IDENTIFICATION OF GOOD PRACTICES IN THE OPERATION OF NUCLEAR POWER PLANTS

by
Haibo Chen

M.S., Nuclear Engineering, Tsinghua University, Beijing (2000)
B.A., Economics, Tsinghua University, Beijing (1998)
B.Eng., Engineering Physics, Tsinghua University, Beijing (1997)

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Signature of Author ....
Haibo Chen
Department of Nuclear Science and Engineering
January 27, 2005

Certified by ....
Michael W. Golay
Professor, Department of Nuclear Science and Engineering
Thesis Supervisor

Certified by ....
Kent F. Hansen
Professor Emeritus, Department of Nuclear Science and Engineering
Thesis Reader

Accepted by ....
Jeffrey A. Coderre
Chairman, Department Committee on Graduate Students

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ABSTRACT

This work developed an approach to diagnose problems and identify good practices in the operation of nuclear power plants using the system dynamics technique. The research began with construction of the ORSIM (Nuclear Power Plant Operations and Risk Simulator) model, with its operational component modified from an existing model, and its risk component newly created in this research. A matrix of high-level performance indices was also created to measure plant performance as a function of continuous operation. The research continued with development of an interface program to provide a user-friendly environment, and then culminated with a report of the results obtained from a pilot project, and a demonstration of using ORSIM to investigate EPRI (Electric Power Research Institute) good practices. Both problem diagnosis and policy investigations were conducted in the pilot project. It was found that the performance matrix developed in this work was able to measure stability, reliability, and economic performance in a concise and clear manner. With this matrix, ORSIM was able to pinpoint bottlenecks of current operations and to project into the future what would be the implications of various policy changes. It was also found that the tracking capability of ORSIM makes it easy to locate the root causes of problems and aids in identifying places where operational improvements might be implemented. In the EPRI good practices investigation, it was demonstrated that ORSIM is a good tool that assists plant managers in evaluating the benefits and risks of applying new practices. The pilot project and EPRI practices study showed that ORSIM is a good tool for plant managers to identify potential problems and to better understand the implications of their policy changes. It therefore can help improve the quality of decision-making and help achieve more stable, reliable, and economic operations of nuclear power plants.

Thesis Supervisor: Dr. Michael W. Golay, Professor of Nuclear Science and Engineering

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CHAPTER 1 – INTRODUCTION

1.1 Review on the Operation of Nuclear Power Plants

The restructuring of electric power sectors around the world in the late 1990's sparked fierce competition in the electric power industry [1], which had driven nuclear power plant (NPP) owners to operate their plants more reliably and efficiently.

The safety and economic performances of a NPP do not solely depend upon its physical system designs, but also rely upon how well it is operated. Experience suggests that the best performing plants combine excellence in design with excellence in management and organization. Today, however, while many efforts have been devoted to researching physical system designs, the studies to improve NPP operations performance, although recognized as important, had not advanced accordingly, mainly due to great complexity and the lack of knowledge in NPP operations [2]. Consequently, there is not a comparable state of understanding of the mechanisms by which organizational design and policy decisions influence plant performance.

Fundamentally, the operational performance of a NPP can be viewed as a time-dependent result of the interactions among a large number of system constituents, both physical and organizational. The relationships between these building-block components are often non-linear and coupled, with many feedbacks through which a small deviation from normal condition can be amplified and may develop into a severe situation. Because of their complexities, however, these relationships are often beyond one's capability to figure out mentally. As a result, traditional policymaking in NPP operations has relied more upon instincts and good sense rather than quantitative evaluation.

Although it is widely accepted that traditional NPP operations have been adequate in protecting public health and safety, it is also well-recognized that a better understanding of the influences of the policies can be very helpful in accessing, managing, and improving NPP performance. Today, with high-speed computers available, the once "mission impossible" task of modeling complex NPP systems and interactions among their components has become feasible. Our research is set up to lay out such a computerized framework to construct a computer model to quantitatively capture how management policies influence plant performance under different circumstances, and to pinpoint problems and identify good practices in the operations of nuclear power plants.

1.2 Motivation for the Research

Most people, including NPP organization leaders, are still far from being systems thinkers. Some commonly held beliefs, including the following, are often wrong enough to perform the research reported here:

- One cause produces one effect. There must be a single cause, for example, of low productivity. All we need to do is to discover and remove it;
- The future is to be predicted, not chosen or created. It cannot be shaped;
- A problem does not exist or is not serious until it appears and does damage;
- Relationships are linear, non-delayed, and continuous; there are no critical thresholds; feedback is accurate and timely; systems are manageable through simple cause–effect thinking;
- We know what we are doing.

But in fact, very often we do not know what we are actually doing. The hidden feedbacks and delays of system reactions punish on us fiercely, causing us to be busy all day long, dealing with one symptom after another, while seeing no hope that our problems can come to an end. Figure 1-1 presents the basic structure of a generic two-loop action-consequence archetype from reference [3]. The characteristics of this archetype are as follows:

1. It is composed of an intended consequence feedback loop which results from an action initiated in one sector of an organization with an intended consequence over time in mind;
2. It contains an unintended consequence feedback loop, which results from a reaction within another sector of the organization or outside;
3. There is a delay before the unintended consequence manifests itself;

4. There is an organizational boundary that ''hides'' the unintended consequence from the ''view'' of those instigating the intended consequences.

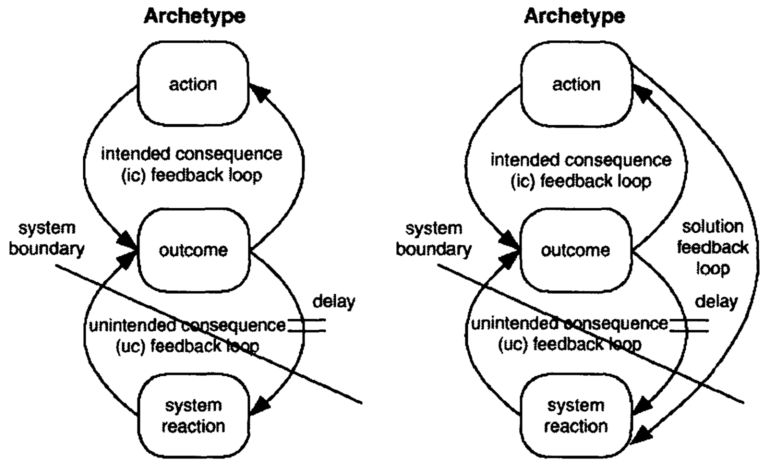


Figure 1-1: Structure of a generic two-loop action-consequence archetype. On the left, the system reaction loop is hidden; on the right, there is a mechanism that breaks the boundary.

The motivation of the work reported here is to remove the boundary that hides unintended consequences as shown on the right figure in Figure 1-1. By introducing a system dynamics approach in developing and using computer models of organizational structure and physical systems, we can quantitatively study the effects of policies and practices upon NPP performance, and we can identify slow decay of operational effectiveness when these interactions lack harmony.

1.3 Problem Description

The objectives of our research are the following:

1. Creation of a simplified, easy-to-use nuclear power plant operations and maintenance simulator program for use at nuclear power plants;
2. Development of a matrix of performance indices to measure plant performances in terms of stability, reliability, and economic performance;
3. Work with utilities in support of model customization and identifying ways of using the simulator program beneficially at nuclear power plants.

The underlying problem surveyed in our research is the fact that NPPs have yet to fully recognize and utilize the dynamic interactions between organizational and physical systems, which often drive plant performance. The first objective therefore is to develop a computer model that represents these interdependent systems in a quantitative way, and to develop a matrix of performance indices to measure plant performance in terms of stability, reliability, and economic performance; the next objective is to show how this framework can be applied in practice. For example: how to use the model to diagnose current problems, to investigate implications of different policies, and to prioritize good practice candidates with regard to their economic improvement and risk reduction. The framework developed is not intended to be a black box. Rather, a good understanding of what within it is necessary for any interested users. The product model (vanilla model) should describe a typical well-run nuclear power plant for use as a tool to introduce to utility staff the principles of system dynamics and to illustrate for them the benefits of tools based upon such modeling. This model is scalable so that any interested plant that desires to use this tool in their plant can tune the model into a 'level 2' model by substituting plant-specific processes and adjusting plant data that are different from those in vanilla model. In both cases, the model shall be able to qualitatively indicate non-linear feedback amplifications of unanticipated work demands in nuclear power plant operations and to identify vulnerabilities to degrading nuclear power plant performance, and the 'level 2' model should be able to match quantitatively with operations data for specific plants. Ultimately, we hope that these experiences will stimulate more users in nuclear power industry to employ this model more extensively and in more detail in supporting various aspects of their operational decision-making.

1.4 Research Approach

One way to understand the full implications of the policies is to perform a pilot trial in a real NPP. However, this intrusive approach can be very expensive and is often too risky. In our research, we will take another approach to investigate and identify the good practices of NPP operations, in which carefully chosen candidate policies are tested on a computerized model that represents the structure, processes, interactions, and relationships of the underlying target NPP systems.

The model that we used is ORSIM (Nuclear Power Plant Operations and Risk Simulator). Its operational component is derived and modified from a HGK Associates, LLP product called

OPSIM (Nuclear Power Plant Operations Management Simulator), while its risk component as well as performance matrix were developed in this work. Risk is treated as being dependent upon the plant material condition, level of maintenance activities, and human performance, and the performance matrix includes indices that measure plant stability, reliability, and economic performance.

The modeling technique applied in ORSIM modeling is that of System Dynamics. As shown in Figure 1-2, with 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. It describes how operational policies affect NPP performance through its direct effects on a given set of system variables, which then propagate the effects to the whole system through interactions among system variables. This computer model uses systems feedback analysis to describe the mutual dependencies of nuclear power plant teams in achieving the coupled cooperation required for obtaining good operational results.

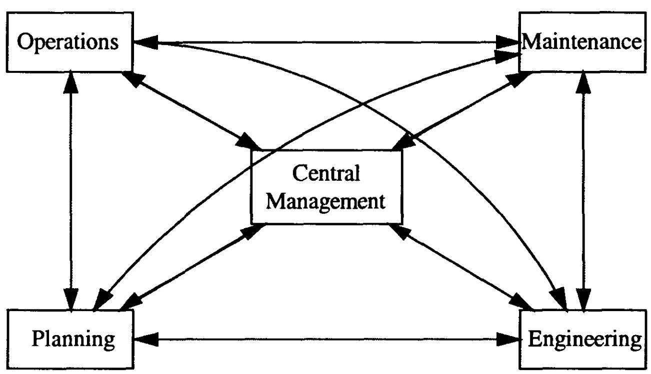


Figure 1-2: ORSIM model skeleton structure

In order to introduce tools such as ORSIM into utilities it is necessary to make available user-friendly versions of them and to establish a track record of successful uses with the potential users. In order to foster this goal we developed a simplified ORSIM model using Vensim, a user-friendly simulator program ORSIM Simulator using Microsoft Visual C++ 6.0, and an ORSIM Input interface using Microsoft Excel spreadsheet coded with Visual Basic for Applications. Figure 1-3 shows how ORSIM Simulator and ORSIM Input bridge the user and the underlying ORSIM model.

It should be noted that both the underlying model and ORSIM Input need to be tuned for any specific plant that wants a customized version of this tool. We assisted in making these adjustments and deployment with our pilot plant (see Chapter 5).

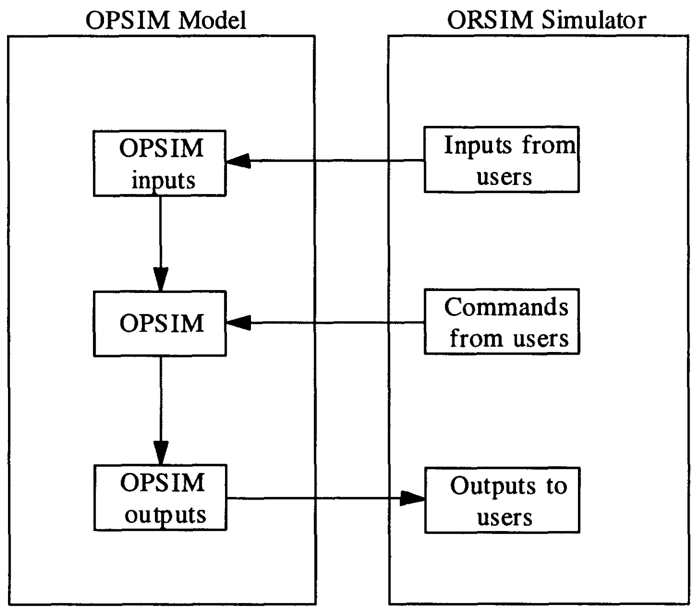


Figure 1-3: Interface program takes inputs from users, transfers them to ORSIM, and returns simulation results from ORSIM to the interface program and presents them to the users.

We also worked with our pilot plant to demonstrate how to use ORSIM to investigate the Excellence Matrix of EPRI (Electric Power Research Institute) practices and to identify ways of using the simulator program beneficially. The demonstration is concerned with benefiting from the expert knowledge in utility organizations for information and feedback of study results on practices identified in the EPRI Excellence Matrix. It is also concerned with identifying ways of using the simplified nuclear power plant model to support nuclear power plant problem diagnosis and operational decision-making.

1.5 Summary

The objective of our research is to develop a methodology for identifying problems and investigating good practices in a systematic and quantitative way. The type of analyses that can be performed with a tool such as ORSIM include: diagnosis of current problems; assessment of proposed policy changes, impacts of personnel transfers/retirements and appropriate responses to them; evaluations of productivity enhancements, of improved resource allocation policies, etc.

Quite apart from studies of the type mentioned above, ORSIM can also be used as a training tool for new managers. The impacts of changes can occur in surprising ways and after considerable delays in time. It is difficult for management to develop deep insights without years of experience. However, with a simulator such as ORSIM it becomes possible for new (as well as experienced) managers to simulate the effects of changes in a realistic and nondestructive manner and to explore responses to them. The ability of the model to allow for tracing back through many variables provides an extraordinary opportunity to relate remote causes with effects.

An individual plant was used as study object, using its historical operation data to identify problems and validate plant-specific good policies. The policies identified can then be used to improve the performance of the NPP operations. The methodology can also be applied to multiple plants and the results from different plants can be compared to identify the commonalities and differences in plant operations. Again, the goal of the research is not to obtain a complete list of good operating policies, but rather to develop and demonstrate a systematic approach by which we can identify good policies and validate their usefulness.

In order to carry out such analyses it is necessary to create model parameters using existing plant databases. The structure of ORSIM is sufficiently generic that major changes to the model would not be necessary. However, as each plant uses different means to conduct their business, the model must be made specific to each application. The design of ORSIM is sufficiently general that variations in policy can be easily represented, and users can dig down to any level of detail as they desire.

CHAPTER 2 – LITERATURE REVIEW

2.1 Development of Good Practices Identification

The Nuclear Energy Plant Optimization (NEPO) program, initiated in the year 2000, supports research and development focused on improving the operations and reliability of currently operating nuclear power plants while maintaining a high level of safety. The goal of this program is to ensure that current nuclear plants can continue to deliver adequate and affordable energy supplies up to and beyond their initial license periods. The research and development conducted under the NEPO program are categorized into two programs: Aging Management and Generation Optimization, the latter of which focuses on improving the long-term economic performance of current plants through development of technologies that will improve equipment reliability, lower operating costs, and increase power output while maintaining high levels of safety. The work presented in this work was designed to address this second objective from an operational point of view, i.e., to develop a tool that can help plant managers diagnose current problems and investigate possible implications of their proposed policies.

To date, the identification of good practices in the operation of NPPs has been based mainly upon empirical experience, that is, good practices have the same meaning as practices from the best-operated plants. Both INPO (Institute of Nuclear Power Operations) and EPRI have conducted research on identifying best practices in this framework [4,5]. They believe that operations in different NPPs are essentially similar, and one can borrow good practical experience from other plants. In terms of existing problem identification, theses studies use gap analysis to find discrepancies between a specific plant and the virtual 'world class plant' that combines all good practices. Any big gap represents a circumstance that needs to be improved.

Identification of existing problems and good policies from empirical past experience has many advantages, but at the same time, it has its shortcomings in the following aspects:

- Scope limitation. Only existing practices can be identified;
- Shortsightedness. Long-term feedbacks are often missed;

- Dependence is ignored. Often times a specific practice is an organic part of the whole organizational system and thus will not work as it is supposed to when it stands alone;
- Descriptiveness. Good practices are descriptions of what should be done and what should not – often stated in terms of desired conditions, what policies should exist and what should not, with no quantitative reasoning for justifying these policies or implementing them;
- Intrusiveness. In order to introduce a new practice, it requires pilot experiments in real operations, which is not desirable given the magnitude of economic loss under worse scenarios, and is often prohibited by regulatory agencies like the NRC;
- Incomparability. Important comparisons among best practices are infeasible due to the lack of quantification and a measuring matrix.

In view of these weaknesses, it is desired to have a tool that can make use of an excellence matrix obtained from the current framework while at the same time not being subject to these defects. After extensive research, we found that a technique called System Dynamics can serve these purposes well.

2.2 System Dynamics Technique

2.2.1 Systems Thinking

Human beings tend to solve problems in a linear way. This approach works well for simple problems, such as those encountered in primitive societies. However, as problems become more complex, such as addressing operational management problems that are cross-functional or strategic, it does not work well.

The method of systems thinking, or system dynamics, provides us with a tool to better understand these difficult management problems. The system dynamics approach was introduced in the post World War II era by Jay Forrester, a former electrical engineer at MIT, and has been used for over fifty years. This approach requires a shift in the way that we think about things. In other words, we must move away from looking at isolated events and their causes (usually assumed to be some other events), and start to look at the organization as a system made up of interacting parts [6].

The term 'system' means an interactively interdependent group of entities. In the work presented here, the objective is to study the management processes, and the focus is on systems of people and technology that are involved in the organizational interactions and work processes.

People tend to explain business performance by showing how one set of events causes another. The difficulty with this 'event causes event' orientation is that it does not lead to very powerful ways to alter undesirable performance. This is because yet another event can be found that causes the one that was thought to be the cause. For example, if the work completed is lagging behind schedule, we may conclude that this is because of low productivity, but why is the productivity so low? It may be because the workers are overworked (the cause of a new problem). Why are workers overworked? It may be because work is lagging behind schedule. This process of seeking fundamental causes could continue almost forever, making it difficult to determine what should be done to improve performance.

If this event orientation is shifted to focus upon the internal system structure, the possibility of improving business performance becomes more likely. This is because system structure is usually the underlying source of the problems that surfaced. Unless the system structure deficiencies are corrected, it is likely that the old problems will resurface, or be replaced by even more severe problems.

2.2.2 System Behavior

The four patterns of behavior shown in Figure 2-1 often show up, either individually or in combinations, in systems [7]. In this figure, 'Performance' refers to some variable of interest. This is often a measure of financial or operational effectiveness or efficiency.

With exponential growth (Figure 2-1a), an initial quantity of something starts to grow, and the rate of growth increases with the quantity itself. The term "exponential growth" comes from a mathematical model for this increasing growth process where the growth follows a particular functional form called the exponential. In work processes, the growth may not follow this form exactly, but the basic idea of accelerating growth holds. This behavior is what we would like to see for productivity of the workers, although more often productivity follows an s-shaped curve when new technology is deployed.

With goal-seeking behavior (Figure 2-1b), the quantity of interest starts either above or below a goal level and over time moves toward the goal. Figure 2-1b shows both of the two possible cases, one where the initial value of the quantity is above the goal, and the other where the initial value is below the goal.

With s-shaped growth (Figure 2-1c), initial exponential growth is followed by goal-seeking behavior, which results in variable leveling off.

With oscillation (Figure 2-1d), 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.

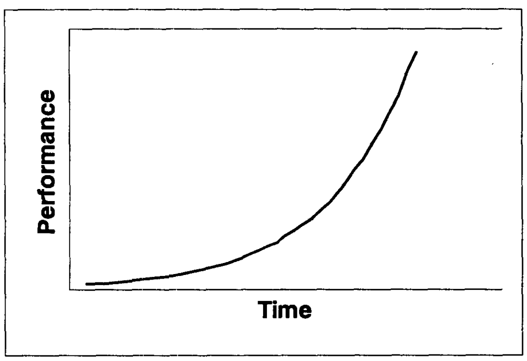


Figure 2-1 a: Exponential growth pattern

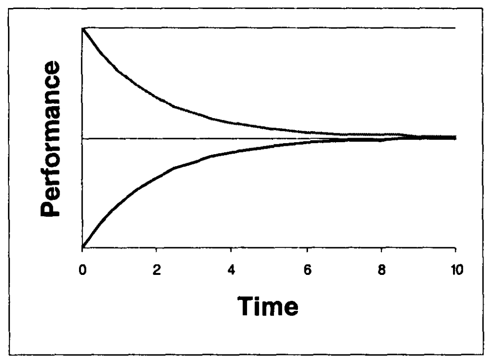


Figure 2-1 b: Goal-seeking growth pattern

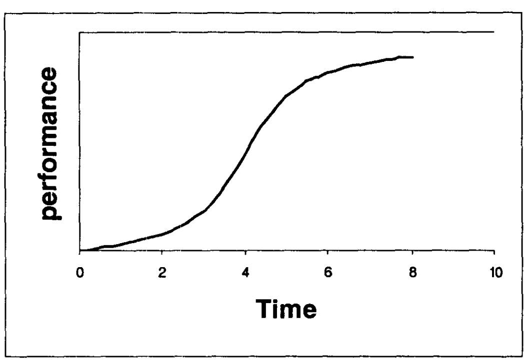


Figure 2-1 c: S-shaped growth pattern

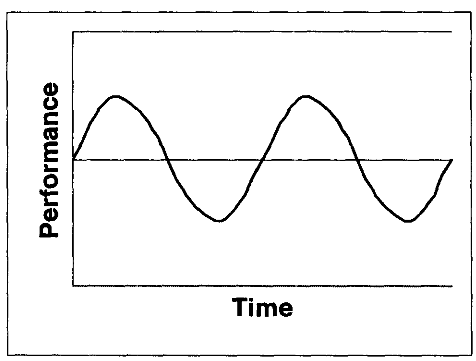


Figure 2-1 d: Oscillating growth pattern

Figure 2-1: Characteristic patterns of system behavior

2.2.3 System Representation: Levels, Rates, Auxiliary Variables, Data, and Constants

In order to study the 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 [8].

Figure 2-2 shows an example of a causal loop diagram. It describes a simplified workflow in a generic work implementation process. The project is finished when all the work moves from "Work to be Done" to "Work Completed". The rate of the flow, the "work completion rate", is determined by "workforce" and "productivity". When the work lags behind schedule (work completed is less then scheduled work completed), the schedule pressure increases, requiring us to hire more workers in order to catch up with original schedule. However, a large size of workforce can produce congestion problem: workers have to sit-and-wait for the space to work, and this effectively decreases the productivity.

We will use this typical causal loop diagram to illustrate different types of variables used in System Dynamics Models: levels, rates, auxiliary variables, data, and constants.

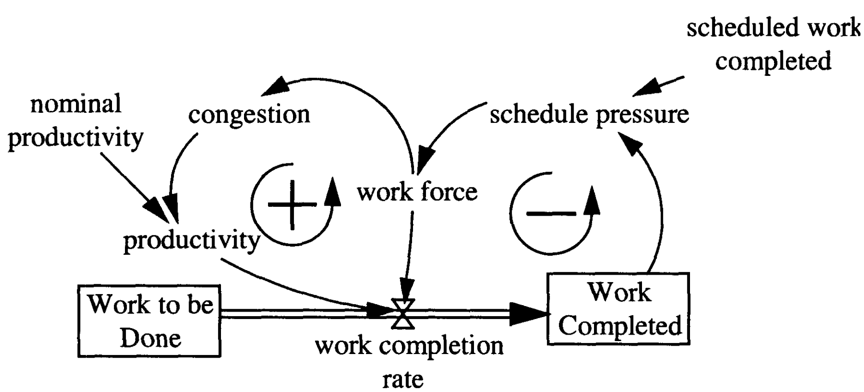


Figure 2-2: System structure example: a simplified work flow diagram

Levels (also called stocks, accumulations, and states): Levels describe the magnitudes of conserved entities. They have memory and change over time. The values that they take on at any time depend upon the value that they and other variables took on at the previous time step. The quantities "Work to be Done" and "Work Completed" in Figure 2-2 are Levels. Equation 2-1 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:

$$\begin{aligned}\text{Work Completed(t)} &= \int_0^t \text{work completion rate(t)dt} \\ &= \text{Work Completed(t - dt)} + \text{work completion rate(t - dt)} \times \text{dt}\end{aligned} \quad (2\text{-}1)$$

Rates (also called flows): Rates are the variables that directly change the magnitude of the Levels. They decide the rate of change of the conserved quantities. Rates are essentially the same as Auxiliaries and differ only in the way that they are used in a model. The "work completion rate" in Figure 2-2 is a rate variable.

