stage. However, this is inadequate from the theoretical point of view. With a qualitative graphical comparison, one does not explicitly analyze the numerical error or quantitative uncertainties in the predictions and experimental results. Such a comparison also gives little indication of how the agreement varies over space and time. Generally speaking, several issues complicate such a model validation process:

At first, there exists uncertainty in both model prediction and actual observation. The uncertainty in model prediction arises because of variability and uncertainty of the input data, as well as errors, approximations, and assumptions in the model. The uncertainty in the actual observation, which is to be compared against the model output, arises from random variability, qualitative description, measurement errors and other factors. Therefore, a comparison between model prediction and actual observation under uncertainty is not straightforward at all, and it requires the definition of appropriate validation metrics;

On the second, model validation requires the careful design of validation experiments;

Last but not least, since the model is usually a simplified abstraction of reality, the validation is satisfactorily done only under controlled experimental conditions. Thus, the model validation exercise needs to provide enough information about the limitations for model utilization. In other words, it should be made known to the users that under what conditions and data ranges the model will be valid. If the model is used to predict reality, the corresponding amount of confidence should also be quantified.

Regarding the model's quantitative validation analysis and parameter update, standards pointing out clear and accepted are yet to be developed. Perhaps, the hypothesis testing concepts and Bayesian statistics methodology can be employed in this context.

The quantitative validation of the quantitative human reliability analysis (HRA) subsystem model can be an example. The SPAR-H model makes use of eight performance shaping factors (PSFs), The overall human error probability (HEP) is computed as the product of a baseline probability, p_0, and the multiplier values for each PSF. The multiplier value of the ith PSF is represented by the variable F_i. Each of the multipliers F_i is a discrete variable with possible values $\{f_{i1}, f_{i2},..f_{ij}\}$ and corresponding probability mass function (PMF) $p_{Fi}(f_i)$. Limited knowledge of the actual shape of the PSF distributions has been combined with expert judgment to estimate the prior PMFs for each of the performance shaping factors. Next, consider the Human Event Repository and Analysis (HERA) System being developed at INL, which is collecting typical nuclear power plant incident reports. These reports indicate error occurrences along with the description of the performance shaping factors. With such observational data, it is easy to perform Bayesian statistics calculations to compute the posterior PMF of the model output, which in this case is overall human error probability p. The Bayes factor is then simply the ratio of the posterior and prior PMFs of p, leading to inference about the level of data support for the SPAR-H model.

REFERENCE

[1] Energy Information Administration, U.S. Department of Energy, Washington, DC, U.S. "International Energy outlook", June, 2006

[2] NUREG/CR-6753, "Review of Findings for Human Performance Contribution to Risk in Operation Events", 2002.

[3] Idaho National Laboratory, "Developing Human Performance Measures", Project Milestone Deliverable: Letter Report, March, 2006

[4] John D. Sterman, "Business Dynamics: System Thinking and Modeling for a Complex World", McGraw-Hill, 2000

[5] Haibo Chen, "Identification of Good Practices in the Operation of Nuclear Power Plants", Ph.D. Dissertation, Nuclear Science and Engineering, MIT, Cambridge, MA, 2005

[6] Hansen, K.F., Golay M.W., and Kwak, S., "OPSIM: The Nuclear Power Plant Management and Operations Simulator," HGK Associates, LLC, 2000.

[7] NUREG/CR-6883, INL/EXT-05-00509, "The SPAR-H Human Reliability Analysis Method", 2005

[8] Pekka Pyy, "Human reliability analysis methods for probabilistic safety assessment", VTT Technology Research Center of Finland, 2000

[9] Pekka Pyy, "An analysis of maintenance failures at a nuclear power plant", Reliability Engineering and System Safety, 72(2001)

Appendix A-HRA methods comparison (Source: NUREG/CR-6883, INL/EXT-05-00509, "The SPAR-H Human Reliability Analysis Method", 2005)

HRA Method	Release Date	Authors	Abstract
CREAM [1]	1998	E. Hollnagel	Human performance classification based on error modes and consequences (phenotypes) and causes (genotypes). Uses simple Contextual Control Model (CoCoM) of cognition that includes continuous revision and review of goals and intentions. Assesses cognitive function failures and common performance conditions (CPCs) to support failure rate estimations.
HEART [2]	1988	J. Williams	HRA based on nine generic tasks with individual nominal error rates. Analysts identify error-producing conditions (EPCs). EPCs operate as multipliers to increase base failure rates; their basis is in the behavioral sciences literature.
THERP [3]	1983 NUREG/CR-1278 [Developed in the 1970s and refined in early 1980s].	A.D. Swain and H.E. Guttmann	Developed to provide representational modeling of human actions (HRA Event Trees) and estimation of HEPs. Emphasis is on nuclear power plant applications to support PRA Provides HEP tables based on data gathered from various domains.
ASEP [4]	1987 NUREG/CR-4772	A.D. Swain	Developed to provide an efficient method for estimation of screening HEPs for pre- and post-accident human actions. Based on THERP.
SHARP1 [5]	1990	Wakefield, et al	Developed to provide a consistent approach to HRA assessments. Contains performance shaping factor information. Addresses pre- and post initiator conditions. Revision to early work in this area under the same name.