Auxiliary: Auxiliary variables provide 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, and their current values are independent of the values of such variables at previous times. The "schedule pressure" in Figure 2-2, for example, is an Auxiliary variable. The equation for it is shown in Equation 2-2.

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

Data (also called exogenous variable): Data are input variables that have values that change over time but are independent of anything that happens to other variables. The "scheduled work completed" is a Data variable. Its values as a function of time are specified before the simulation. During the simulation, the value of the Data variable at any current time can be retrieved to calculate other variables.

Constants: These are variables that do not change with time. For example, "nominal productivity" in Figure 2-2 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 originates. Depending upon the relationships between variables, the returning information can amplify or attenuate the initial information, forming a 'reinforcing' or 'balancing' feedback. For example, in Figure 2-2, there are two feedback loops. (1) Work Completed (less than scheduled work completed)→ schedule pressure (increase) → work force (increase) → completion rate (increase) → Work Completed (catch up with the schedule). This is a balancing feedback loop, in the sense that an increase in the magnitude of one of the serial factors in the loop leads to a decrease in the quantity of the initial factor. (2) Work Completed (less than scheduled work completed)→ schedule pressure (increase) → work force (increase) → congestion (increase) → productivity (decrease) → completion rate (decrease) →Work Completed (less than scheduled work completed further). This is a 'reinforcing' feedback loop, in the sense that an increase in the magnitude of one of the serial factors in the loop leads to an increase in the quantity of the initial factor. The net amplification of a loop is obtained as the product of the individual amplification of the serial factors. Negative net amplification is stabilizing.

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 quantified by writing equations for each relationship, which is called "quantification". Equations 2-1 and 2-2 are examples of quantification.

When the model is built and quantified, it can then be used to simulate the system being represented. As shown in Figure 2-3, based upon inputs entered into the model and the knowledge already built along the process of modeling, the model can:

(1) Provide dynamic temporal variation of system variables based upon initial conditions, in-process events and corresponding actions input as parameters to the system, and

(2) Identify and correct the system defects by testing the system with hypothesized external impacts.

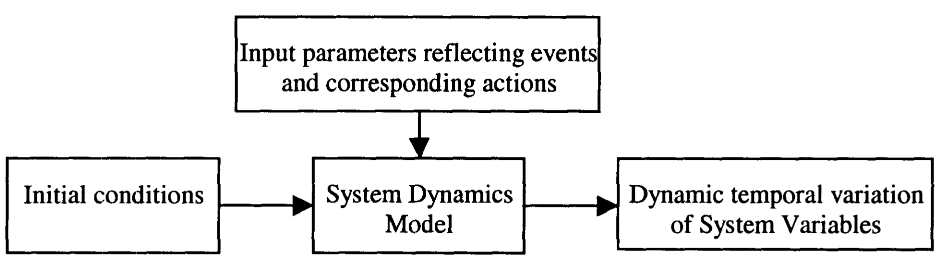


Figure 2-3: Schematic diagram showing how the system dynamics model works

2.2.4 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 [2], and Vensim® is used in the work presented here because:

- It supports a compact, but informative, graphical notation;
- The Vensim equation notation is compact and complete;
- Vensim provides powerful tools for quickly constructing and analyzing process models;
- Vensim provides a full Dynamic Link Library of functions (Dlls), making it very easy for a third-party development platform to integrate its features to develop customized applications, which is part of the work presented here.

CHAPTER 3 – THE ORSIM MODEL

3.1 Introduction

The ORSIM model replicates the organizational structure of a typical nuclear power plant and the activities carried on in the course of plant operations [10]. The organizational structure is represented by sectors that include management, operations, engineering, maintenance, and planning, all of which interact with plant physical systems and themselves in one way or another.

Generally, within a typical work sector there is a work generation rate governed by specific mechanisms, an inventory or backlog of work to be done, and a work accomplishment rate. Work creation occurs during operation and is unique for each work sector. These rates accumulate into backlogs. The backlogs are reduced at the rate at which work is accomplished, which is determined by the number of people assigned to the tasks and the productivity at which they perform their work.

The workforce in each work sector is composed of work 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.

Workforce productivity and quality are represented as dynamic variables that change continuously throughout simulations. They are calculated for all elements of the workforce in each work sector. The value of every model variable is calculated at every simulation time step.

A matrix of performance indices is developed to measure plant conditions as a function of continuous operation. The matrix includes a reliability index, an economic performance index, and plant stability indices.

3.2 Model Structure

Figure 3-1 presents an organization overview consisting of the central management and four functional work sectors. Numerous other aspects of actual NPP management and operations, including the activities of plant security, personnel, health physics, etc., are not modeled endogenously either because their influence upon actual operations is small or because they can be represented as exogenous influences.

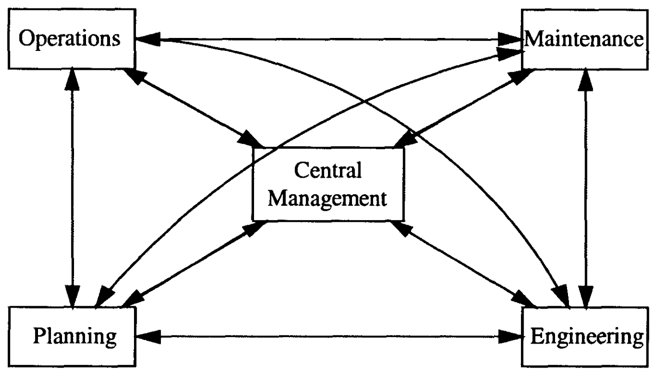


Figure 3-1: ORSIM organization structure and the interactions between functional divisions (source: [2]), each arrow reflects the flow of work products, people, and/or information.

3.3 Model Work sectors

What must be represented for each work sector are the mechanisms by which work is created and the mechanisms by which work is accomplished. We now turn to the modeling of these work sectors in detail.

All model variables are named according to the following naming 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 representing initial values. Example: "i old equipment" represents the quantity of old equipment in the plant at 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. Thus, the vector

elements are dimensionally homogeneous, and correspond to elements of different categories of the same quantity.

- '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 respective supervisors in different departments allocate their time to different responsibilities.

3.3.1 Physical Systems Sector

A nuclear power plant has a large number of structures, systems, and components (SSCs). Ideally they function together in order to produce electricity in a safe and reliable manner. Because physical system design is not a focus in this research, it is assumed that there is no design problem for all SSCs.

However, we do model the aging and degradation behaviors of SSCs: The rate at which defects are generated increases as SSCs age or as the inventory of defects in the plant equipment grows.

As symptoms of the physical systems, transients and trips (i.e. forced shutdowns) are also modeled in order to reflect the working conditions of the physical systems. These are described in detail in the Performance Matrix Sector.

In the ORSIM model, SSCs are covered in one of three programs: The Surveillance Testing Program (STP) covers safety-critical SSCs that, by NRC regulations, are required to be tested periodically; The Preventive Maintenance Program (PMP) covers safety-important SSCs, and Other (OTHER) Program covers all SSCs not covered in STP or PMP. Typically, equipments covered in different programs have different characteristics such as mean times to failure. However, it is assumed that SSCs covered under the same program share the same characteristics because the level of detail of ORSIM does not go down to treatment of individual SSCs. Instead all SSCs are viewed as the level of collections. The characteristics therefore are averaged across the population of equipment in each program.

See Figure 3-2. As a nuclear power plant operates, defects are created in the physical systems. When this occurs, defects flow into the backlog of 'Undiscovered Defects' at a 'defect growth rate x', which is determined by the total quantity of equipment ('D Equipment x'), the likelihood for a piece of equipment to develop a defect in a unit time ('hazard rate defect generation x'), and the simulation time step ('time step'). Here we assume that defects are created only during plant operation (when the variable 'plant state' equals to unity, which indicates the 'on' state).

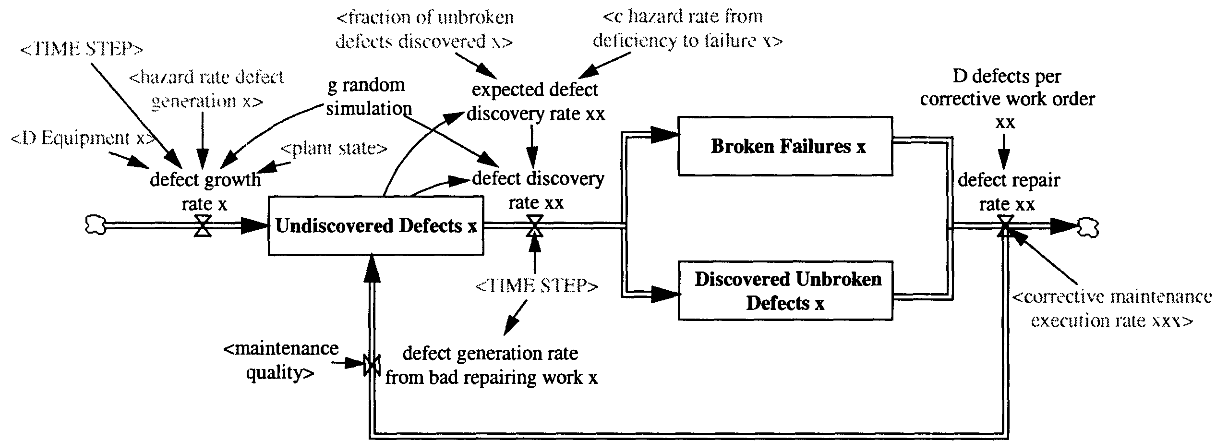


Figure 3-2: Flow diagram of physical system defect generation, identification, and restoration.

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 in 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 priority of the work, it is performed either immediately or after some time delay. The repairing brings equipment with defects back to a normal state at 'defect repair rate xx'. Because of the imperfect quality of the repairing work, a repaired defect may flow back into "Undiscovered Defects" if the defect is not repaired properly or if some deficiency is introduced in the course of repairing.

A relevant issue from Figure 3-2 is how defects are generated, or, how to compute the hazard rate – the likelihood that a piece of equipment develops a defect within a unit time. In ORSIM, the hazard rate $\lambda(t)$ is calculated according to Eq. 3-1. It is assumed that the arrival of defects follows a non-homogeneous Poisson process governed by this hazard rate $\lambda(t)$:

$$\lambda(t) = \lambda_0 \cdot f_\lambda(t)\,. \tag{3-1}$$

In Eq. 3-1, λ_0 is the baseline hazard rate, and $f_\lambda(t)$ is an adjusting factor reflecting actual conditions as compared to the nominal or baseline conditions. Factors considered in ORSIM are wear and tear, poor-quality parts installed during repair, workmanship errors caused by maintenance staff when performing their work, and the material condition of the plant – that is, poor material condition may place undue stress on components and lead to premature defect generation.

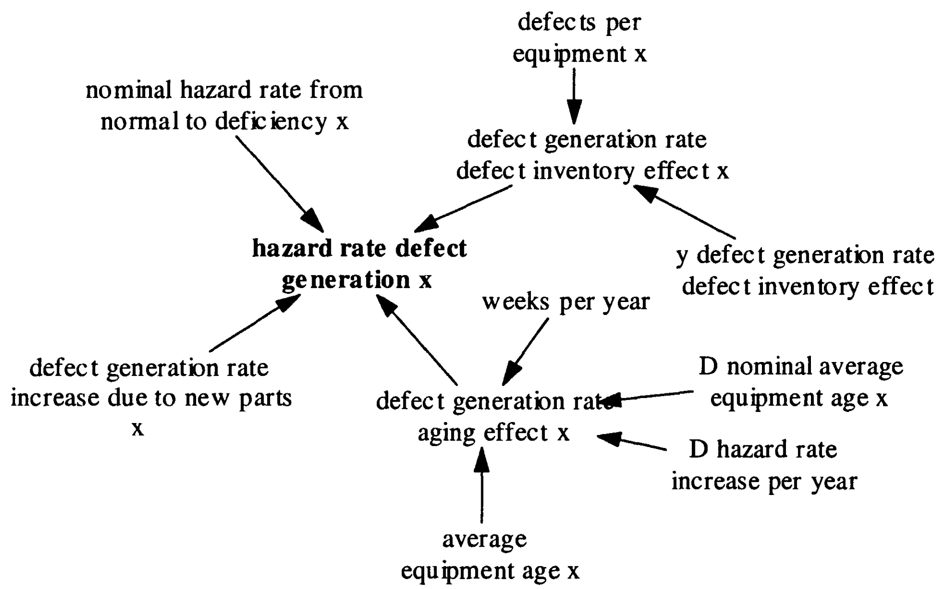


Figure 3-3: Factors affecting defect generation rate: poor-quality replacement parts, aging and degradation, and defect inventory

Figure 3-3 shows the above-mentioned defect generation rate is affected by inventory of defects, new parts installation, and wear and tear. The workmanship quality factor has been included in Figure 3-2 by the flow from repair rate to 'Defects Undiscovered".

The 'defect generation rate defect inventory effect x' reflects the fact that more defects are likely to occur when there are more defects already present in the system due to worsening operating condition. Its value is determined by average defects per piece of equipment and a function 'y defect generation rate defect inventory effect' that specifies the relationship between the defect generation rate and average number of defects per piece of equipment.

"Defect generation rate increase due to new parts" represents the effect of poor-quality new parts upon defect generation. When a poor-quality new part is installed, a defect is created immediately. Factors relevant to this effect are the quality of new parts and the rate at which new parts are installed, as shown in Figure 3-4.

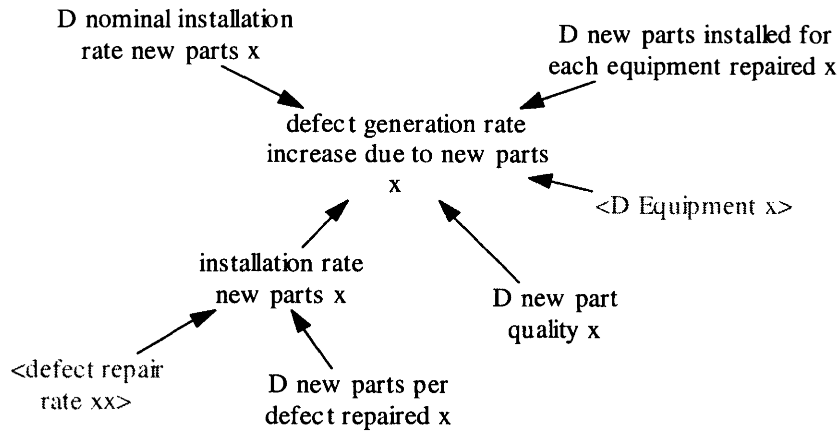


Figure 3-4: Quality of new parts affects defect generation

In ORSIM, the 'wear and tear' of equipment is represented by the average age of all equipment covered in each program. Assuming that the defect generation rate increases linearly as a function of its age at 'D hazard rate increase per year', the aging effect can be easily computed using actual average age of equipment and a baseline average age of equipment, because under this assumption the average hazard rate of equipment with different ages is the same as the hazard rate of equipment with an age equal to the average age of all equipment:

$$\lambda(x) = ax + b \Rightarrow \frac{1}{n}\sum_{i=1}^{n}\lambda(\mathrm{T_i}) = \lambda\left(\frac{1}{n}\sum_{i=1}^{n}\mathrm{T_i}\right) \tag{3-2}$$

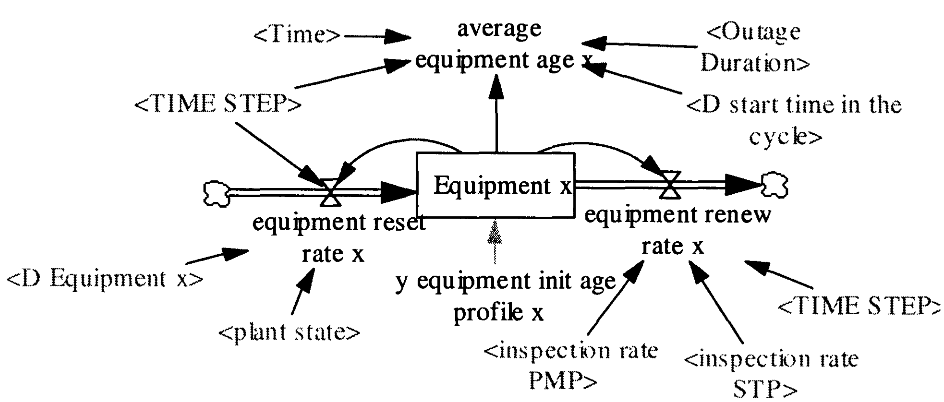


Figure 3-5: Equipment aging and renewal flow diagram

In order to obtain average equipment age, we model the aging of equipment as shown in Figure 3-5. As time goes on, equipment grows older and older. However, we assume that the age of equipment is reset to zero every time it is surveillance tested or preventively maintained. At such time it flows out of existing 'Equipment x' and re-enter immediately as new equipment. The 'average equipment age x' is computed as the sum of all equipment age divided by total quantity of equipment.

3.3.2 Maintenance Sector

Maintenance begins with identification of deficiencies in SSCs. The existence of deficiencies becomes known by several mechanisms, i.e., inspections, preventative maintenance, observations, or breakdowns. To some extent, the defect discovery rate is a function of the organizational structure and policies via existing mechanisms for preventative maintenance, inspections, and observations. Breakdown discovery can even be affected by internal policies in terms of plant instrumentation and monitoring.

Figure 3-6 describes how defects are identified in STP, PMP, and OTHER programs. The fraction of defects identified is determined by how often SSCs are surveillance tested, preventively maintained, and observed, as well as the efficiencies of these activities.

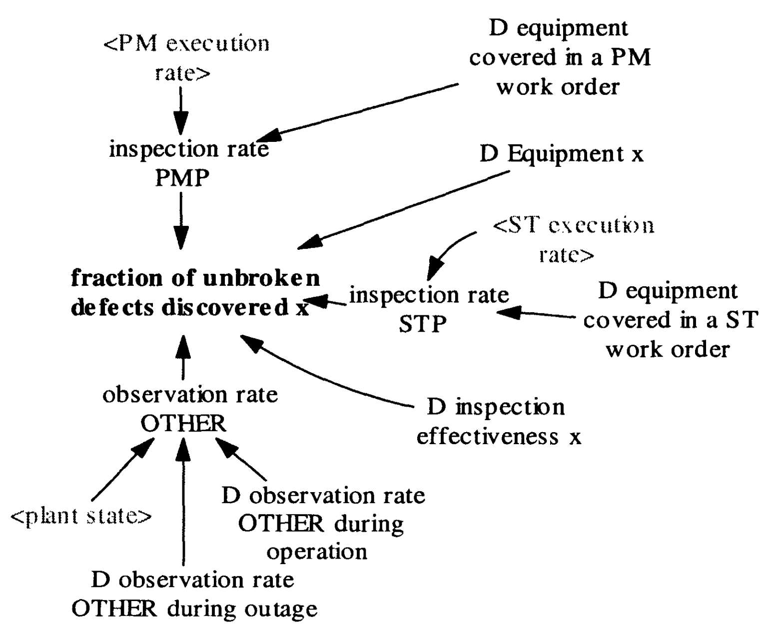


Figure 3-6: Fraction of defects being discovered before breaking down depends on how often SSCs are inspected, maintained, and observed (through plant walk-downs), and how effective these practices are.

The discovery of defects creates work downstream in order to remove the defect. The downstream work involves characterizing the defect in terms of its safety and/or operational significance. Thus, defects are distributed into various categories. 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 parts of the organization, e.g. engineering and operations. Finally, after actual execution of the repair work, it may be necessary to inspect and approve the repair. This review may lead to rework which is a form of feedback.

Figures 3-7 and 3-8 represents the above workflows. The types of work in the maintenance sector include the following:

- surveillance testing;
- preventative maintenance;
- planning and scheduling;
- priority 1 repair work (focused upon acute safety problems);
- priority 2 repair work (focused upon keeping the plant operating);
- priority 3 repair work (focused upon corrective maintenance work orders);
- "quick-fix" (also termed "fix it now" or "tool pouch") repair work (focused upon simple maintenance work).

In ORSIM, because they are required by safety regulations, the surveillance testing and preventative maintenance are assumed to require a constant top priority level of effort. The priority 1, 2, and 3 repair work vary as functions of time (determined by defect discovery rate), as does the quick-fix work.

The priority 1 work is the highest priority variable work 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 operations severely. An example of this is a coolant pump failure. These events occur occasionally in each operation cycle. Priority 3 work is routine corrective work. The work is sufficiently complex that it requires planning and scheduling and coordination with the other work 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 operational data, the fractions of each category can be obtained.

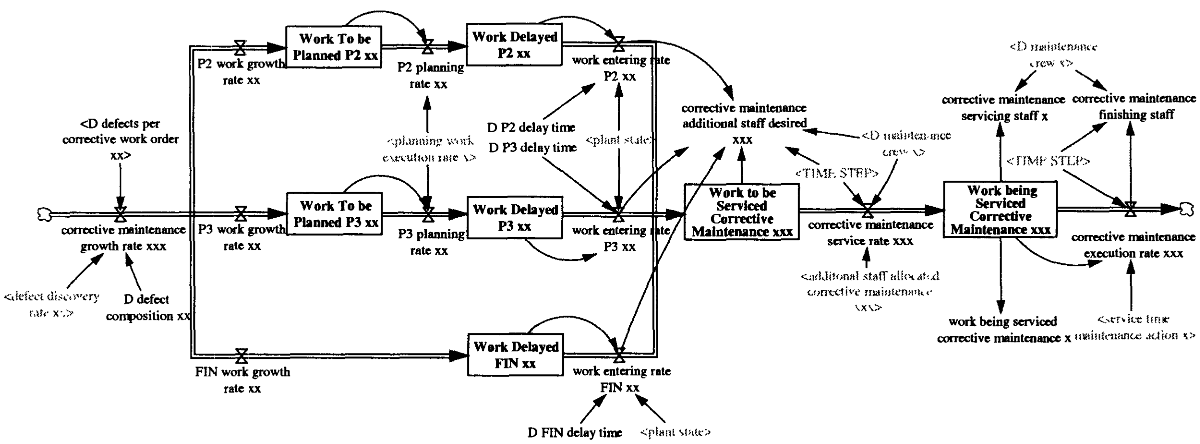


Figure 3-7: Workflow for corrective maintenance work. Corrective maintenance work orders are categorized into three groups: priority 2, priority 3, and tool pouch. They have reporting, planning, and scheduling delays before they are ready for execution. When workers are available, they work on open work orders following specified priority rules. Work orders flow out of the maintenance department after they are completed.

The flow of work orders in the maintenance system, as well as other work flows, occurs in a similar way as do that of customers going through a motor vehicle registration branch: Customers arrive randomly, are categorized by the front desk into different groups by the services they ask for, they each wait in the line for a period of time determined by the number of customers in service/in line and speed of services, and then they enter service, spend a period of time with a staff, and leave. In a maintenance system, after each defect is identified, it goes through a characterization process, which identifies what kind of work category the defect belongs to, as shown in Figure 3-7. The work then flows into stocks of different categories and is recorded as work orders. Scheduling and planning, if necessary, is performed before the execution of these work orders. The execution of the repair work requires allocation of workforce to the tasks. The number of workers assigned is determined by the tasks' respective priority and worker availability. Only workers who are idling or those who have finished their previous work orders can be allocated to perform incoming work orders. The time needed in order to finish a work order is random, governed by a distribution with expected value determined by average worker productivity. Once a work order is performed, it leaves the system.

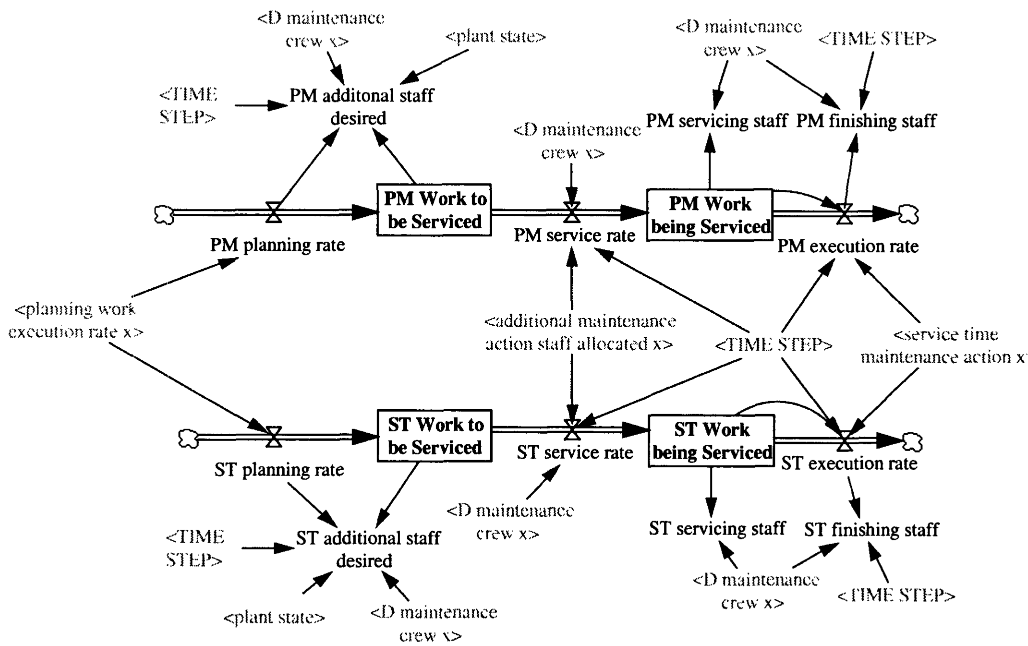


Figure 3-8: Surveillance testing and preventive maintenance workflows. Preventive maintenance and surveillance testing workload are constant from cycle to cycle.

The flow of surveillance testing and preventive maintenance work orders differs from that of corrective work orders only in how the work is created. Surveillance testing and preventive maintenance 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.

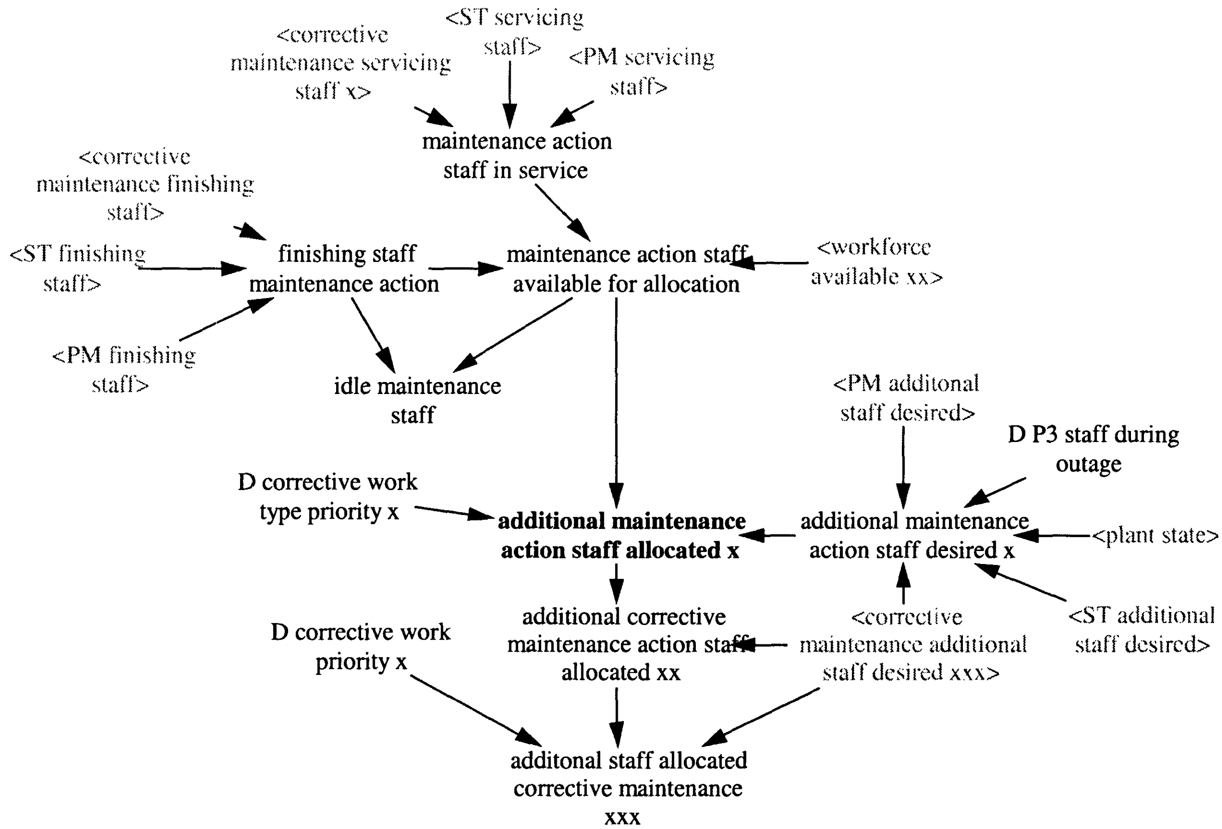


Figure 3-9: Actual allocation of workforce to different maintenance tasks is a function of desired workforce, available workforce, and priority rules.

The allocation of maintenance workers is described in Figure 3-9. Priority rules are applied here when the number of workers is less than that which is desired by all tasks. A first priority rule assigns workers to perform different categories of work orders. One typical rule is ST>P2>PM>P3>TP. For the same category of work, a second priority rule designates that broken defects are fixed first, then unbroken defects. For a same-category same type of work coming from different programs, there is a third priority rule to assign workers to work orders from different program. One example is STP>PMP>OTHER, the actual priority rule used in that of the NPP being modeled.

So far we have not discussed how work flows in the maintenance management level. In fact, in the maintenance sector, as well as in other work sectors, sector management staff and workload are modeled in a fashion analogous to that of the central management that is described in detail in the Central Management Sector.

We segregate all work sector staff into journeymen and apprentices in order to represent varying the degrees of technical/management skill affecting the productivity and quality of the work they perform. Similar to other sectors/hierarchy levels, the population of maintenance journeyman crafts increases due to new hires and promotion of apprentices, and it decreases as a result of staff downsizing, retirements, or departures. The Human Resource Management Sector of the model discusses this in detail.

Now we come to the modeling of productivity and quality of maintenance workers. In ORSIM, the productivity and quality of the maintenance staff work are represented by a set of time-dependent variables.

The productivity is determined as shown in Figure 3-10. A factor model is used. Starting with a nominal productivity, ORSIM adjusts it up or down based upon factors affecting productivity: these are skills, management efficiency/availability, and support and coordination from the operations sector and the engineering sector.

Craft productivity declines when central management is occupied with other things. The unavailability of management can delay their assistance, approvals of plans, and the purchases of supplies. Similarly, the productivity of the crafts declines when supervisors are not available to oversee and sign-off on work that is done.

The maintenance skill ratio is a measure of the amount of experience in the work crews. The factor is equal to unity if all the crafts are journeymen, and is at a minimum if all the crafts are apprentices. Engineering support affects productivity in terms of timely assembly of needed materials and complete work preparation. Finally, the operator coordination quality is used to represent how well operations have prepared to coordinate the maintenance work.

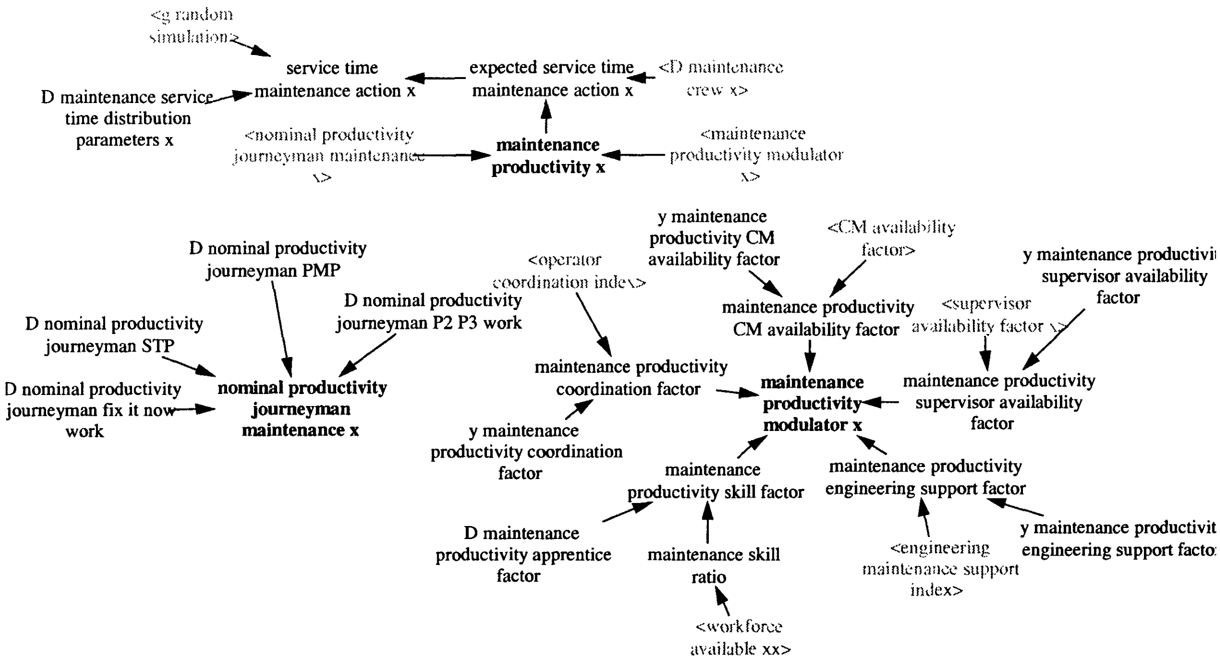


Figure 3-10: Maintenance productivity is modeled as the product of a nominal productivity and a modulator reflecting the effects of skills, maintenance availability, and support and coordination from other departments.

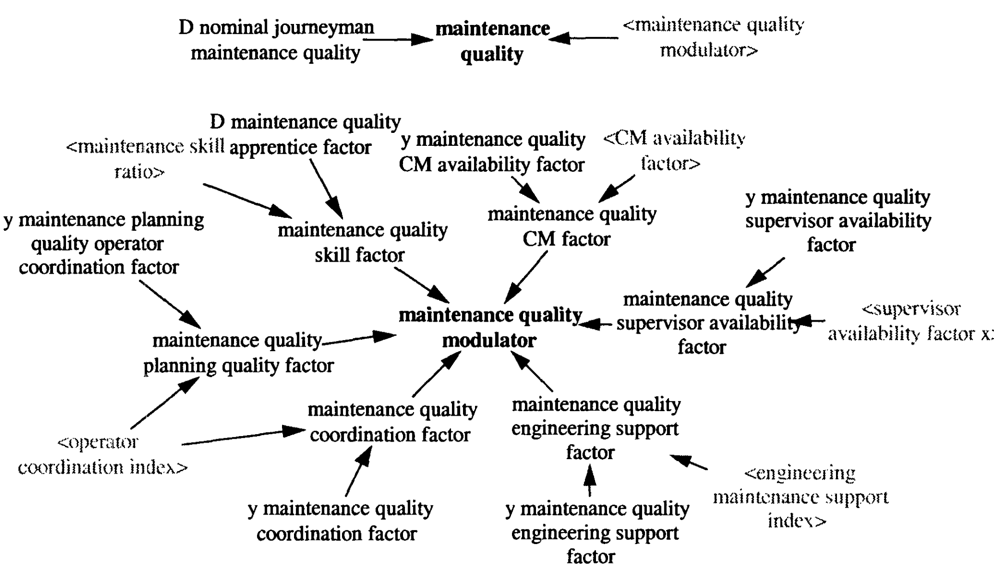


Figure 3-11: Maintenance quality is modeled as the product of a nominal quality and a modulator reflecting effects of skills, maintenance availability, and support and coordination from other department

Figure 3-11 shows the analogous parameters that affect maintenance quality in a similar way. The quality is used as a measure of what fraction of the work is done correctly the first time and will not require re-work.

3.3.3 Operation Sector

This sector describes operators who operate the plants: what they do, how they interact with other sectors, and how they are trained and qualified.

A NPP is staffed around the clock. 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 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 will manipulate the fuel and transfer new fuel into the reactor while removing old fuel from the reactor.

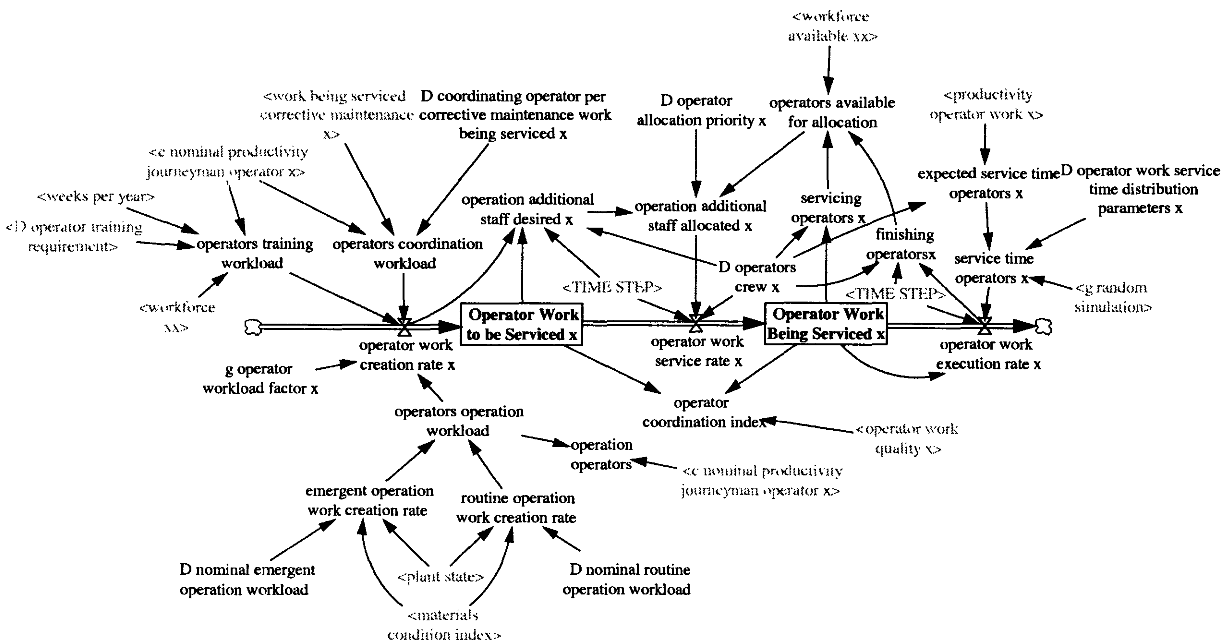


Figure 3-12: Besides operation work, operators also coordinate with maintenance teams and spend time on training. Desired operators to perform each task are determined by rates at which different tasks are generated, and productivity rates at which tasks can be performed

Figure 3-12 shows how work is generated in the operation department, and how ORSIM determines how many operators are allocated to perform all awaiting tasks. The tasks include operating, coordination, and training. 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 available operators are less than desired, priority rules is applied. Figure 3-12 also represents this staff allocation process.

The "operator coordination index" is computed as a ratio of actual number of operators assigned to do coordination work to the operators desired to do coordination work. This index reflects the timeliness and degree with which maintenance workers can obtain coordination from operators when needed.

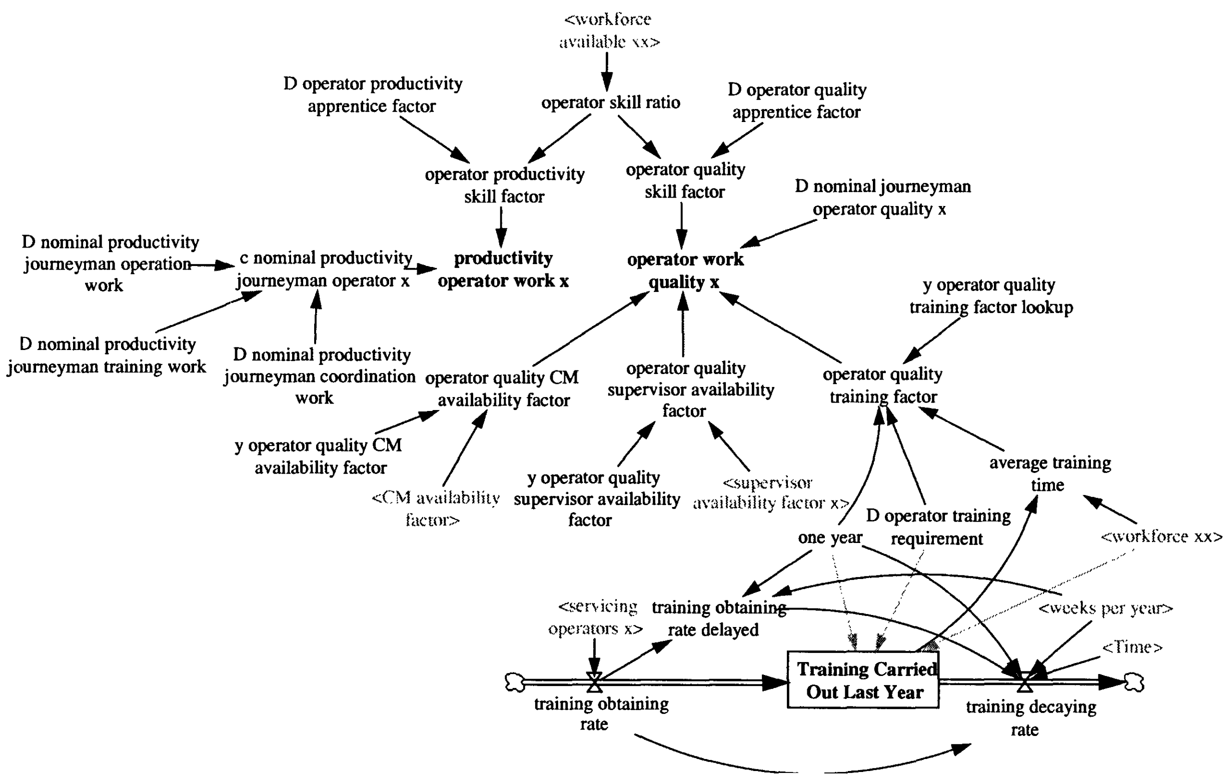


Figure 3-13: Operators are required to be trained periodically to prove competency. The training they complete and other factors such as skills and management availability all affect how fast and how well they can perform their tasks.

The knowledge, skills, and ability requirements for reactor operators have been specified by the NRC. The 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. Figure 3-13 models the training required for operators and its influence on the quality of operation work.

Besides training, operator skills and management availability also affect the quality as well as productivity of operation work, as shown in Figure 3-13.

3.3.4 Engineering Sector

Functions that the engineering sector performs include maintenance support, plant modification, licensing, and unexpected workloads (surprises). Unlike other organizational sectors, the engineering sector needs to spend time and resources on information acquisition (googling, reading, attending seminars and conferences, etc.).

Figure 3-14 represents the work creation, engineer allocation, and work execution in the engineering 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. For maintenance support and plant modification work, we can determine them from priority 3 maintenance work – the major component of maintenance work that derives engineering support and engineering modifications work to engineers. While all types of work mentioned previously are generated internally, the exogenous part of the work is reflected by the surprise work.

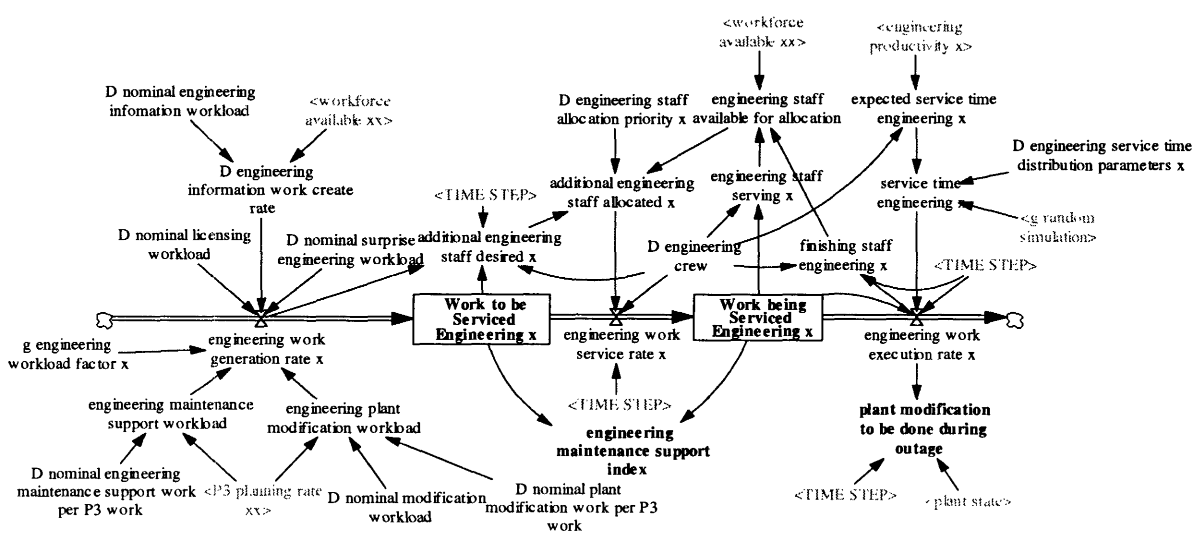


Figure 3-14: Work creation and execution in the engineering sector

After a specific type of work is generated, it flows into the work backlog awaiting execution. Based upon specified priority rules, available engineers are allocated to different tasks to work down the backlog. A special type, plant modification work, is executed during plant outage periods after the engineering work has been completed. It therefore has impact on the expected length of outage duration, as is discussed in the Planning Sector.

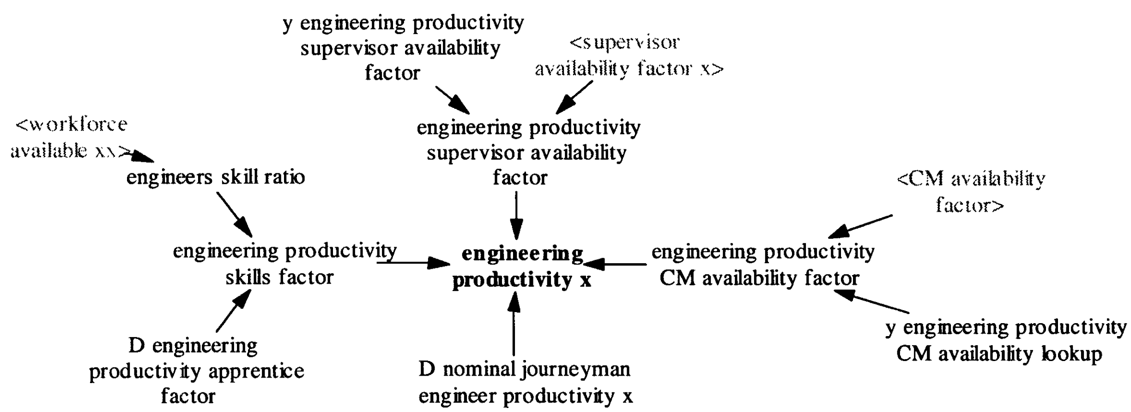


Figure 3-15: Engineering productivity is the product of baseline productivity and a modulator reflecting the effects of engineers' skills and management availability.

Similar to maintenance productivity, engineering productivity is also modeled as a product of a nominal value and modulators that adjust this nominal value up and down with factors affecting engineering productivity.

3.3.5 Planning Sector

The planning sector performs maintenance planning and scheduling as well as outage planning tasks. The types of work therefore include surveillance testing planning, preventive maintenance planning, corrective maintenance planning, and outage planning. From Figure 3-16, it can be seen that the allocation of planning staff to these tasks is similar to aforementioned sectors. When resources are not enough to meet demands, priority rules are applied to allocate resources to different tasks.