[1] Cognitive Reliability and Error Analysis (CREAM) Method.
[2] Human Error Analysis and Reduction Technique (HEART).
[3] Technique for Human Error Rate Prediction (THERP).
[4] Accident Sequence Evaluation Program (ASEP) Human Reliability Analysis Procedure.
[5] Systematic Human Action Reliability Procedure (SHARP1)

Appendix B-Action PSF Comparison Matrix, at power (PSFs=8)

SPAR-H PSFs	SPAR-H PSF Levels	SPAR-H PSF Multipliers	HEART Multipliers	CREAM Multipliers	ASEP Multipliers	THERP Multipliers
Available Time	Inadequate Time	P(failure)=1	/		P(failure)=1-Table 7.2	P(failure)=1-Table 20.1
	Time available =time required	10	11-EPC	5-CPC 20	10 -Table 7.2	10-Table 20.1
	Nominal Time	1	1	1-CPC 19	1- Table 7.2	1-Table 20.1
	Time available>=5x Time required	0.1				
	Time available>50x time available	0.01		0.5-CPC 18	0.01- Table 7.2	0.01-Table 20.1
Stress/Stressors	Extreme	5			5-Table 7.3	5,25-Table 20-16
	High	2	1.3-EPC 29 1.15-EPC 33	1.2-CPC 22		2,5-Table 20-16
	Nominal	1		1-CPC 21		
Complexity	Highly complexity	5	5.5-EPC 10	2-CPC 17	2.5,5	
	Moderately complexity	2		1-CPC 16		
	Nominal	1		1-CPC 15		
Experience/ Training	Low	3	17-EPC 1 3-EPC 15 8-EPC 6 6-EPC 9	2-CPC 25	10-Table 8.3	2-Table 20-16

			4-EPC 12 2.5-EPC 18 2-EPC 20 1.6-EPC 24			
	Nominal	1	1	1-CPC 24	1	1
	High	0.5		0.8-CPC 23	0.1-Table 8.3	
Procedures	Not available	50			P(failure)=1-Table7.1, Table8.1	50-Table 20.7
	In complete	20	5-EPC 11 3-EPC 16, 17 1.4- EPC 28 1.2-EPC 32	2-CPC 14		10- Table 20.7
	Available, but poor	5	5-EPC 11 3-EPC 16, 17 1.4- EPC 28 1.2-EPC 32	2-CPC 14		10- Table 20.7
	Nominal	1		1-CPC 13		
Ergonomics/HMI	Missing/Misleading	50			P(failure)=1-Table 7.1, 8.1	100,1000-Table20.12
	Poor	10	10-EPC 3 9-EPC 4 8-EPC 5,7 4-EPC 13,14 2.5-EPC 19 1.6 EPC 23 1.4-EPC 26 1.2-EPC 32	5-CPC 11 2-CPC 7		6-Table 20.9,11,12 10-Table 20.10,13,14
	Nominal	1		1-CPC 9,10,6		

	Good	0.5		0.8-CPC 5 0.5-CPC 8		
Fitness for duty	Unfit	P(failure)=1.0				
	Degraded fitness	5	1.8-EPC 22 1.2-EPC 30 1.1-EPC 35			
	Nominal	1				
Work process	Poor	2	2-EPC 21 1.6-EPC 25 1.4-EPC 27 1.2-EPC 31 1.06-EPC 36	5-CPC 29 2-CPC 4 1.2-CPC 3 1-CPC 28		
	Nominal	1		1-CPC 2,27		
	Good	0.8		0.8-CPC 1 0.5-CPC 26		

Appendix

Appendix C-PSF Comparison Matrix of action and diagnosis (At power)

PSFs	PSF levels	PSFs for diagnosis	PSFs for action
		Multiplier	Multiplier
Available Time	Inadequate time	P(failure)=1	P(failure)=1
	Barely adequate time	10	10
	Nominal time	1	1
	Extra time	0.1	0.1
	Expansive time	0.01	0.01
	Insufficient information	1	1
Stress/Stressor	Extreme	5	5
	High	2	2
	Nominal	1	1
	Insufficient Information	1	1
Complexity	Highly complex	5	5
	Moderately complex	2	2
	Nominal	1	1
	Obvious diagnosis	0.1	/
	Insufficient information	1	1
Experience/Training	Low	10	3
	Nominal	1	1
	High	0.5	0.5
	Insufficient information	1	1
Procedures	Not available	50	50
	Incomplete	20	20
	Available, but poor	5	5
	Nominal	1	1
	Diagnostic/symptom oriented	0.5	/
	Insufficient information	1	1
Ergonomics/HMI	Missing/Misleading	50	50
	Poor	10	10
	Nominal	1	1
	Good	0.5	0.5
	Insufficient information	1	1
Fitness for Duty	Unfit	P(failure)=1	P(failure)=1
	Degraded fitness	5	5
	Nominal	1	1
	Insufficient information	1	1
Work Processes	Poor	2	5
	Nominal	1	1
	Good	0.8	0.5
	Insufficient information	1	1