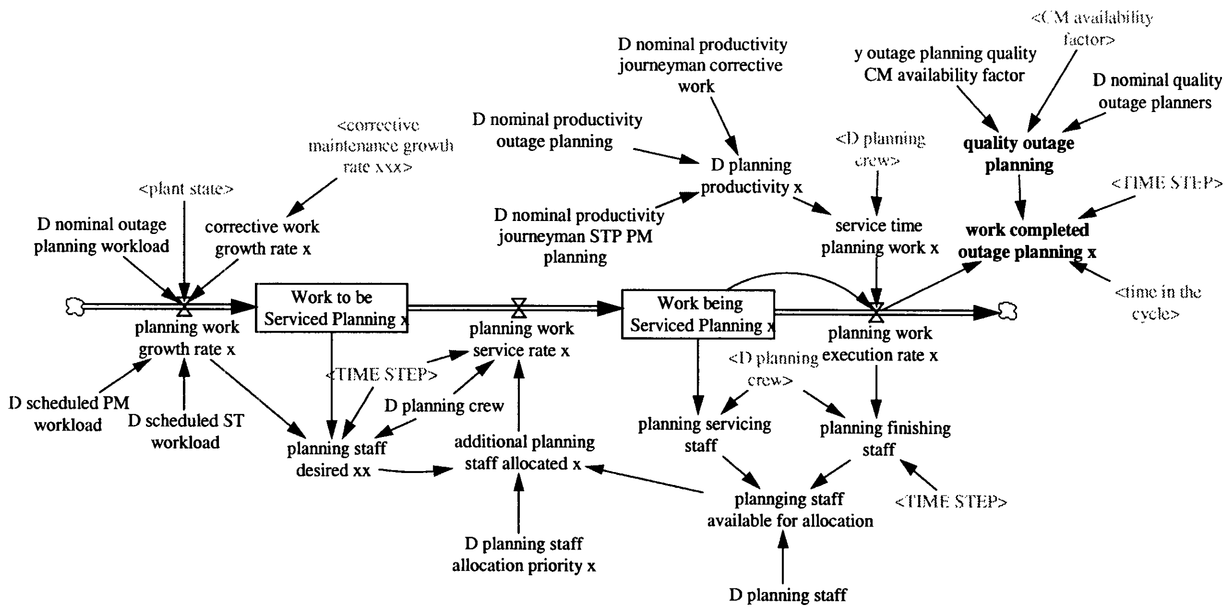


Figure 3-16: Planning work creation and execution

In the planning sector, outage planning is often at the lowest priority but at the same time it is quite important because how well outage planning is performed prior to outages affects the duration of outages. Because of the scale economy of NPPs, it is very expensive to keep the plant shut down for even a day. Exactly for this reason, NPPs have tried their best to shorten planned outage periods so that their plants can go back to production and generate revenues as soon as possible. In order to streamline and shorten the 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 projects the length of outage periods based upon how well the planning is performed prior to outages. Once an outage begins, ORSIM assumes that the outage goes smoothly and is finished in projected time, and NPP and relevant maintenance, operations, engineering, and other functions and activities restart after the outage period.

After outage planning work is executed, it flows to "Work Completed Planning". At the end of the cycle when a planned outage comes, the length of the outage period is projected based upon how well outage planning work has been performed, along with other factors shown in Figure 3-17, and then all unexecuted work still in backlog as well as all completed work is reset to zero.

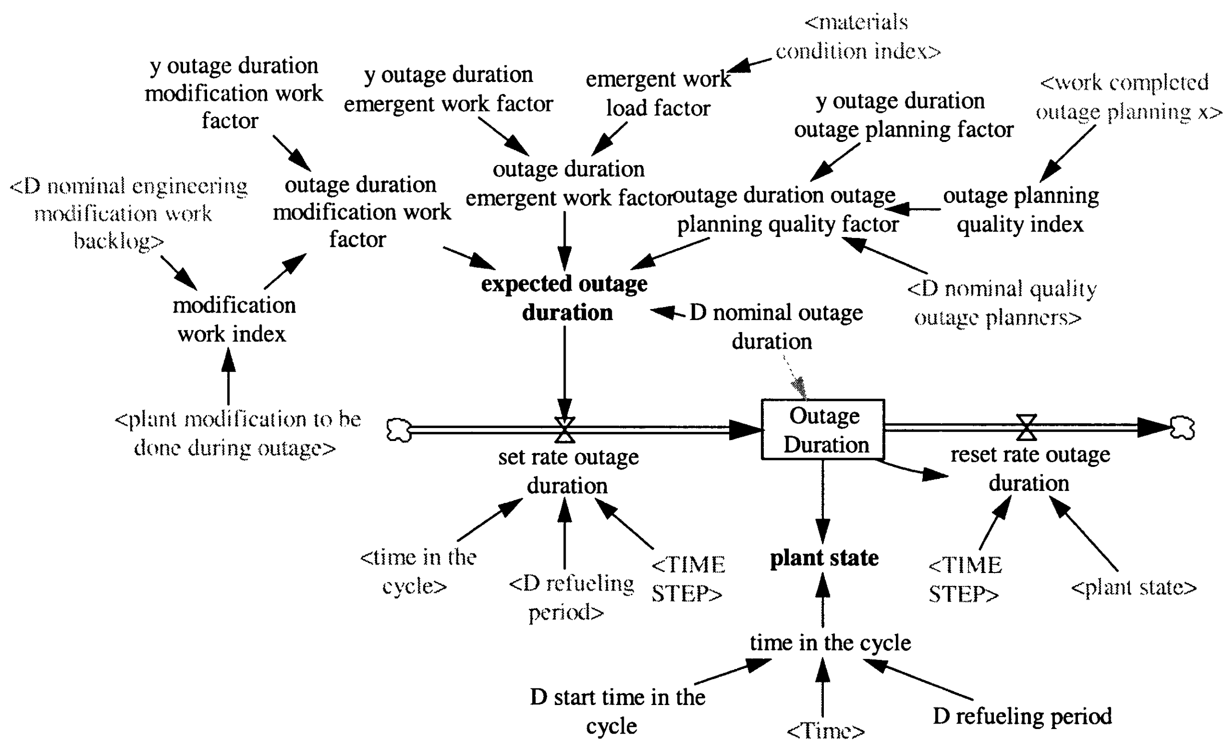


Figure 3-17: Outage duration is projected right before the outage begins based upon how well the outage is planned, how much work is required to be performed during the outage, and how good the plant overall material condition is.

A factor model is also used in determining outage duration. Aside from outage planning work execution quality, the amount of emergent work (work that is unanticipated and the need for which becomes revealed as corrective maintenance work is performed and so its amount is dependent upon the inventory of defects) is the first factor that will affect the length of outage duration. The second factor is the amount of plant modification work, which also can only be performed when the plant is shut down. These factors modulate the nominal outage duration to obtain the projected outage duration, and set this value when the outage begins. NPPs then remain shut down for this specified time period, and reset the outage duration to zero at the end of the outage period and restart the plant.

3.3.6 Management Sector

We define the central management as the set of senior managers that have oversight for the entire plant. Figure 3-18 is a causal loop diagram of the work creation and accomplishment for the central management of an NPP.

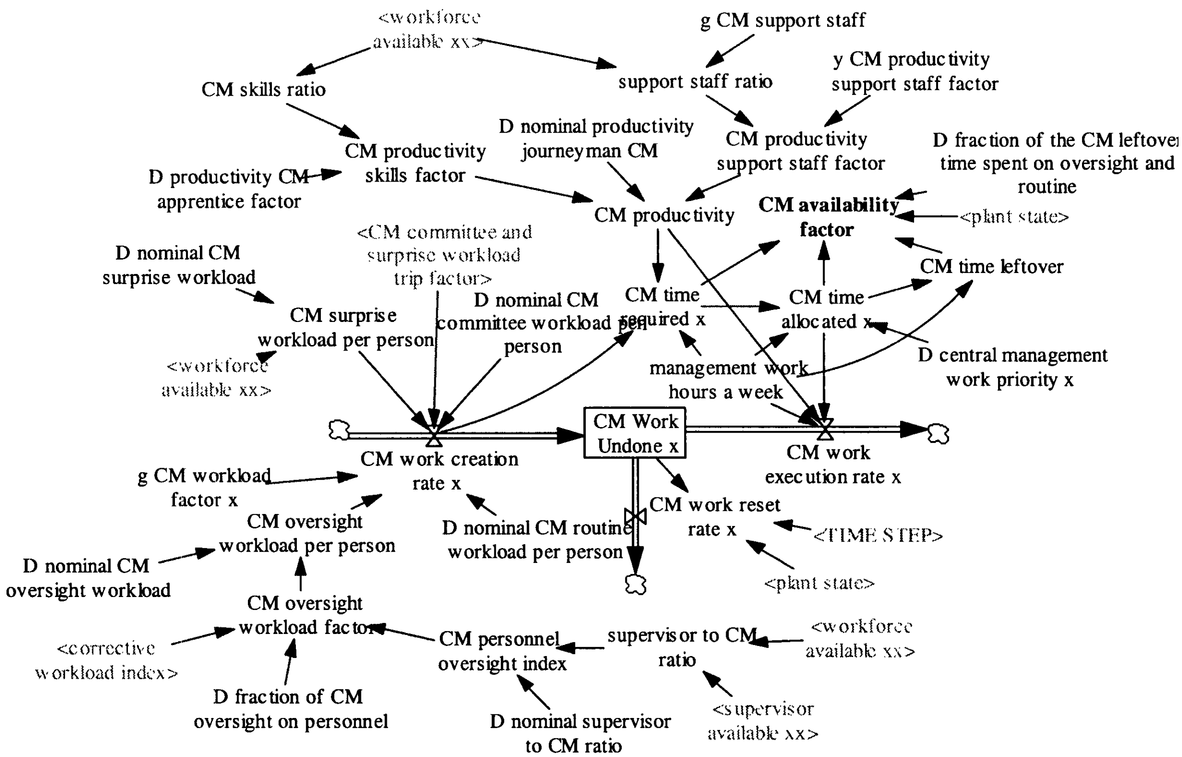


Figure 3-18: Network determining the central management workloads. Central management workloads include committee meetings, oversight, routine work, and unexpected surprise work. Managers are assigned to different tasks based upon how many managers are desired for each task and priority rules. Central management availability is the ratio of actual number of managers assigned to oversight, routine, and outage supervision to the number desired.

The managers are required to attend many committee meetings that inform them about the plant, the personnel, the rest of the utilities' activities, etc. These meetings are important aspects of management's activities and constitute one form of work. In addition, management time is consumed in dealing with unscheduled and/or unanticipated work. We combine all forms of such work under the rubric of "surprises". Discussions with many plant managers assure us that such activities are a significant, and perpetual, part of management work. Finally, the 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 the central management role is overseeing the organization. At last, the "routine" work represents the routine daily work for managers, such as paperwork, replying to emails, reading reports, etc.

Managers' skills and experience affect the productivity and quality of central management work, which in turn affect their workloads. This is a feedback to management workload: For a management team of a given number of managers, the less efficient they are, the heavier their workloads, and thus the less available they are to oversee their subordinates, which slow down the operations within the organization. This will ultimately build up central managers' workloads.

As mentioned just now, central management availability for oversight is the point where central management interacts with other sectors. It is computed as the quotient of actual number of managers allocated to oversight and routine work to that desired by oversight and routine workloads. Since managers are allocated to different tasks following specified priority rules, the number of managers allocated to a specific task depends on its desired number as well as the number of managers left to be allocated to this task after fulfilling higher priority tasks. It is important to recognize that any priority rule can be built into a simulation model.

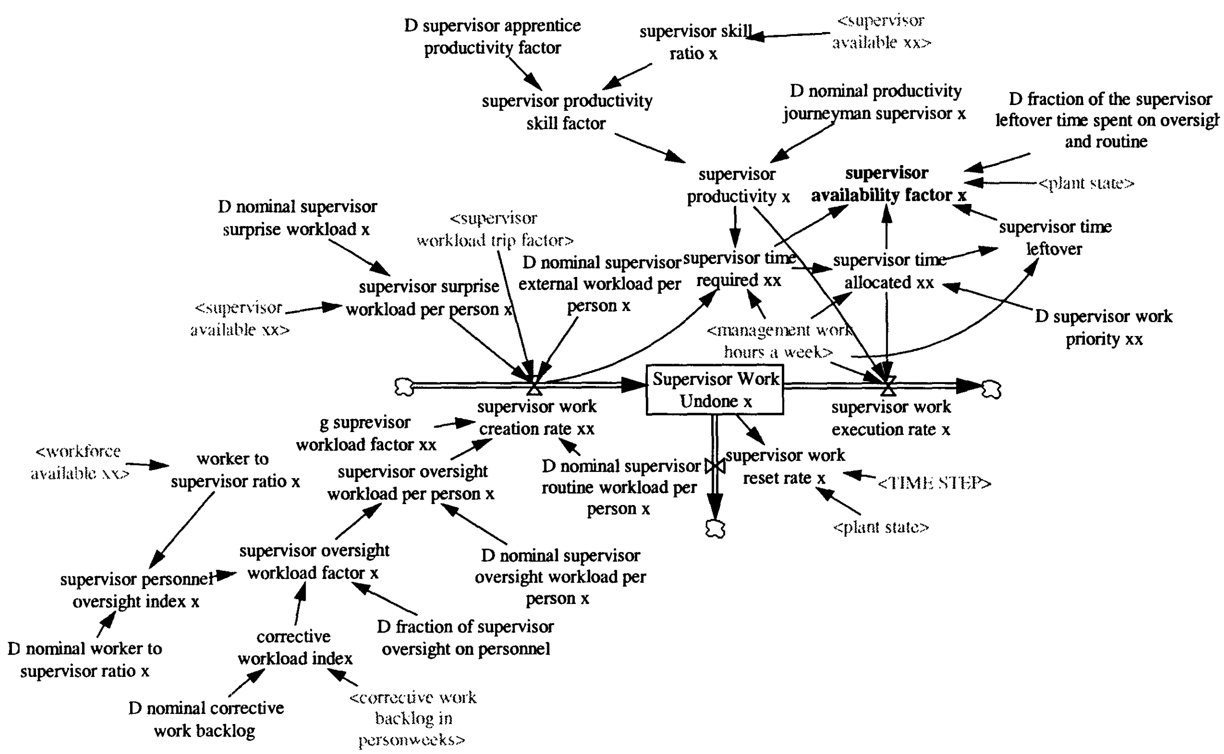


Figure 3-19: Network determining supervisors' workloads. Supervisors' workloads include oversight, routine work, unexpected surprise work, and external work. Supervisors are assigned to different tasks based upon how many supervisors are desired for each task and priority rules. Supervisor availability is the ratio of actual number of supervisors assigned to oversight and routine work to the number desired.

The way the supervisory staff is assigned to different tasks is similar to central management staff (see Figure 3-19). When work volume is more than can be accomplished, they will allocate their time with regard to some priority rules, and the availability of staff is determined by the time resources allocated to routine work and oversight work.

3.3.7 Human Resource Management Sector

In ORSIM, organization sectors have two types of workforce: sector management staff, and sector staff. Sector management staff, or supervisors, are modeled in a fashion analogous to that of the Central Management and is described in the Management Sector. Sector staff is composed of workers or engineers.

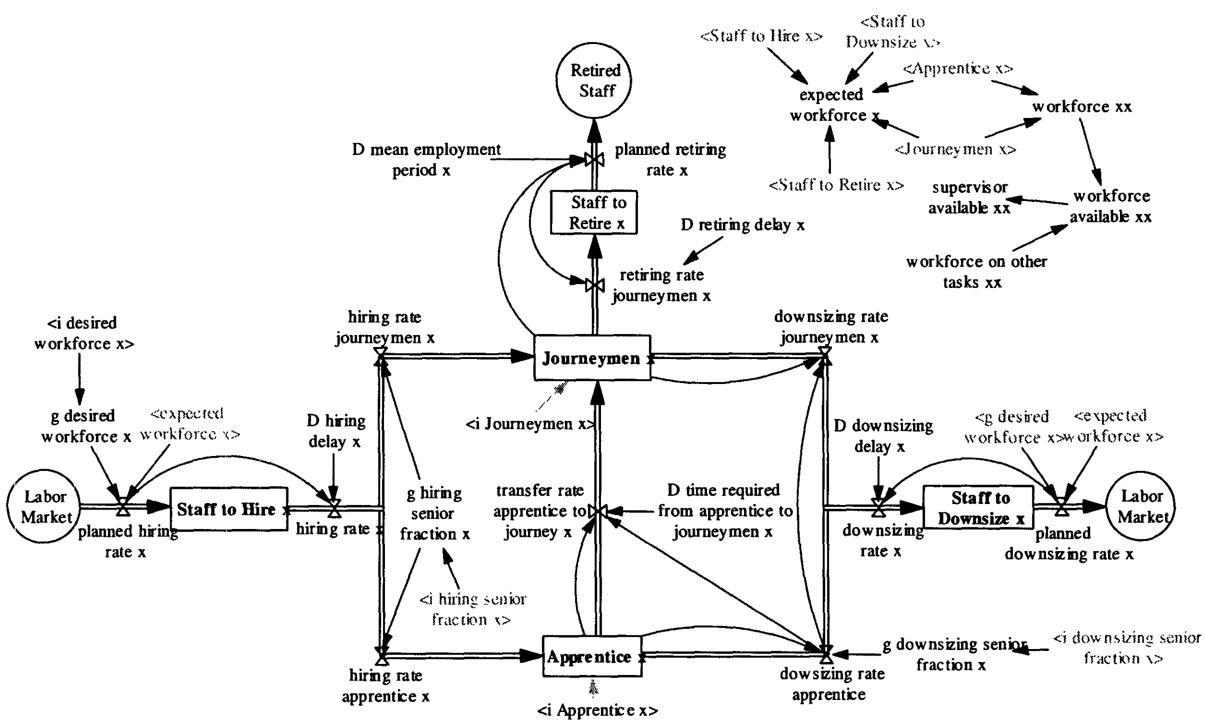


Figure 3-20: Workforce flow diagram. Workforce flow starts from desired work force. Either hiring or firing is executed to adjust current workforce to desired workforce. Apprentices are promoted to Journeymen after a number of years of service, and Journeymen retire after they become old.

We segregate all sector staff into journeymen and apprentices to represent varying degrees of efficiency/skill. The workforce is represented in a fashion shown in Figure 3-20. We have the population of journeymen crafts increasing due to hires or promotion and decreasing due to downsizing, retirements, or departures. The importance of the relative mix of crafts relates to their productivity and the quality of the work they perform.

In ORSIM, hiring/downsizing is treated as an exogenous policy, or, in other words, the number of staff to be hired and downsized is not computed by the ORSIM model but rather is input by model users by setting the quantity of "desired workforce". The ORSIM model will then automatically adjust the size of current workforce to be the same as this specified level, but with a time delay reflecting the time required to make adjustments after a hiring/downsizing decision.

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 "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 (see Figure 3-20).

3.3.8 Performance Matrix Sector

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

While all aforementioned sectors are modified from an existing model OPSIM that was developed by HGK Associates, the performance matrix sector was newly created. The text here describes the big picture of how each index is modeled, while detail derivations are deferred to Chapter 4.

3.3.8.1 Reliability Performance

Transient and trip events, rather than a core damage event, are used to represent the safety aspect of NPP operations. The rationale is because core damage is rare as well as catastrophic; so rare that it will more likely not occur during the life of NPP, and so catastrophic that once it occurs, the NPP is typically shut down and operations cease. However, we do model the conditional core damage probability (not event) in ORSIM to directly quantify operational risks (Figure 3-22).

Since the probability of a trip given a transient event can be estimated from historical operation data, we only need to obtain the transient frequency (*TF*) in order to calculate the reactor trip frequency:

$$Trip\ Frequency = P(Trip \mid Transient) \times TF \qquad (3\text{-}3)$$

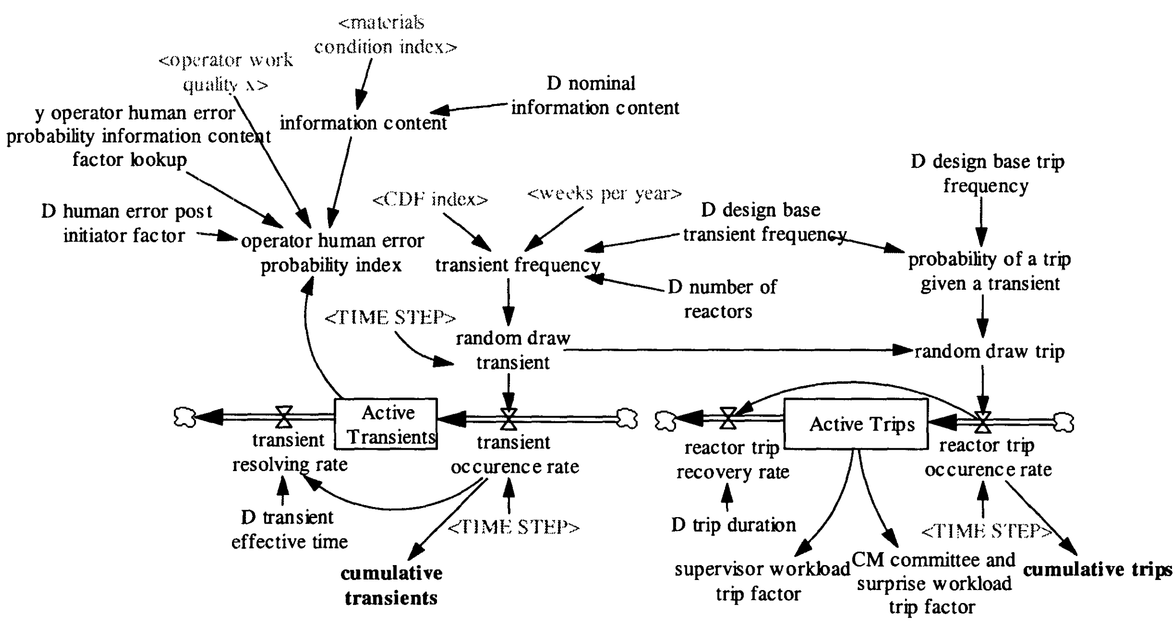


Figure 3-21: Factors affecting occurrence of transient and trip events. Transient and trip event frequencies are functions of material condition and operator performance (human reliability). In ORSIM, human reliability is modeled using information theory.

Here is how transients and trips are modeled in ORSIM (see Figure 3-21):

1. ORSIM is simulated from starting time. At any time t, ORSIM arrives at a state with known state variables such as inventory of defects, equipment breakdowns, etc.;

2. The CDF index is calculated that reflects current material condition and human error probabilities;

3. The transient frequency is calculated based upon the CDF index;

4. Random draw is performed using transient frequency from step 3 as expected value to determine whether or not a transient event occurs within time period (*t, t+ dt*] (random draw with probability = transient frequency×dt);

5. The relationship $Trip\ Frequency = P(Trip\,|\,Transient) \times TF$ is used to determine whether a trip event occurs within a certain time period $(t,\ t+dt]$ (random draw similar to that in 4);

6. If a transient or trip event occurs, ripple effects go through the rest of the system (operators, engineering, maintenance, and management).

As mentioned in the beginning of this section, although core damage events are not modeled in ORSIM, we do model the conditional core damage probability (not event) in order to directly quantify operational risks (Figure 3-22). In fact, what we really model is an index, or a ratio of actual conditional CDF to the nominal CDF. Conditional CDF and nominal CDF differ in several ways:

- The nominal CDF assumes that no failures occurred, however, the conditional CDF is subject to broken failures;
- The nominal CDF assumes nominal SSC failure probabilities, however, the conditional CDF uses actual SSC failure probabilities given material condition;
- The nominal CDF assumes a nominal human failure probability, however, the conditional CDF uses an actual human failure probability given what actually happened.

The index reflects these differences and is computed as the ratio of actual conditional CDF to nominal CDF, therefore, the smaller this index is, the better.

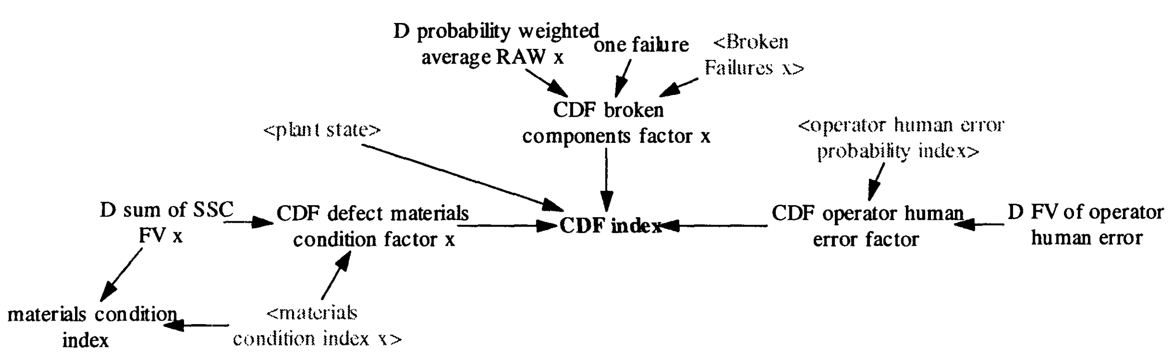


Figure 3-22: Factors affecting the CDF index. Reliability index is the ratio of actual conditional CDF to nominal CDF. It considers the effect of broken failures and actual human error probability as a function of continuous operation.

3.3.8.2 Economic Performance

Outages, whether expected or unexpected, shut down NPPs and cause economic losses due to the inability to produce revenues from electricity production. This process is represented in Figure 3-23, where two components of economic losses are shown. One is electricity loss from scheduled outages, another from unexpected trips. The losses per unit time depend upon capacity of the NPP (nominal capacity times its "capacity factor" – a factor to reflect utilization of nominal capacity). The total losses are equal to the sum of these two components.

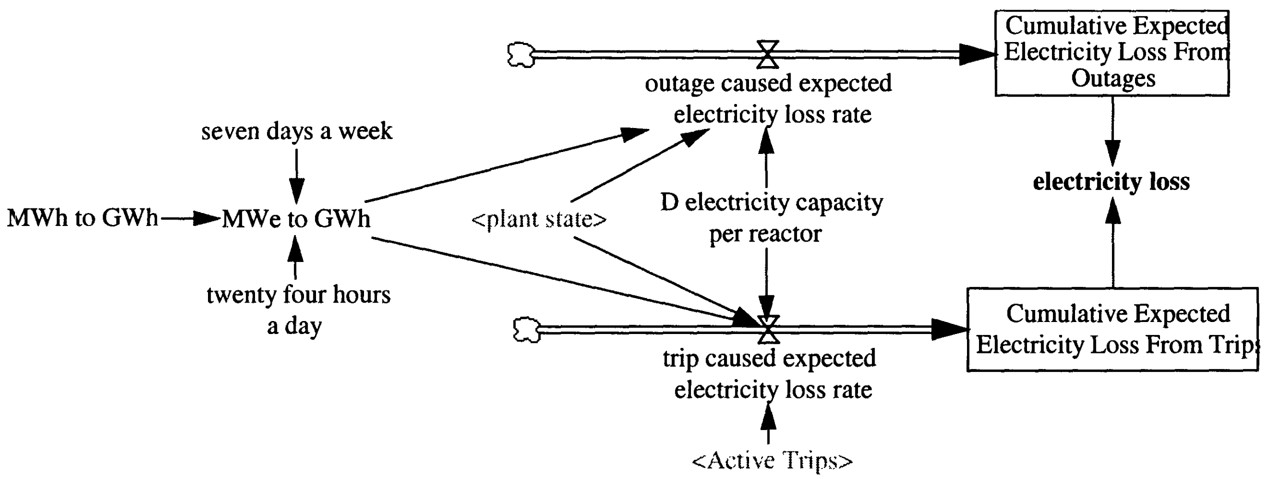


Figure 3-23: Factors affecting lost electricity production. Electricity loss can be caused by either a planned outage or an unexpected outage (trip). It is desired to have shorter planned outage durations and less trips.

3.3.8.3 Stability Performance

Stability performance measures stability of the system. A system is said to be stable if the work creation rate is less than the maximum work execution rate possibly achieved.

The first variable that ORSIM keeps track of is the level of work backlog in the maintenance program (see Figure 3-24). It is computed by aggregating all work orders remaining in the system. Since a P3 work order requires much more effort than a TP work order, nominal productivity of work orders is used to convert all work orders into a uniform notion: work order in unit of person-weeks, i.e. number of person-weeks required to work down current work backlog. Obviously, the smaller the backlog, the better. If this backlog oscillates around a steady state value, we say the plant is able to maintain stable operation.

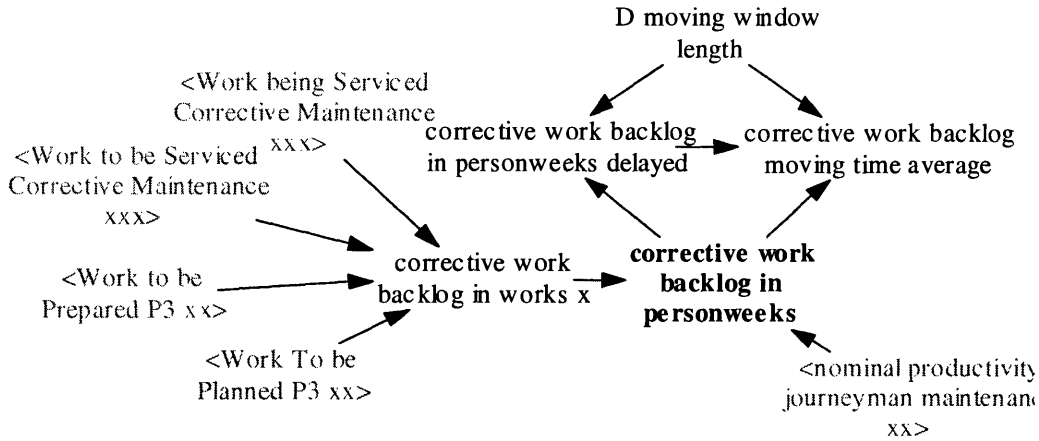


Figure 3-24: Corrective work backlog in the maintenance program

One drawback of using the corrective work backlog as an indicator of stability is its lack of foresight. When we see a sharp increase in the backlog, we are already in a bad situation. It is desirable to have a indicator that signals us before bad things happen, and our second variable, the stability index, serves this purpose (see Figure 3-25).

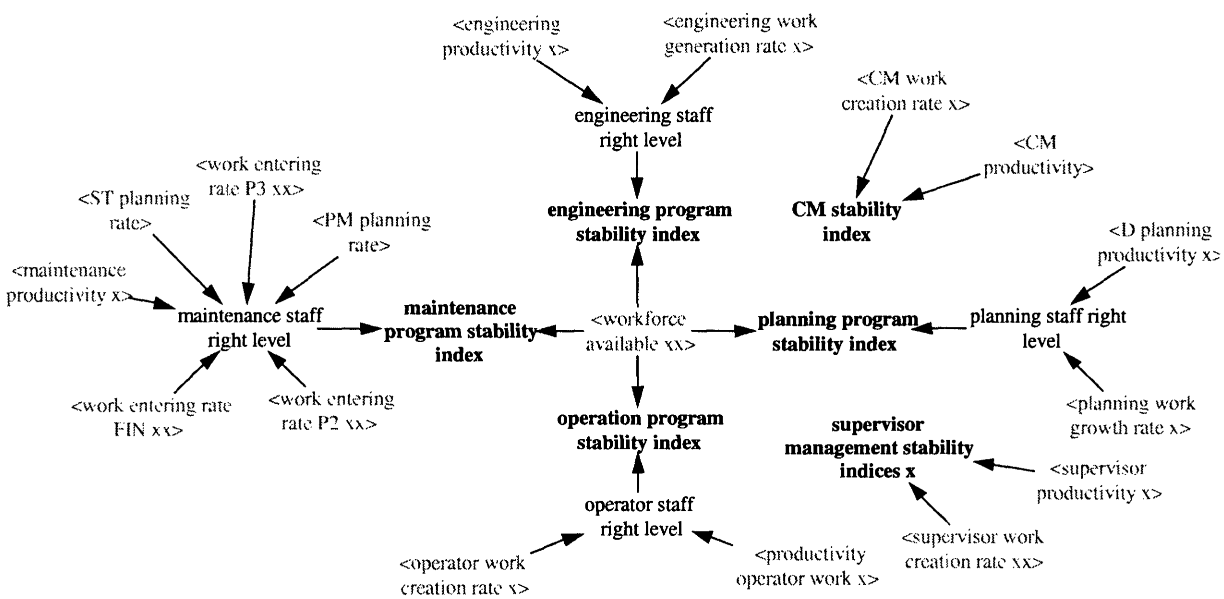


Figure 3-25: Factors of the maintenance program stability index

The stability index measures how much margin we have on average in our operation and is a function of expected work arrival rate, average work execution time, and number of workers we have available. Its normal value is 0~1, with '1' meaning that the system is absolutely stable and '0' meaning at the brink of instability. A negative value is reached when average work arrival rate is greater than maximum work execution rate (with all workers working on work orders). Generally, this value should be close to zero (meaning high utilization rate of workers) but positive (meaning stability is maintained).

CHAPTER 4 – PERFORMANCE MATRIX

4.1 Introduction

A matrix of high-level performance indices was developed in the work presented here in order to measure plant performance as a function of continuous operations. The matrix includes the reliability index, the economic performance index, and the operation stability index. The economic performance index is simply represented by electricity loss due to outages – both expected and unexpected. It is therefore a function of scheduled outage frequencies, outage durations, and unexpected plant shutdowns. In this chapter, the focus is upon the development of the reliability index as well as the stability index.

4.2 Reliability Index

A risk model was developed to represent risk as a function of the conditions of continuous operation. The output information is contained in an index named conditional core damage frequency (CDF) index, or 'CCDF index'. It measures how the conditional CDF compares to a nominal design-based CDF and reflects the effects of materials conditions (which measures the likelihood of having new defects), of broken failures (which can alter the conditional CDF), and of human reliability (as a function of skills, training received, post-initiator pressure, and the magnitude of information to be handled):

$$\text{CCDF index}_t = \frac{\text{CDF}_t}{\text{CDF}_0} \tag{4-1}$$

During the operation of a NPP, the actual CDF (CDF_t in Equation 4-1) varies as conditions vary from the default conditions, implied by nominal CDF (CDF_0 in Equation 4-1): First, there are failed components that are incapable of performing their desired functions; and second, material conditions and human performance change the underlying hazard rates of currently normal components and/or human error probabilities. The effects of these two changes are quantified from a high-level perspective and are incorporated in a CCDF index.

4.2.1. CDF Conditional Upon n Broken Failures

It is desired to be able to utilize data generated by existing tools, models, and state of knowledge for a plant to model the CCDF index. For this purpose, we make the following assumptions:

1). Component failure events are unconditionally independent;

2). Component failure events are conditionally independent, given a core damage event.

First let us look at P(CD| one component failed), the probability of core damage given that some component has failed.

By definition, Risk Achievement Worth (RAW) of *i*th component is:

$$\mathrm{RAW_i} = \frac{\mathrm{P(CD\,|\,ith\ component\ failed)}}{\mathrm{P(CD)}}$$

$$\Rightarrow \mathrm{P(CD\,|\,ith\ component\ failed) = P(CD)RAW_i} \qquad (4\text{-}2)$$

Since in ORSIM we do not know which of the components actually failed, we want to find the expected core damage probability:

$$\mathrm{E[P(CD\,|\,one\ component\ failed)]}$$

$$= \sum_{\mathrm{i}} \mathrm{P(CD\,|\,ith\ component\ failed)\cdot P(ith\ component\ failed\,|\,one\ component\ failed)} \qquad (4\text{-}3)$$

By Bayes's theorem,

$$\mathrm{P(E_i\,|\,B)} = \frac{\mathrm{P(B\,|\,E_i)P(E_i)}}{\sum_{\mathrm{j}} \mathrm{P(B\,|\,E_j)P(E_j)}},$$

we have:

$$\mathrm{P(ith\ failed\,|\,one\ failed)} = \frac{\mathrm{P(one\ failed\,|\,ith\ failed)P(ith\ failed)}}{\sum_{\mathrm{j}} \mathrm{P(one\ failed\,|\,jth\ failed)P(jth\ failed)}}$$

$$= \frac{\mathrm{P(ith\ failed)}}{\sum_{\mathrm{j}} \mathrm{P(jth\ failed)}} \equiv w_i \qquad (4\text{-}4)$$

And therefore,

$$E[P(CD \mid \text{one component failed})] = \sum_{i} P(CD) \cdot RAW_i \cdot w_i = P(CD) \sum_{i} RAW_i \cdot w_i$$

$$\equiv P(CD)\overline{RAW} \tag{4-5}$$

In Equation 4-5, $\overline{RAW}$ is the average of all components' RAW, weighted by components' failure probabilities.

What about P(CD| two components failed)? Suppose these two events are i and j, then:

$$E[P(CD \mid \text{two components failed})] = \sum_{i \neq j} P(CD \mid i \cap j) \cdot P(i \cap j \mid \text{two failed}).$$

Again, by Bayes's theorem:

$$P(CD \mid i \cap j) = \frac{P(i \cap j \mid CD)P(CD)}{P(i \cap j)} = \frac{P(i \mid CD)P(j \mid CD)}{P(i)P(j)} P(CD) \quad \text{[assumptions 1) and 2)]}$$

$$= \frac{P(CD \mid i)P(i)/P(CD)}{P(i)} \frac{P(CD \mid j)P(j)/P(CD)}{P(j)} P(CD)$$

$$= \frac{P(CD \mid i)}{P(CD)} \frac{P(CD \mid j)}{P(CD)} P(CD) = P(CD) RAW_i RAW_j \tag{4-6}$$

$$P(i \cap j \mid \text{two failed}) = \frac{P(\text{two failed} \mid i \cap j)P(i \cap j)}{\sum_{m \neq n} P(\text{two failed} \mid m \cap n)P(m \cap n)} = \frac{P(i)P(j)}{\sum_{m \neq n} P(m)P(n)}$$

$$= \frac{P(i)P(j)}{\sum_{i} P(i) \sum_{j} P(j) - \sum_{k} P^2(k)} \approx \frac{P(i)P(j)}{\sum_{i} P(i) \sum_{j} P(j)} = w_i w_j \tag{4-7}$$

$$E[P(CD \mid \text{two components failed})] = \sum_{i \neq j} P(CD \mid i \cap j) \cdot P(i \cap j \mid \text{two failed})$$

$$= P(CD) \sum_{i \neq j} RAW_i RAW_j \cdot w_i w_j = P(CD)\left(\sum_{i} RAW_i w_i \sum_{j} RAW_j w_j - \sum_{k} (RAW_k w_k)^2 \right)$$

$$\approx P(CD)\left(\sum_{i} RAW_i w_i \sum_{j} RAW_j w_j \right) = P(CD)\overline{RAW^2} \tag{4-8}$$

Using the same argument:

$$E[P(CD|\text{ n components failed})] \approx P(CD)\ \overline{RAW}^{\,n} \tag{4-9}$$

And consequently:

$$E[CDF\,|\,\text{n components failed}] = CDF_0\left(\overline{RAW}\right)^n \tag{4-10}$$

4.2.2 CDF Conditional Upon Changes in Failure Probabilities

Here we discuss how CDF changes as failure probabilities of all components change. We assume that the following are true:

1) Fussell-Vesely values of the component are small;

2) Changes of component failure probabilities are small;

3) Failure dependencies are stationary.

First let us look at how CDF changes as the failure probability of *i*th component changes.

Let P_i be the failure probability of the *i*th component in the system. Because each component appears as a factor in many accident sequences but at the most once in each, CDF can be represented as a linear function of P_i [13]:

$$CDF = a_i P_i + b_i\,. \tag{4-11}$$

where aP is the sum of all the accident sequences which contain P, and b represents all other accident sequences. This is particularly the case where failure dependencies are stationary. For a specified SSC, a large value of the a parameter reflects either a high frequency of initiating events for which the SSC is needed or large basic event probabilities of the other SSCs in the same accident sequences. It is a measure of the functional redundancy or "defense in depth" with respect to the safety challenges faced by the specified SSC. A small value of a suggests a high degree of functional redundancy, or, that there are many alternative SSCs should the specified SSC fail.

By definition:

$$FV_i = \frac{a_i P_i}{a_i P_i + b_i}, \tag{4-12}$$

where FV_i is Fussell-Vesely value of ith component. If FV_i is small (assumption 1 above), then:

$$FV_i \approx \frac{a_i}{b_i} P_i \tag{4-13}$$

Because all other components' failure probabilities remain unchanged, a_i and b_i remain constant, with the result:

$$FV \propto P_i. \tag{4-14}$$

Next: $$\frac{\partial CDF}{\partial P_i} = a_i = \frac{FV_i \times CDF}{P_i} = \frac{FV_{i,0} \times CDF}{P_{i,0}} \tag{4-15}$$

And $$dCDF = \frac{\partial CDF}{\partial P_i} dP_i = \frac{FV_{i,0}}{P_{i,0}} CDFdP_i \tag{4-16}$$

$$d(\ln CDF) = d(\frac{FV_{i,0}}{P_{i,0}} P_i) \Rightarrow CDF = CDF_0 \exp\left(FV_{i,0}\left(\frac{P_i}{P_{i,0}} - 1 \right)\right) \tag{4-17}$$

Since human error can also be factored in a similar fashion as Equation 4-12, Equation 4-17 is also true for human error probability change.

Equation 4-17 is exact for one component (or one type of human error). In the case where all components' failure probabilities change, it does not hold because $FV \propto P_i$ requires that all but one components' failure probabilities remain unchanged. However, if the change is small (by assumption 2 above), then a_i and b_i in 4-8) for all components only slightly changes, and approximately $FV \propto P_i$. Therefore, in the case of small changes, we can extend (4-17) to all components and obtain the result:

$$CDF \approx CDF_0 \exp\left(\sum_i FV_{i,0}\left(\frac{P_i}{P_{i,0}} - 1 \right)\right) \tag{4-18}$$

Divide components into four groups reflecting different intensities of their maintenance programs:

(1) Components covered by surveillance testing program (STP),

(2) Components covered by preventive maintenance program (PMP),

(3) Components covered by OTHER program (other than STP and PMP), and

(4) Human error events,

and assume that $\frac{P}{P_0}$ is the same within each group (but can be different across groups), let

$$\delta = \frac{P}{P_0} - 1, \tag{4-19}$$

then:

$$CDF = CDF_0 \exp\left(\delta_1 \sum_{i \in g_1} FV_{i,0} + \delta_2 \sum_{i \in g_2} FV_{i,0} + \delta_3 \sum_{i \in g_3} FV_{i,0} + \delta_4 \sum_{i \in g4} FV_{i,0} \right)$$

$$= CDF_0 \exp\left(\sum_g \delta_g FV_g \right) \tag{4-20}$$

Equation (4-20) is not exact with large changes because $FV_i \approx \frac{a_i}{b_i} P_i$ no longer implies $FV \propto P_i$ due to changes of a_i and b_i. To be exact, we may use the event sequences equation:

$$CDF = \sum_{i,j,k} \prod_i IE_i \prod_j CCF_j \prod_k P_k \tag{4-21}$$

where IE – initialing event frequency;

CCF – common caused failure probability;

P_k – k-th component failure probability.

When failure probabilities change, the terms in 4-21 can be adjusted in order to recalculate CDF. The disadvantage of this approach lies in the difficulty in collecting data. At the same time, since ORSIM only models average components but does not differentiate amongst individual components, this approach does not fit in our settings.

On the other hand, problems in using Equation 4-20 can be evaded by setting different FV_0 values for different time to reflect baseline changes – when large change occurs. When change is not large, which is true for most plant operations, 4-20 gives us a good estimate while data collection is easy. We therefore use 4-20 in ORSIM and remind model users to change FV_0 when a large change occurs.

4.2.3 CCDF index

From 4-10 and 4-20, we can obtain a CCDF index according to:

$$\text{CCDF index} = \frac{E[CDF]}{CDF_0} = \prod_g \left(\overline{\text{RAW}_g}^{\,n_g} \right) \times \exp\left(\sum_g \delta_g FV_g \right) \qquad (4\text{-}22)$$

In ORSIM, n_g is modeled as "equipment with broken failure", δ_g is modeled as "defect generation modulator". Both of these two variables are functions of continuous operations in ORSIM, and are calculated as the simulation proceeds.

4.3 Stability Index

Before developing a model for a stability index, let us first look at a queue model.

In our work, queue theory was introduced in order to model workflows in all sectors as non-preemptive priority queuing processes with random arrivals, random delays in the system, and random service times (all can take their expected values if the user wants to run non-stochastic simulations, however). This change better reflects work processes in the system, and provides a measure for the effects of randomness being taken into account.

Figure 4-1 shows an example of a M/G/1 (memoryless or Poisson arrival/general service time distribution/one server) queue. It finds many applications in communication networks.

First let's look at a simulation example. In this example, we specify that:

- expected arrival rate = 4/week, Poisson distributed;
- expected service time = 0.24 week, normally distributed with σ=0.024week.

In one simulation, we assume that both arrivals and service times are deterministic; in another simulation, we assume that they are both random, governed by their distributions.

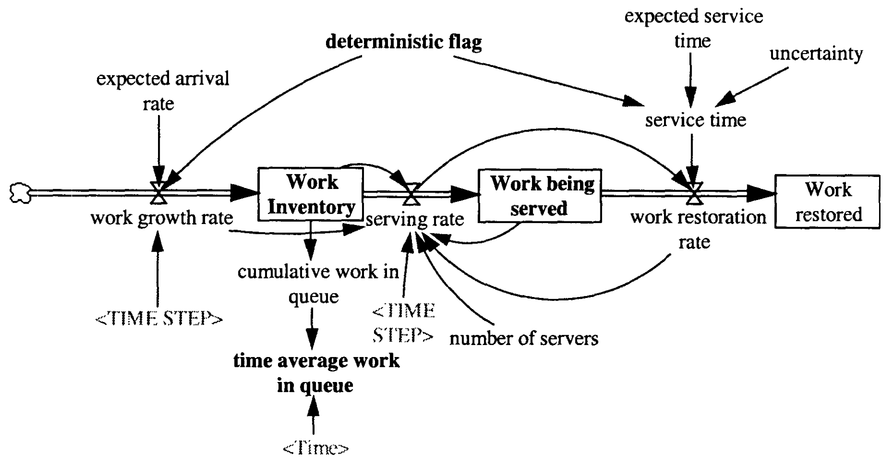


Figure 4-1: A queuing example

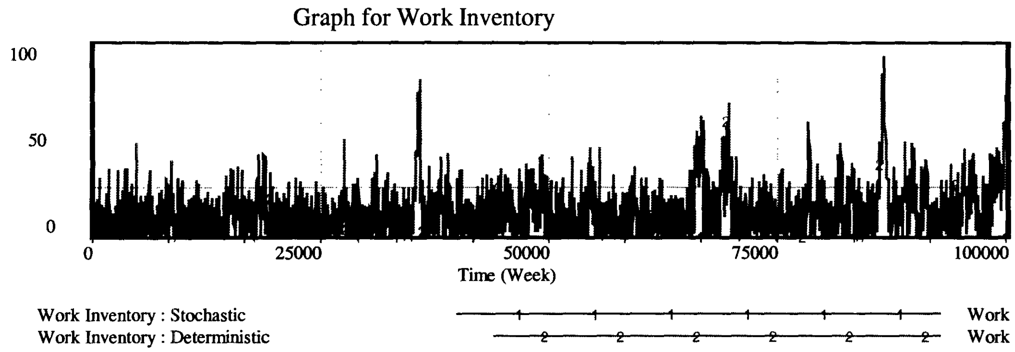
Figure 4-2 shows "work in queue" and "time average work in queue".

In is not surprising that in the deterministic case that the work in the queue is equal to zero because the service time (0.24 week) is shorter than arrival interval (1/4=0.25 week). But in the stochastic case, there is a 'slow truck effect' - a task that requires a long service time keeps tasks following it in the queue until it is completed. This effect becomes more and more pronounced as the system becomes more and more congested – as expected service time intervals approach expected arrival intervals. In our example, the system is quite congested, and from Figure 4-2 we see that every now and then there are tasks piled up by tasks requiring longer than expected service times. The time average of tasks piled up reaches a steady state value as time goes to infinity.

This is one of the reasons why we want to model the flows of work as queues. The arrival process of work in our model is in reality random, and because the system behaves differently in 'expected' case and random case, we will fail to represent the system properly if we model them deterministically.

Another reason for modeling workflows as queues, as can be observed from this example, is that it is easier to understand. People understand this process because we see it every day: going to a popular restaurant, buying tickets to a major league baseball game, etc. And just because of this, the variables involved can be more easily quantified.

A third reason for modeling flows of work as queues is that we can easily derive our stability index. The stability index is used to represent the degree to which the system is able to reach a steady state. In our example above, this index should be able to tell us whether the "time average work in queue" will reach a steady state or not before we run the simulation and see the results, and if it does, how much margin we have. Sometimes a system can reach steady state but is near the brink of losing control, while sometimes there is a lot of margin.



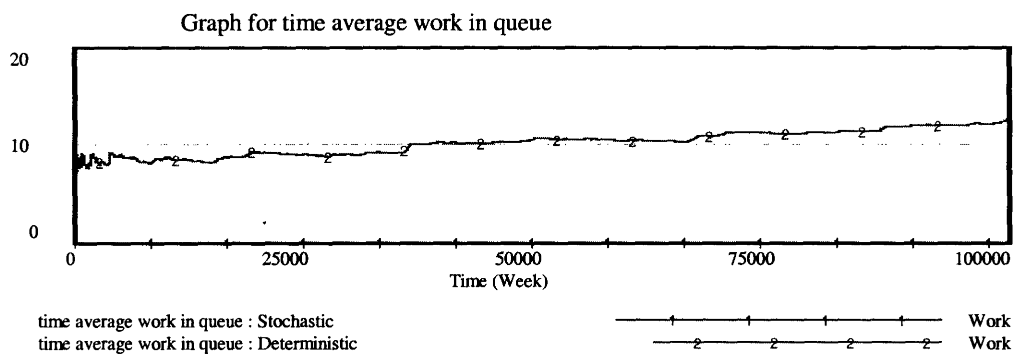


Figure 4-2: Comparison of instant work inventory and time average of work inventory under deterministic case (deterministic arrival rate and service time) and stochastic case (random arrivals and service times)

In this example, as long as arrival rate*service time≤ 1, in the deterministic case the work inventory is always equal to zero, while in the stochastic case, according to Little's Theorem ([12]):

$$W_q = \lambda \cdot E(T), \qquad (4\text{-}23)$$

where W_q is the time average number of tasks waiting in the queue, λ is arrival rate, and T is time spent in queue. (1) is true for all G/G/1 queues.

If the queue is M/G/1, then according to the Pollaczek-Khinchin formula:

$$E(T)=\frac{\lambda E(X^2)}{2[1-\lambda E(X)]}=\frac{\lambda[E^2(X)+Var(X)]}{2[1-\lambda E(X)]}, \qquad (4\text{-}24)$$

where X is service time. With other types of queues, we do not obtain a formula as easily as 4-24, but these factors are present in a similar way. For example, from 4-24, it can be seen that in order to reduce the average work in queue, we can:

- Reduce λ
- Reduce E(X)
- Reduce Var(X)
- In our model, we have other delays, such as those for planning and work preparation. Reduction of these delays will also reduce the work inventory (it turns out that these delays contribute to most of the backlog).

Now, from equation 4-24, we can develop our stability indices to quantify the degree of stability of all sectors. We observe that as $\lambda E(x)\to 1$ from 0, $W_q\to\infty$, therefore we can define a system stability index as:

Stability Index=$1-\lambda E(x)$. (4-25)

In the multiple server (in our model, this means more than one worker) case:

Stability Index=$1-\lambda E(x)/$n. (4-26)

Taking the maintenance sector as an example, a maintenance sector stability index can be defined as:

Maintenance sector stability index

$$=1-\sum_i\frac{\text{expected work creation rate}_i\,[\frac{work}{week}]\times\text{expected service time}_i\,[\frac{week}{work\cdot person}]}{\text{available workers}\,[person]}$$

$$=1-\frac{\text{expected workers required}\,[person]}{\text{available workers}\,[person]}$$

This index reflects a tradeoff between system reliability and salary expenses: fixing work creation rates and service times, if we want to have the 'right' or close to 'right' number of workers, the system is either not stable (index=0), or work inventory is unendurably high (1-$\lambda E(x) \rightarrow 0$ in 4-24)). To have a comfortable margin, however, we must acknowledge the fact that very often many workers are idling (but also are available for other assignments).

CHAPTER 5 – ORSIM PILOT PROJECT

5.1 Introduction

This chapter describes a pilot project in which ORSIM is used on a Canadian nuclear power plant to diagnose existing problems and study the implications of proposed operational practice changes.

The first step in using ORSIM for a specific plant is model structure tuning and parameter calibration. The ORSIM model can be tailored to represent the details of any nuclear power plant. For example, additional sectors and their interactions with other sectors can be easily incorporated when needed. Once the structure is settled, the internal parameters of the model are calculated from utility-specific data such as historic manpower levels, historic corrective work order backlogs, etc. The model structure and parameters are then adjusted until they can reproduce the historic plant performance. Since each simulation requires only ~1 minute of time on a PC, it does not take a long time to calibrate the parameters to conform to those of a specific plant.

Once the model is customized for a specific plant, two uses of the model are immediately available: problem diagnosis and policy change investigation.

Each simulation tracks the time-dependent variation of all model variables. By simulating using the model as customized and looking at the resulting performance indices, bottlenecks or potential problems in the operation of this plant can be identified. For example, if the stability index of the maintenance department is negative, it indicates that over the long run, the maintenance work backlog will keep increasing; if it is positive but just slightly positive, it implies that there is not much margin for dealing with surprises, and when sometime in the future there is a surprise that takes away some of the workforce, it may cause instability in the plant operations.

With ORSIM, once we identify the problems, we can dig deep to find out what the weakest links are. The software has a "track back" capability so that the root causes of complex behavior can be determined. For example, a negative maintenance stability index may be because of low productivity, or because of insufficient workforce, or low work quality, etc.

The second use of the customized model, policy change investigation, is the most important use of ORSIM. It studies the implications of proposed policy changes on the plant performance by presenting what is going to happen after we apply these proposed policy changes. The repeated exercises of the model simulation give managers a high degree of insight into the dynamics of the organization that would be difficult to achieve otherwise. For complex managerial systems, it is very hard to foresee consequences of decisions beyond the immediate impact. ORSIM will display all the consequences and give management the wherewithal to avoid unintended consequences. This is particularly important where complex feedback paths exist within and between sectors.

Besides internal changes, the model also provides a powerful tool for dealing with externally imposed changes such as regulations. The ability to demonstrate quantitatively the full impact of proposed regulations can allow a utility to understand and refine the level and types of changes proposed.

5.2 Model Structure Tuning

ORSIM has a "vanilla" version model, which is built based upon and calibrated to a light water nuclear power plant in the U.S.. Because nuclear power plants share many features and processes, it takes much less time to adjust our vanilla model to a specific plant than to build a model from scratch for this plant.

The first question that we ought to ask when tuning the ORSIM model to a specific plant is 'what are the structural differences between vanilla plant and this specific plant?'. In order to answer this question, we need to determine the following:

(1) The organizational structure of the plant;

(2) The functions of each organizational division;

(3) The work processes in each organizational division;

(4) Interactions, information flows and feedbacks between different organizational divisions.

It is almost always true that we will find differences in the above-mentioned aspects between the vanilla plant and any specific plant, although they have many similarities. For example, you will find that each nuclear plant has an engineering department, but you will also find that their functions are not all the same. In our pilot plant, they serve a function called 'system health monitoring', which is not in our vanilla model; and they do not have a type of work called 'licensing' which our vanilla model contains.

The rest of this section discusses model structure adjustments that we made to tune our vanilla model to pilot plant.

The first adjustment was on corrective maintenance processes. This pilot plant has a dedicated team of around forty people for maintenance work assessment, which our vanilla model does not contain such a group. The function of this team is to assess each maintenance work request in terms of its urgency, procedures, required parts readiness, etc. It comes into play after work request generation and before scheduling and planning.

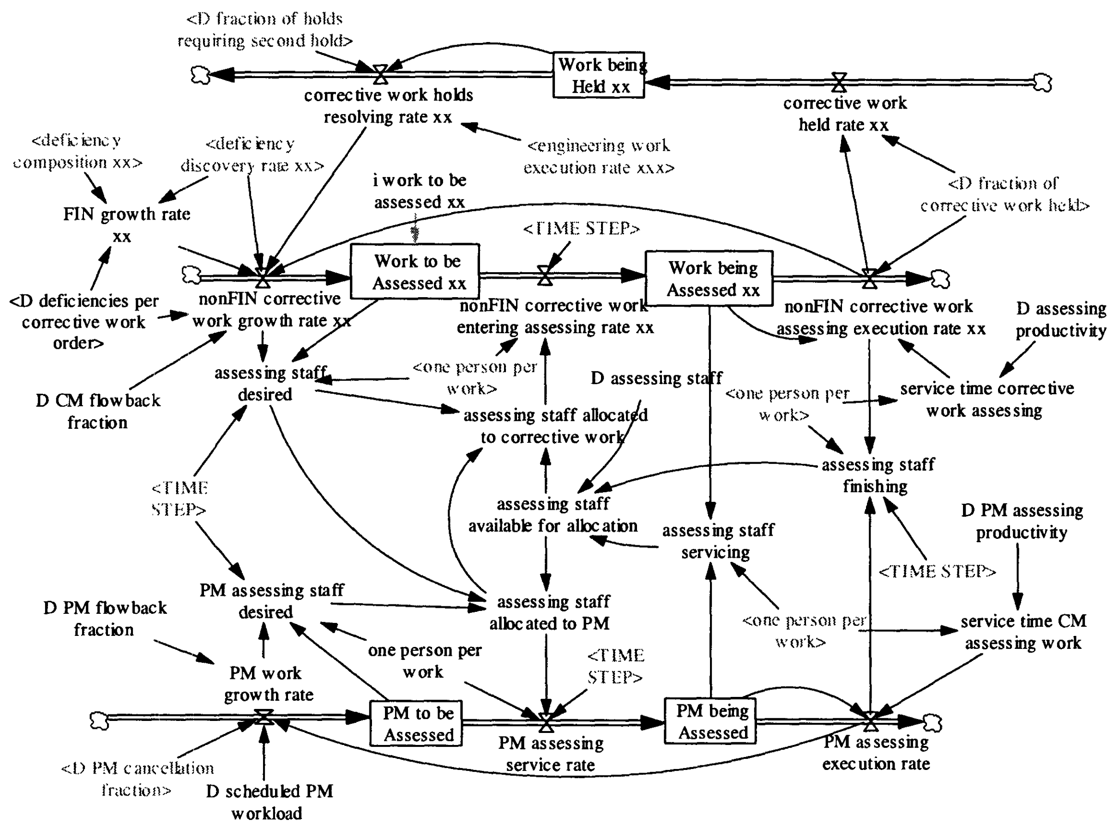


Figure 5-1: Work requests assessing flow diagram

Figure 5-1 shows how assessing is performed. There are two types of work requests to be assessed: corrective maintenance work requests and preventive maintenance work requests. For each type, there are two sources of inflow to "Work to be Assessed", one being fresh new work requests and another being flow-back work requests of work not yet performed that are to be re-examined. Flow-back work requests are those that are found not able to be planned after assessing – either because parts are not available, or because the only team of people who can perform the work is currently busy with other tasks, e.g.. According to the policies in this plant, these work requests have to be reassessed when they are cleared of their holds. It is worth noting that the flow-back fraction is unexpectedly high in the case of preventive maintenance work, with a value at around 70%.

The fresh work requests for corrective maintenance come after discovery and reporting of defects, either broken or unbroken; the fresh work requests for preventive maintenance come from a scheduled list. They are joined with flow-back work requests and flow into "Work to be Assessed". Notice that FIN work does not require assessing. Based upon their availability, assessing staff is allocated to evaluate these awaiting work requests. Each assessment takes a period of time determined by the productivity of the assessing staff, and then, if a work request is determined to be ready to be performed, it flows out of the assessing stage and enters the next stage, planning. Otherwise, it flows back and waits in line to be assessed again.

The second adjustment was made to model outage maintenance activities, which are not modeled, in the vanilla model. In this pilot plant, because the reactor is a CANDU (CANada Deuterium Uranium) reactor, no refueling outage is required as it employs online refueling. However, it does have scheduled outages, but instead of refueling, these outages are scheduled to work down the backlog of corrective work orders that can only be performed when the plant is shut down. These work orders are called 'offline work orders'.

As can be seen in Figure 5-2, when the plant is operating, defects are discovered, reported, and assessed. After assessment, those that can be performed online flow into online planning backlogs. It takes an interval of time for them to be planned, after which they are ready to be executed. Depending upon their priorities, some are executed with small delays (there will always be delays due to the time required for paperwork, preparation, etc.), some have longer delays. For example, emergency and high priority work orders are generally executed as soon as possible because they endanger the safe operation of the plant; FIN work orders are also executed quite fast because these tasks are very simple and can be easily performed. On the other hand, normal work orders have up to thirteen weeks' delay. These are tasks that are more complicated than FIN task but do not affect safety as emergency and high priority tasks do. In this pilot plant, there is a thirteen-week rolling window for the execution of these tasks, reflecting a policy of performing maintenance upon a specific SSC four times annually on a steady basis. That is, at any point in time, an incoming normal work order is planned to be executed in the next thirteen-week window, which makes the delay range anywhere from one day to thirteen weeks.

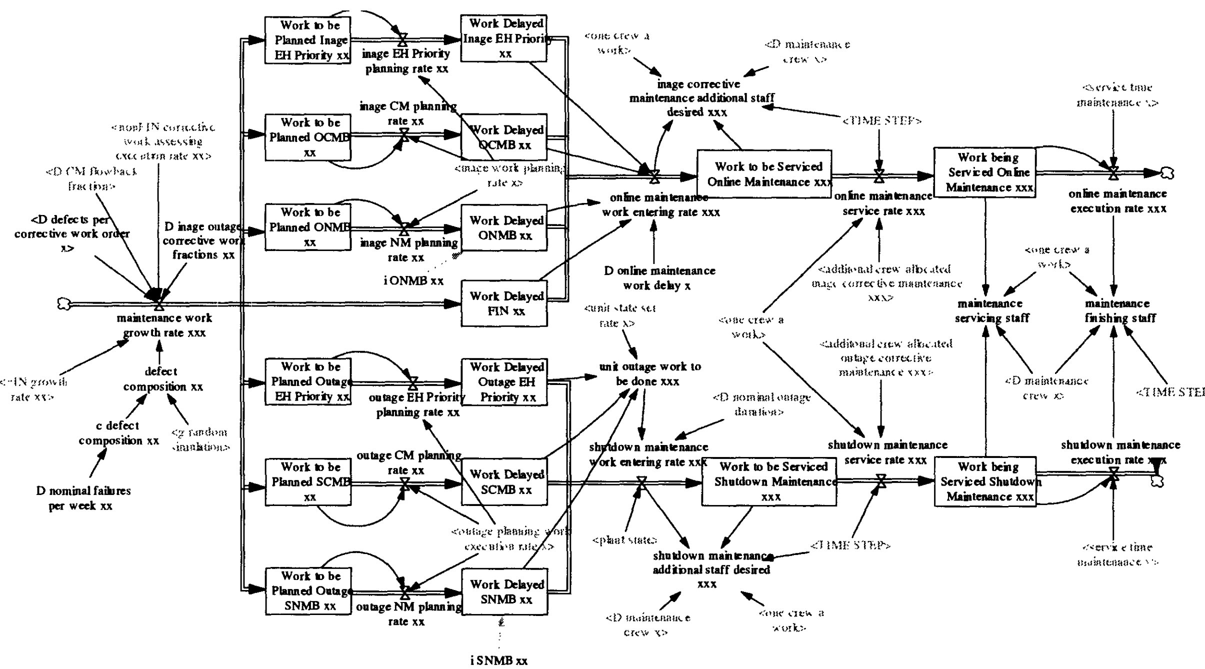


Figure 5-2: Inage and outage work flow diagram

For those work orders that can only be performed when the plant is shut down, they flow to offline backlogs after being discovered and assessed. After planning, they simply wait until the next outage comes, upon which time they flow out of the waiting backlogs and are executed before the restarting of the reactor. Both online and offline maintenance share a similar work process, except for the difference of the time when they can be executed. Because offline work cannot be performed while the plant is operating, and because all of the maintenance workforce is working on the offline work backlog when the reactor is shut down in order to return the reactor to production in the shortest time possible, online work and offline work are rarely performed at the same time. The only exception is that some high priority online work may be performed during outages.

The third adjustment is to planning. This pilot plant has a centralized planning department, which is different from our vanilla model, where planning functions are embedded in the maintenance department and outage planning functions are a joint effort between maintenance and operation. This centralized planning department serves functions that include preventive maintenance planning, corrective maintenance planning, and coordination.

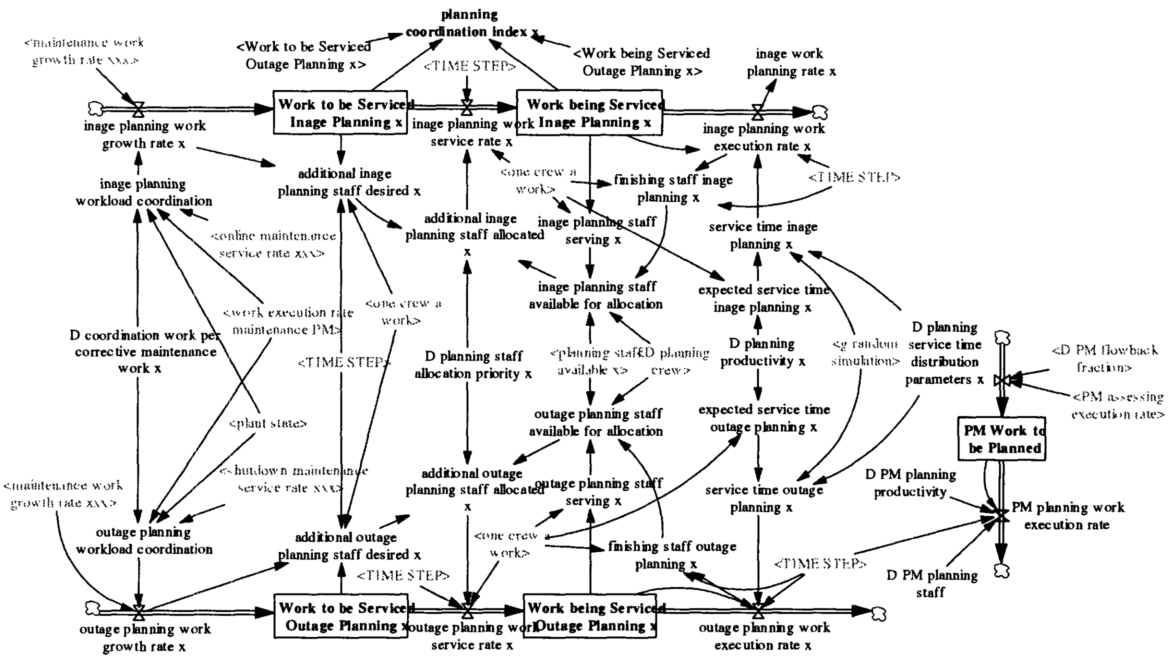


Figure 5-3: Planning workflow diagram

Figure 5-3 shows the workflows in the planning department. Because corrective work backlogs are split into two parts – online and offline work backlog, planning staff are also divided into two teams, online planning and offline planning. They serve the same set of functions, i.e. planning and coordination. It should be noted that although they are in the same department, these two teams are independent. Workforce is not shared between them.

For each leg of the corrective workflows, planning work is generated after work requests are assessed by the assessing team. Work flows into the queue “Work to be Serviced Planning”, and then, depending upon availability of planning staff, flows to ‘Work being Serviced Planning”, where it stays for a period of time determined by the productivity of the planning staff before it leaves the planning stage. Notice that it is possible that, after planning, it is determined that a work order needs some engineering clearance before execution, and in such cases the work order flows to the engineering department to obtain a clearance. When it comes back, it has to be planned once more before execution.

For preventive maintenance planning, similar planning work is generated after assessing. In this pilot plant, there is only one person who is in charge of preventive maintenance planning. This person is actually a senior engineer. Because his sole function is to plan preventive maintenance, we include him as staff in the planning department, while recognizing that he is a one-person team, of course. We have argued that this person can be a bottleneck in their operation, but this plant insisted that his role is appropriate.

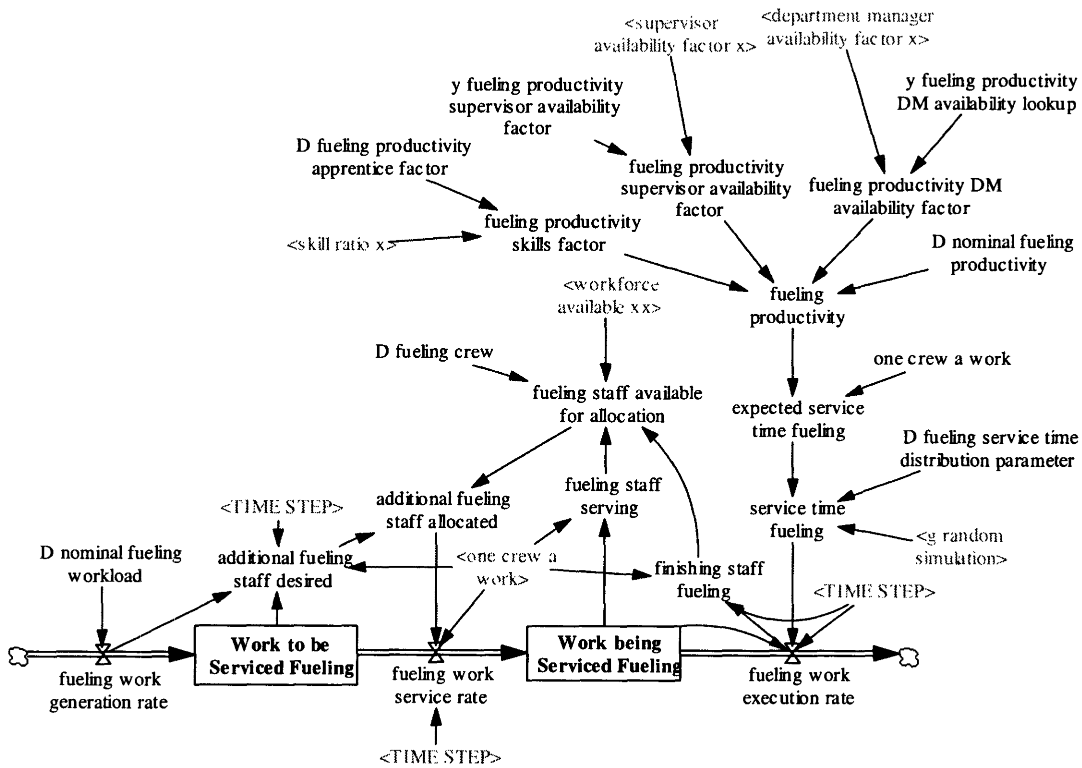


Figure 5-4: Fueling workflow diagram

The fourth addition to the model organization structure is a fueling department. Because CANDU reactors are refueled online continuously, this pilot plant has a dedicated fueling team to carry out this function, serving all operating reactors in parallel. Figure 5-4 shows the workflow in the fueling department. The incoming workflow is scheduled and thus known at any point in time. A team of fueling staff is assigned to work on the fueling work orders, and upon completion the work orders flow out of the system. The time it takes this team to perform a fueling work order is relatively stable, although affected by factors such as department manager availability.

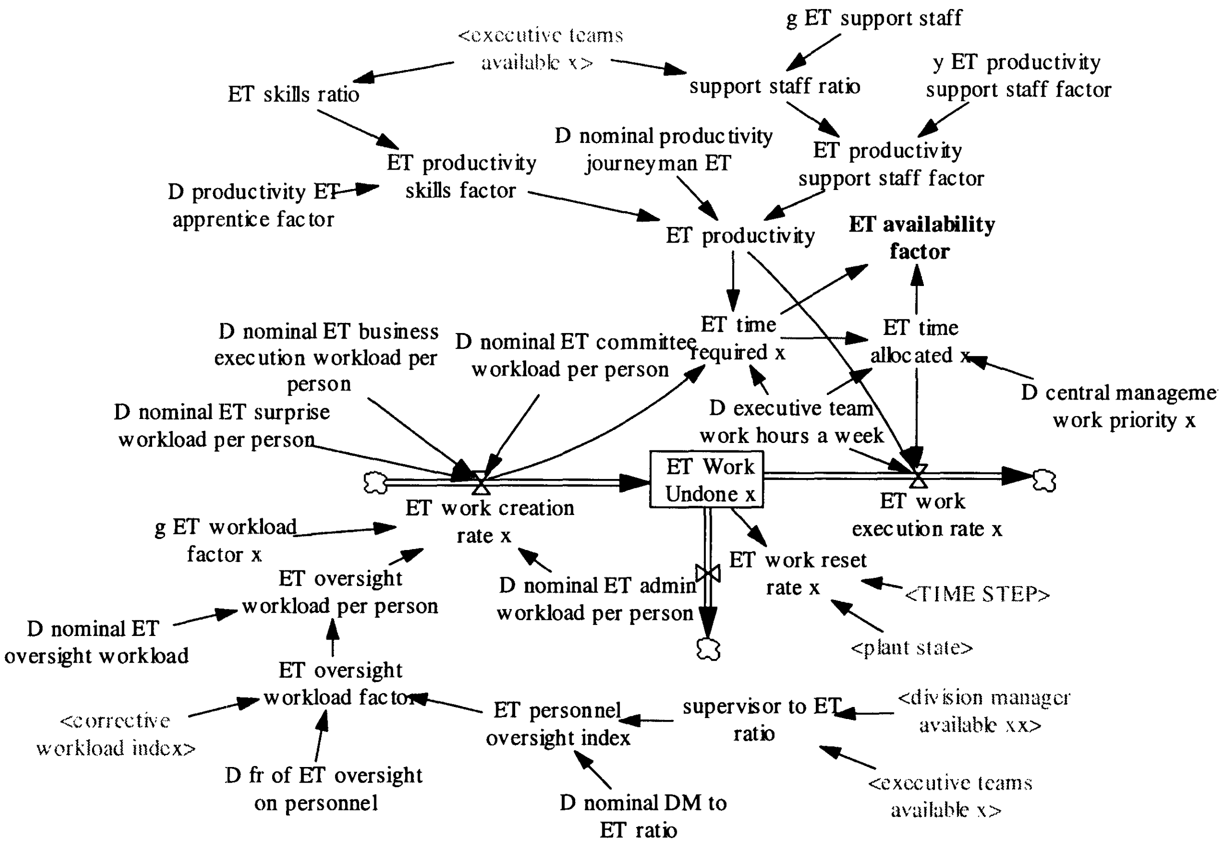


Figure 5-5: Executive team workflow diagram

The fifth change in the model structure is an executive team. In our vanilla model, we have a team of central managers that include plant executives and department heads who serve functions that include "surprises" handling, committee meetings, supervision, and administration. In our pilot plant, they prefer to separate the executive team from department managers since the executive team serves more strategic functions while the department managers serves more tactical functions. We therefore replaced the central management with two layers, one of which is the executive team, with the other being department managers. The types of work for the executive team, as shown in Figure 5-5, include business execution, committee meetings, "surprises" handling, oversight, and administration. The flows of their work are similar to those of central management in the vanilla model as described in Chapter 3.

These five changes are structural. There are other nonstructural changes. First, the types of work in each department are somewhat different from the vanilla model. For example, surveillance testing work is performed by operators in this pilot plant, while in the vanilla model it is performed by maintenance staff; also, in this pilot plant, engineers perform system health monitoring, which is not part of the work engineers do in the vanilla model.

Secondly, this pilot plant has four units, while in the vanilla model we have only one. Each of the units is shut down every two years in equal intervals, i.e. every six months, there is a unit being shut down for maintenance.

Thirdly, many variables are renamed according to this pilot plant's naming conventions. For example, priority 2 work is called 'emergency and high priority work', and priority 3 work is called 'normal corrective work'. These changes are necessary because it helps to understand the meaning of each variable, facilitating the later parameter calibration step.

To summarize, Table 5-1 lists the differences between customized model and vanilla model.

Table 5-1: Differences between vanilla model and model customized to the pilot plant

Activity	Vanilla model	Customized model
Assessing	No assessing department	Has assessing department
Outage	Outage is scheduled for refueling	Outage is scheduled for maintenance
Planning	Embedded in maintenance department	Centralized planning department, also responsible for coordination
Fueling	No dedicated fueling team	Has a dedicated fueling team
Management	One central management team	Two layers for central management: executive team and department managers
Reactor units	One unit	Four units
Types of work: Maintenance	Surveillance testing, preventive maintenance, corrective maintenance, planning	Preventive maintenance, corrective maintenance
Types of work: Operation	Operation, coordination, training	Operation, surveillance testing, maintenance support, training
Types of work: Engineering	Licensing, maintenance support, plant modification, information acquisition	Maintenance support, maintenance hold resolving, system health monitoring, plant modification
Types of work: Planning	Inage planning, outage planning	Inage planning, outage planning, coordination
Types of work: Management	Surprises handling, committee meeting, oversight, routine	Surprises handling, meeting, oversight, administration, business execution

5.3 Model Parameter Calibration

5.3.1 Parameters Setup

After the structure of the model is adjusted to incorporate the differences in this pilot plant and variables have been renamed according to their naming conventions, the next natural step is to change the values of input variables so as to match data of the pilot plant.

Doing this required a 1~2 full day meeting with a plant manager and a database administrator from the plant. The plant manager is included in this meeting to make sure the definition of variables in the model matches their definitions, and the database administrator is the person to query the relevant data from their database.

All input variables are organized in a coded Microsoft Excel spreadsheet to facilitate this process – we did this because most people are familiar with Microsoft Excel but few people know how to use Vensim software. A Visual Basic for Application script was coded behind this spreadsheet to allow loading of the ORSIM model default values for the inputs and changing of inputs in the spreadsheet. Changes are written to a .cin file ORSIM.cin in Vensim change file format. It is recommended that when we first use this coded spreadsheet to obtain parameters for a baseline, we input all these changes directly into the model at the end of the meeting, thus making them default values from that point forward to represent a baseline. Any future changes will then be a deviation from this baseline.

In the beginning of the simulations, this change file is loaded, and any variable found in this file will take values from this file to override default values defined in the model. For example, if the default value of variable "D nominal journeyman maintenance quality" is 0.98, but changed to be 0.95 in the Excel file, this change is logged in the ORSIM.cin file, and when a simulation starts, VENSIM will load ORSIM.cin and assign 0.95 to be the value of "D nominal journeyman maintenance quality".

Figure 5-6 illustrates how changes are made and applied in simulations.

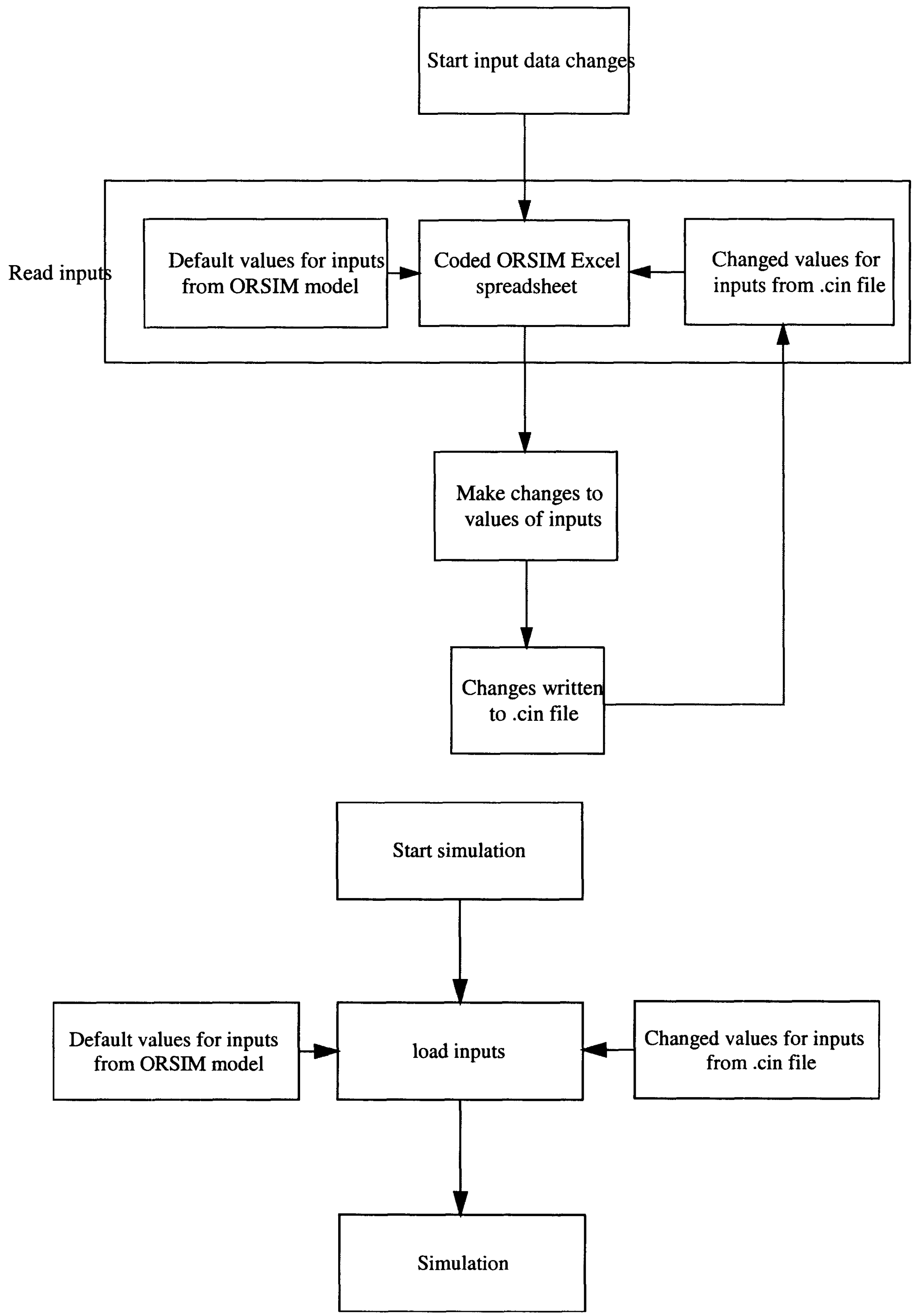


Figure 5-6: Illustration of how changes are made and applied to ORSIM in simulations

5.3.2 Validation of Parameters Using Historical Data

The most straightforward and convincing way of validating model structural changes and parameter setups is to reproduce a period of history. The period chosen for this validation at the recommendation of the plant staff was the time between June 2003 and March 2004. Between June 2003 and September 2003, the maintenance work backlog was decreasing. Then at the end of September, some changes occurred:

- Maintenance staff was reduced by 20
- Operation staff was reduced by 54
- Engineering staff size was reduced to 5/8 of its initial size
- Planning staff size was reduced to 5/8 of its initial size
- Assessing staff size was reduced to 5/8 of its initial size

Figure 5-7 shows maintenance work backlog as a fraction of their levels in June 2003 for both cases of simulation and actual history. Both curves moved downward in the beginning and reversed upward starting in October 2003, one week after these staffing changes were made. The figure also shows a good match in terms of both dynamics and magnitudes of backlog changes.

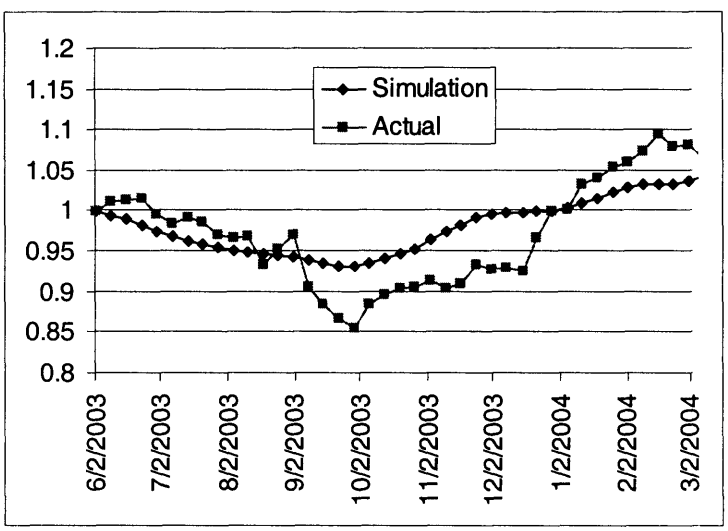


Figure 5-7: A comparison of historical data and ORSIM model simulation results on corrective work backlog as a fraction of their levels in June 2003

Further analysis of the results obtained using ORSIM indicated that the reason for the backlog to turn back up was lower assessing rates. Reduction of staff size in other department does not cause their production rates to decrease because initially there were surplus workforces. However, in the case of the assessing department, Figure 5-8 shows that after the changes, the assessing staff was less than what was required to match the rate at which work was generated. This caused work orders to accumulate in the assessing stage as a function of time – although some maintenance workers did not have work to do downstream (the maintenance program stability index was positive). The ability of ORSIM to simulate the time of reversal of the downward trend to an upward one was judged by the plant staff to be especially impressive and valuable.

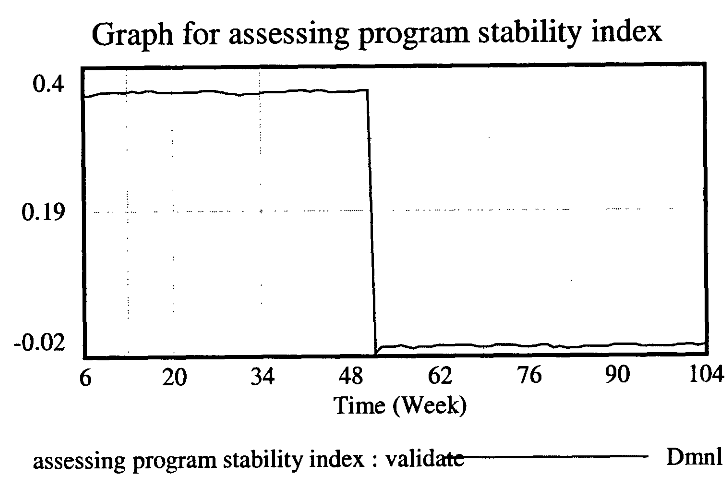


Figure 5-8: Assessing program stability index before and after the change

5.4 Problem Diagnosis

After the model is structurally tuned and parameters set up and validated, ORSIM is then ready to be used. The first use of the model is to identify existing problems.

5.4.1 Existing Problem Diagnosis

To see whether there are existing problems, we can simply simulate the model as it is, i.e., without changing the default values of input variables and assuming everything is normal as it is at present. By looking at the performance indices, we are able to tell whether a given department is in trouble or not.

Simulations were performed for this pilot plant and results were examined. Several problems were identified. The reality of these problems was confirmed by plant managers afterward.

The first problem was identified via a negative value for the assessing program stability index (see Figure 5-9, actually the same as the after-change part of Figure 5-8). It means that the net production rate from the assessing team is less than the net work growth rate, and as time goes on, more backlog is accumulated in this stage of work. Even if we have many maintenance workers available downstream, it is not going to help because assessing now becomes a bottleneck.

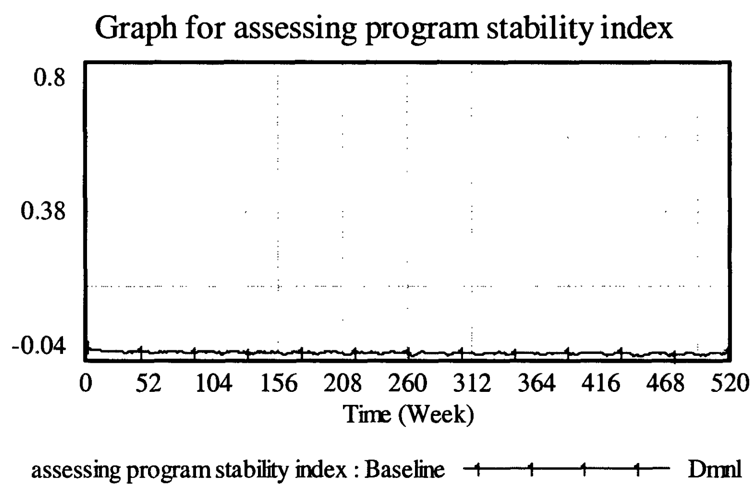


Figure 5-9: Graph for assessing program stability index in baseline case

But what are the root causes for this problem? Using the tracking tool provided by Vensim, we first know that the assessing program stability index is determined by:

assessing program stability index = 1-assessing staff right level/D assessing staff.

Here 'assessing staff right level' means the 'right' number of staff to match the work generation rate, and is proportional to the work generation rate, and inversely proportional to productivity and quality. There are three possibilities that can cause a negative stability index:

(1) Insufficient assessing staff, in which case we should use more assessing staff;

(2) Lower than industry-level productivity or quality, in which case we should adopt good industry practices to improve productivity or quality; or

(3) Unnecessary additional work that flows into the assessing department, in which case we should cut down such workflow streams.

In practice, we should try to find the last two possibilities first. If after that, the stability index is still negative, we should hire more workers. In our case here, (2) was not an issue because productivity and quality data were pulled from the plant database, and they did not think the productivity or quality was low. We therefore looked carefully at (3). We noticed that there are two backflows from work execution rates to work generation rates – if after assessing it is determined that a work order cannot go to planning because (for example) parts are not available, the work order is sent back to backlog. The next time that it is picked up, it has to be assessed again. In the case of preventive maintenance, 70% of assessed work orders were thrown back to the backlog, which produces many repeated tasks for the assessing team that should be prevented! Even in the case of corrective maintenance, there were 10% of work orders flowing back.

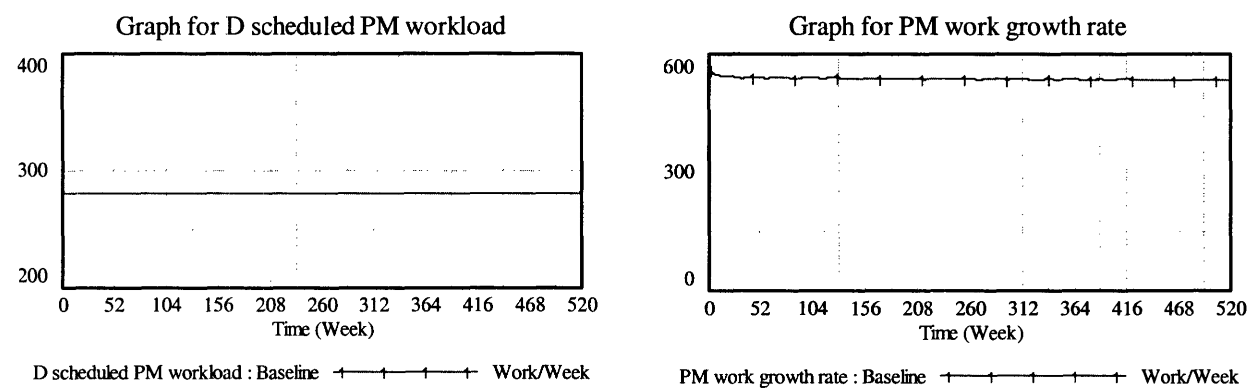


Figure 5-10: Scheduled amount of preventive maintenance work to be assessed per week vs. actual amount of preventive maintenance work to be assessed per week

One way to see if the flow back fraction of the work orders constitutes the problem is to compare the net generation with total generation – the difference of these two are caused by backflows. Figure 5-10 presents these two variables for the case of preventive maintenance. The scheduled preventive maintenance workload was 280 work orders/week, while total preventive work to be assessed was ~530 work orders/week. Obviously the flow back of work orders constitutes a significant amount.

A second way to understand whether these repeated tasks are causes of the problem is to run a simulation with these flow-back ratios cut down to 35% and 5%, respectively. Figure 5-12 shows that the assessing program stability index becomes large and positive after cutting down these flow-back work orders, which means we can not only maintain a stable operation, but can also cut down some staff in the assessing team. Because these assessing workers are very experienced, reallocating some of them to maintenance will help improve the downstream work execution rate as well.

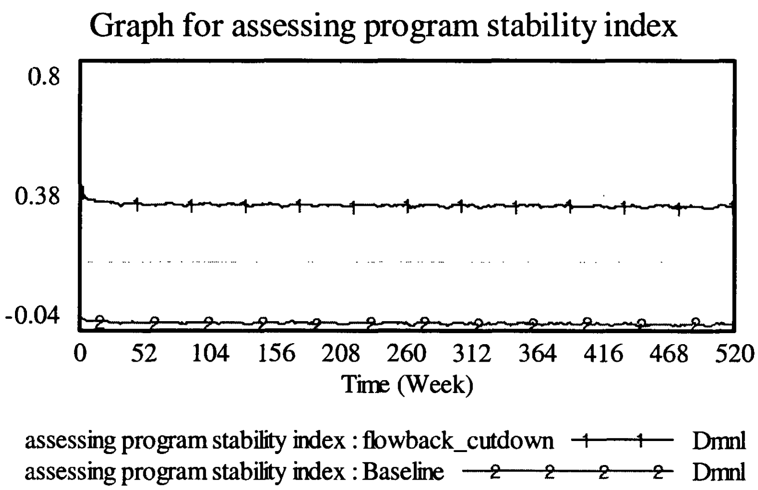


Figure 5-11: Comparison of assessing program stability index between baseline case and flow-back fraction cut down case

The second problem we observed from our baseline simulations was the size of the planning staff. The observation starts with very high stability indices for both the inage planning and outage planning program stability index. As shown in Figure 5-12, the values of both indices are very close to unity.

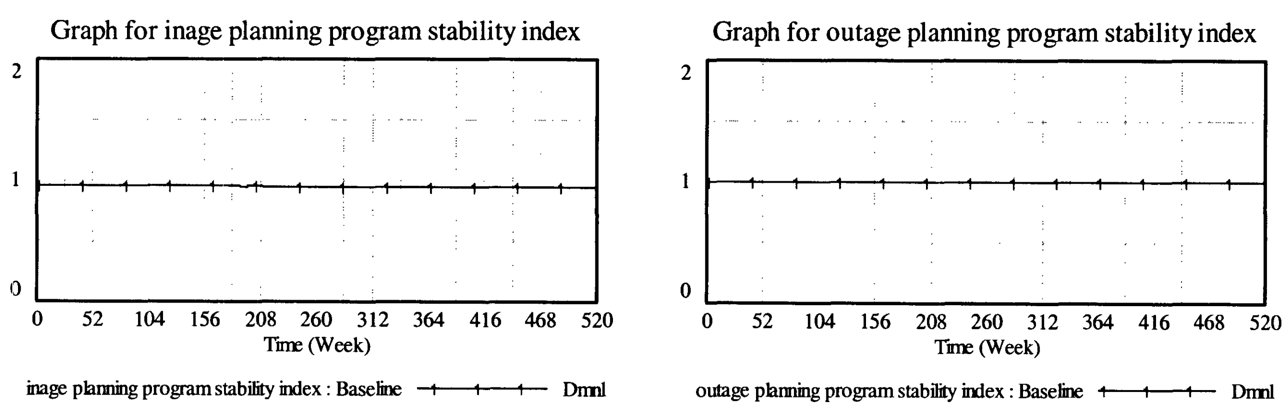


Figure 5-12: In the baseline case, both the values of inage and outage program stability indices are very close to unity

There is only one explanation for this – excessive planning staff. This is clearly seen if we look at how the planning stability index is defined:

Planning program stability index = 1- planning staff right level / D planning staff.

As a matter of fact, the ORSIM calculation told us that only two planning staff are needed for inage planning and less than one person is needed for outage planning, while actually there are 33 and 15, respectively. The finding was confirmed by work order records in the database. It was true that only around 2 person-week was spent on inage planning for an average week.

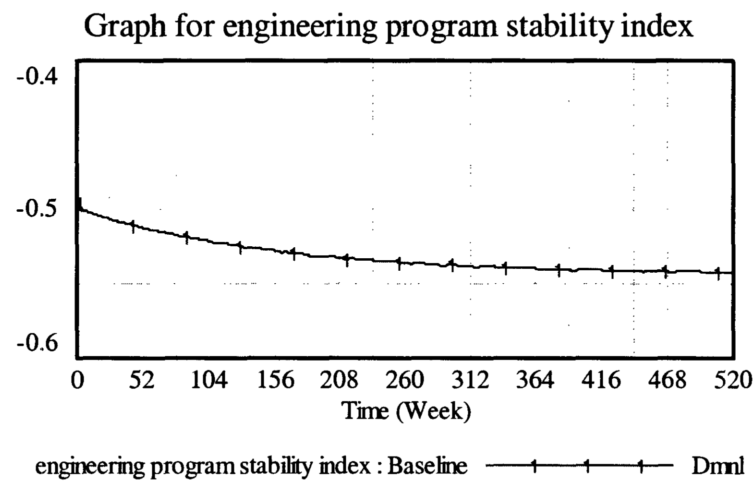


Figure 5-13: Engineering program stability index was large and negative

The third problem identified in the baseline simulation was an insufficient number of engineers. Examine the engineering program stability index in Figure 5-13: we observe that the engineering program stability index is merely -0.5, indicating a huge mismatch between work execution rate and work generation rate. Similar to our analysis regarding the negative assessing program stability index, the causes could be insufficient workforce, or low productivity, or low quality, or too much unnecessary work.

By looking at their productivity and quality, no anomaly was observed. In terms of work generation, there was no repeated work, either. However, if we look at the workloads for each type of work, we noticed that the plant modification workload was 6400 work orders/week!

Given that the productivity of performing plant modification work is 36 work orders/personweek, this task alone requires 178 engineers, but in fact there are only 160 engineers in the plant.

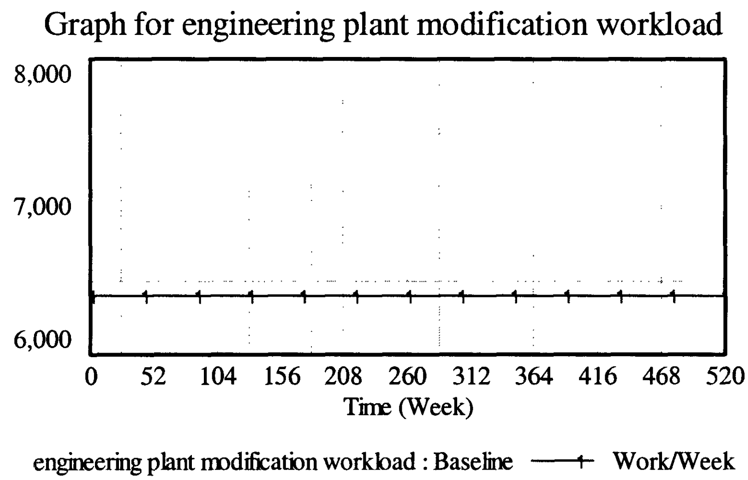


Figure 5-14: Engineering plant modification workload: Engineering plant modification workload is 6400 work orders/week. This alone requires 178 engineers but the pilot plant actually has only 160 engineers.

In the discussion that followed this observation, we were told that the plant never expects the engineers to finish all plant modification tasks. They do have enough engineers to complete all tasks other than plant modification, and since the priorities of other tasks are higher than any plant modification task, the backlog of plant modification does not affect other important functions such as maintenance support, which is exactly why we did not observe ripple effects to the other departments such as maintenance. Then why is there such a substantial plant modification workload? The answer was to keep engineers busy: when they have time, they can always find a meaningful job to do.

5.5 Practices and Policy Changes Investigation

The second use of the customized ORSIM model after the model has been structurally tuned and parameters set up and validated is to study the implication of proposed practices and policy changes upon plant performance. Practically all quantifiable practices and policy changes that can be quantified can be investigated within the ORSIM framework. This section discusses a case study that was conducted in this pilot project.

5.5.1 Assessment Pre-screening

As is pointed out in the previous section, work requests assessment is a bottleneck in the maintenance process. The assessment department has a negative program stability index, indicating a mismatch between net work output and net work generation. Repeated assessment of work requests has also been identified as the root cause of this problem, and in light of this, a practice was proposed to solve this problem: allocation of four of the forty assessment staff as pre-screening staff. With a database linked to the warehouse and the maintenance department, they can quickly decide whether a work request should be processed given the availability of parts and maintenance staff with relevant skills.

The quantification of this practice is listed in Table 5-2. Four individuals from the forty-person assessment team are allocated to pre-screening, leaving thirty-six for detail assessment. It was assumed that the fraction of work that requires repeated assessment would decrease to 50% of the previous level, i.e. 5% for corrective maintenance, and 35% for preventive maintenance.

Table 5-2: Quantification of Assessment Pre-screening practice

Item	Before	After
Assessment pre-screening staff	0	4
Detailed assessment staff	40	36
Fraction of repeated assessment	Corrective maintenance: 10% Preventive maintenance: 70%	Corrective maintenance: 5% Preventive maintenance: 35%

The results from the simulation show that this practice is able to solve the problem. See Figure 5-15. First of all, with the assessment pre-screening practice, the corrective work backlog stabilizes at a level of around 950 work orders, as compared to the 'Before' case where the corrective work backlog increases at about 10% per year.

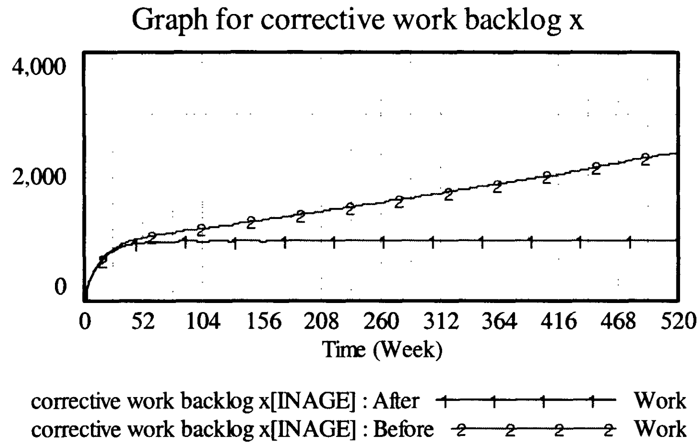


Figure 5-15: Corrective work backlog with alternative policies: Corrective work backlog stabilizes with assessment pre-screening practice

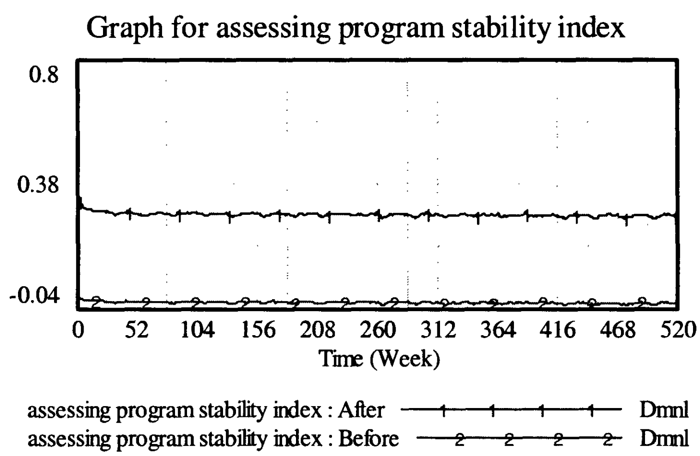


Figure 5-16: Program stability index changes from negative to positive with implementation of the assessment pre-screening practice

The ability of corrective work backlog to stabilize can be explained by the assessing program stability index that changes from negative to positive, as shown in Figure 5-16. Before the implementation of the new practice, the index was at a negative level of around -0.02, while after implementation, it becomes equal to 0.27, indicating that we have 27% more staff than needed to match the work requiring completion. This change not only stabilizes the system, but also increases the capability of the system to overcome surprises in the future. As long as the "surprise" increase of work does not exceed 27% of the current level, it can be dealt with without any adverse effects.

The change in the assessment process not only affects the performance of the assessment team, but also the downstream maintenance team. If we take a look at the maintenance program stability index, it can be noted that the maintenance program stability index becomes smaller with implementation of the assessment pre-screening practice. What this means is that the additional staff in place now is reduced. Since no adjustment was made to the maintenance staff size, why would this happen?

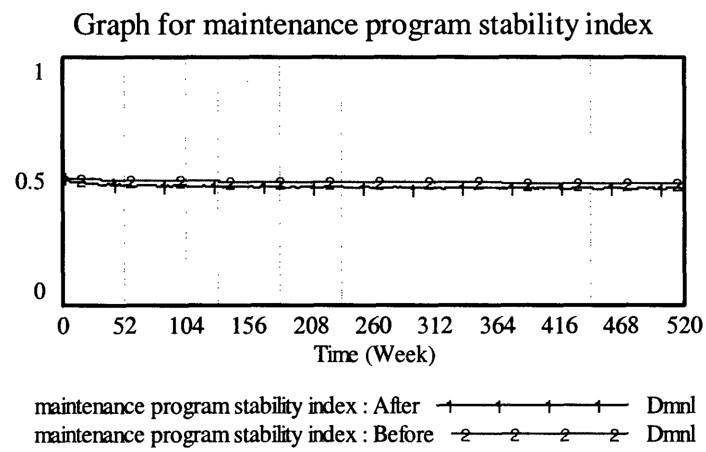
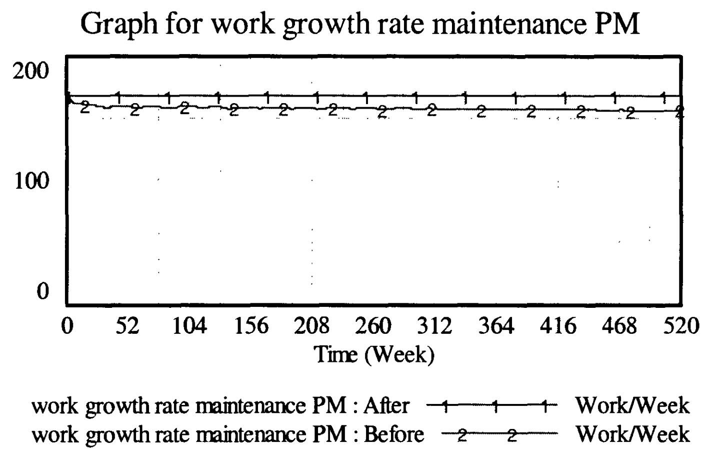


Figure 5-17: Maintenance program stability index: Maintenance program stability index with implementation of the assessment pre-screening practice becomes smaller, but is still positive enough to maintain stable operation.

Figure 5-18 explains why. Before implementation of the new practice, the assessment stage was operating at an unsteady state, with outflow of work less than inflow of work. After the practice, thanks to fewer repeated work to be assessed, the net outflow increases and is now equal to the inflow (otherwise it cannot stabilize). What this implies for the maintenance team is that after implementing the practice the inflow of work for them increases, and therefore the required number of maintenance staff needed to match the inflow of work increases. This increase in 'maintenance staff right level' makes the value of the maintenance program stability index smaller:

Maintenance stability index = 1- maintenance staff right level/available maintenance staff.



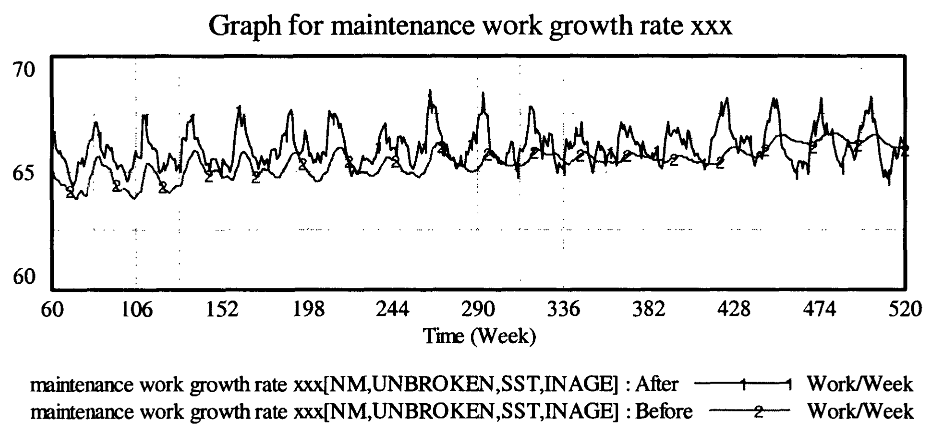


Figure 5-18: Maintenance work growth rates under alternative policies: The reason for a smaller maintenance program stability index is higher work growth rates for preventive maintenance and corrective maintenance with implementation of the assessment pre-screening practice.

The change in this practice also improves the reliability performance of the plant due to a stabilized rather than increasing inventory of corrective works. Figure 5-19 shows the comparison. Notice that the blips in the figures are due to transients (the human error post-transient factor causes sudden increases in CDF index), and aging and degradation of the plant makes both curves upward-sloping. It is the contribution of the existing inventory of defects and separates the two curves apart.

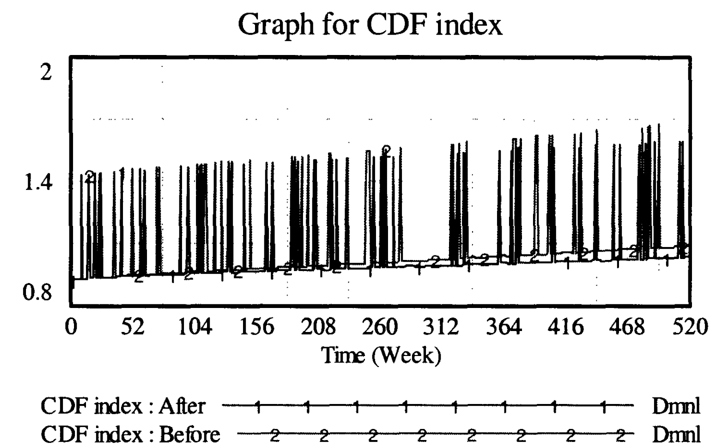


Figure 5-19: CDF index under alternative policies: In terms of risk, CDF index is lower with implementation of the assessment pre-screening practice

Also, because in the assessment pre-screening practice case we have less work backlog, unexpected outages that are closely dependent upon materials conditions also become less frequent, making expected electricity loss due to unexpected plant shutdowns less than that of the 'Before' case, as shown in Figure 5-20.

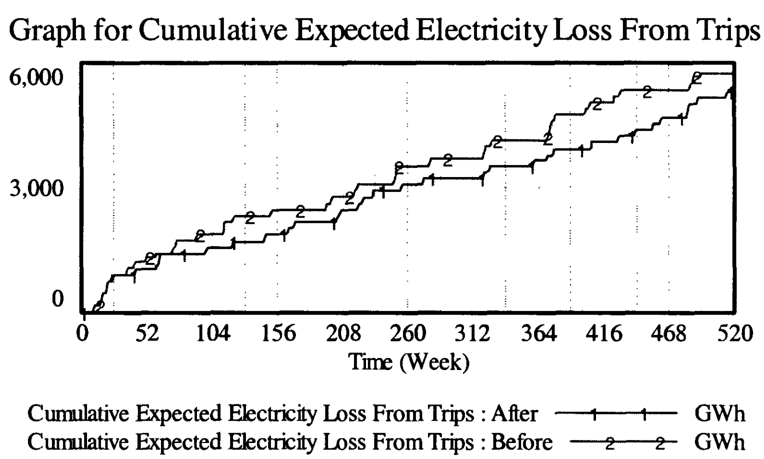


Figure 5-20: Cumulative expected electricity production losses under alternative policies: In terms of electricity loss due to expected outages, the case with implementation of the assessment pre-screening practice is always lower than the case without the assessment pre-screening practice.

To summarize, the implementation of the assessment pre-screening practice stabilizes the assessment program, and prevents the maintenance work backlog from increasing. The lower inventory of defects improves the material condition, and the reliability and economic performance are improved as a result. This change also increases the resistance of the system to surprises, and makes more efficient use of maintenance staff.

This study was conducted on the last day of our visit to this pilot plant. After that the plant has performed many other studies, investigating the effects of alternative policies or external events. These are Influenza Pandemic, Increased Craft Autonomy, and Staggered Operations/Maintenance Start Times. They report appreciation of what ORSIM can do and the person who is using this model said, "I was amazed at the depth of the results I can generate with relatively few tweaks".

5.6 Summary

In this pilot project, ORSIM was first customized and tuned to the baseline of the plant. This pilot project demonstrated that customization of the ORSIM model is not difficult. Once customized, ORSIM is a helpful tool to identify existing problems and investigate practices and policy changes. For this pilot plant, we found that the assessing department was the weakest link in the maintenance process. We also found inefficient use of planning staff and overloaded plant modification work for engineers. In order to solve the problem in the assessing department, a proposed policy change was studied. The policy under consideration was found to be capable of solving the problem. In these studies and investigations, the high level performance indices provided by ORSIM greatly assist in locating the whereabouts of problems and the tracking capability of ORSIM enables its users to pinpoint root causes quickly.

CHAPTER 6 – EPRI EXCELLENCE MATRIX PROJECT

6.1 Introduction

EPRI (the Electric Power Research Institute) has worked with nuclear power plant teams to identify the most important good practices and hallmarks of effective nuclear power plant maintenance management. These practices and the related performance matrix have been summarized in the reports, "Guideline for Assessing Maintenance Effectiveness" and "Matrix for Assessing Maintenance Effectiveness" [4, 5].

Interest in this chapter is focused upon how to model these practices for a given nuclear power plant so as to understand their implications concerning operations performance, and to develop a method for comparing their net benefits.

When using ORSIM to study a practice, what we are trying to answer is the question: "how better or worse shall we become if I apply this practice in our plant?" The answer is therefore dependent upon given conditions of the plant, or "baseline" as we shall call it. Because of this, what we are presenting here is more of a framework on how to use ORSIM to study the implications of an EPRI practice on plant performances given baseline plant conditions. A same practice needs to be reinvestigated if we switch from one plant to another, as the new plant's conditions are different. Since the purpose here is to demonstrate a framework, we will only use several examples from the EPRI practices list instead of a complete one-by-one study on all EPRI practices.

The first step in a practice study is to understand what it is: what is its nature? What aspects of the plant operations are affected by this practice? What are the pros, what are the cons?

The second step is to quantify these effects. For example, if a practice affects maintenance productivity, by how much will the maintenance productivity increase or decrease if we apply this practice?

The third and final step is to simulate these changes and analyze the results. If results do not make sense, find out why. Sometimes it is because of errors made while making changes in the model or input data set, at other times – more importantly – these seemingly unreasonable results actually make sense because feedbacks that are easily overlooked turn out to offset and sometimes surpass expected results.

6.2 EPRI Excellence Matrix

EPRI had worked with nuclear power plant teams to identify the most important good practices and hallmarks of effective nuclear power plant maintenance management. The goal of the work was to establish a metric for assessing nuclear power plant maintenance effectiveness.

These practices and the related performance matrix have been summarized in the reports, "Guideline for Assessing Maintenance Effectiveness" and "Matrix for Assessing Maintenance Effectiveness". The reports include a list of practices perceived to be important in nuclear power plant maintenance programs and was organized in a tree structure: category – elements – sub-elements – attributes. There are four major categories, covering management & work culture, maintenance processes, people skills, and technologies.

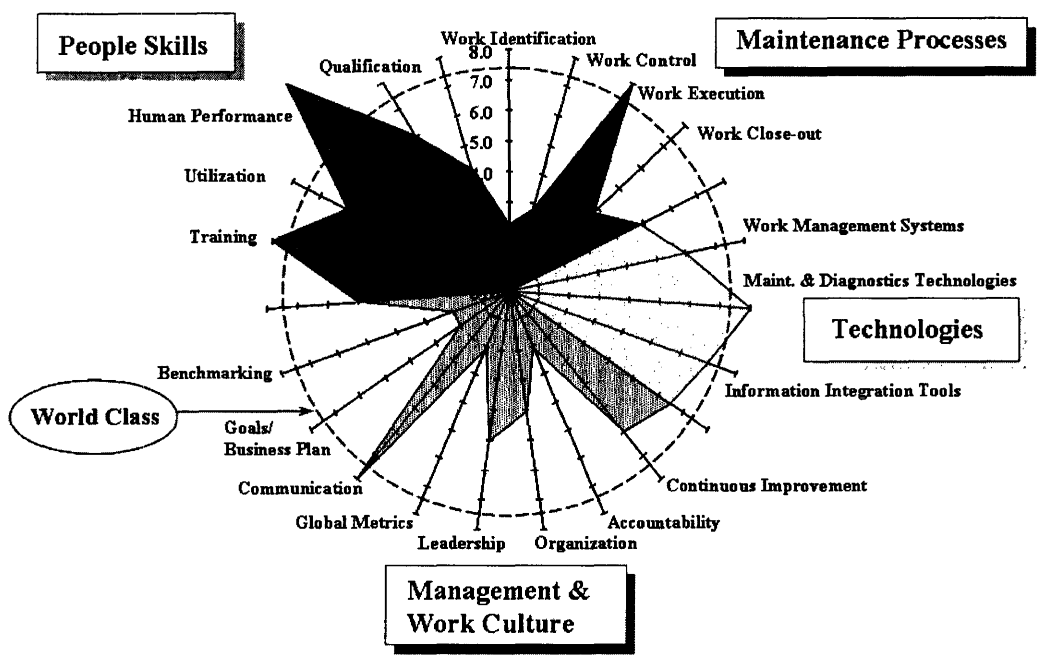


Figure 6-1: Key categories & elements in maintenance effectiveness self-assessment guideline (source: [5])

Figure 6-1 shows an example radar chart of key categories and elements in an effective maintenance self-assessment guide. When using this guide to conduct a self-assessment, scores are obtained for each element. In the chart a matrix of "work-class" scores is also plotted.

Each category consists of a list of elements, which are further made up of sub-elements. Table 6-1 lists this Excellence grid. Each of these sub-elements is broken into attributes that describe the item in detail.

Table 6-1: EPRI Excellence matrix grid (source: [4])

Management & Work culture	Benchmarking	Within Industry	Outside Industry							
	Goals/Business Plan	Org Perf Goals	Maint Dept. Goals	Individual Goals	Business Planning					
	Organization	Roles & Respons.	Specialty Teams	Contract Mngmt	Facilities					
	Leadership	Direction	Policies & Processes	Discipline	Empowermt	Motivation				
	Communication	Ops,Maint, Eng	Mangers to Workforce	Workforce to Mgmt	Peer Group Meetings	Wrkr - Wrkr Comm.	Wrkr to NRC Comm.			
	Metrics	Overall Goals	Department Goals	Plant Goals	Customer Satisfaction					
	Accountability	Personnel Performance	Bus. Plan Adherence	System/ Comp Own						
	Cont. Improvement	SelfAssessment	Change Mgmt Prog	Process Improvement	Use of OE	CAP Program	R&D Activities	MR &PAM Prog IMPL	Empl Ideas Solicited	Team Prob Solving
Maintenance Processes	Work Identification	Work ID Procedures	Maint. Basis	Corrective Maint.	Preventive Maint.	Predictive Maint.	Proactive Maint.	Work Order Generation	Equipment Reliability	
	Work Control	Work Mgmt Process & Procedures	Outage Mgmt Process & Procedures	Prioritize Work	Risk Assessment	Stores/Inv. Management	Planning	Scheduling	Contract Mngmt	
	Work Execution	Work Exec Procedures	Equip Clearance & Tagging	Tools/Mat. Control/Staging	Pre-Job Briefs	Perform Maint Tasks	Work Quality	Safety	ALARA	
	Work Closeout	Work Close Procedures	Post Maint Testing	Post Job Critique	Data Capture & Utilization	House Keeping	Return Equip to service			
People Skill	Training	Processes & Policies	Personnel Skills Dvlpmnt	Plant Systems	Mgmt /Spvr development	Business Literacy	Contractor Training	INPO ACAD	Specialty Training	Training Facilities
	Utilization	Mgmt/Union Interaction	Multi - Discipline	Mbl/Shared Workforce	Productivity / Metrics					
	Human Performance	Behaviors & Values	Procedure Use	Self Check	Peer Check	CAP Prog Utilization	Conflict Resolution			
	Qualifications	Personnel Selection	Qualification Process	Re-Qual Process	Contractor Quals	Qual Tracking Program	Succession Planning			
Technologies	Maintenance Management System	CMMS	Risk Assmnt & Sched.Tools	Scheduling Tools	Reporting & Decision tls					
	Maintenance & Diagnostic Tech	Execution Tools	Cond Mon. On-line	Cond. Mon. Periodic	Technology Software	Process Data Utilization	Equip Perf Mon. Tools			
	Information Integration System	Financial	Budget & Schedule	Equip Cond. Data	Dispatch System	Industry db (EPIX)	Equip Tech. Documents			

The EPRI Excellence Matrix is used as a guide to conduct self-assessment so that individual plants understand the gap between themselves and an industry standard by looking at what practices they do and do not have. However, it is unclear how much benefit a plant can obtain by adopting some practices that they currently do not utilize. ORSIM steps in from here and proves to be a very useful practice evaluation tool.

6.3 EPRI Practices Study Approach

The EPRI practices studies attempt to forecast what is going to happen to the plant in terms of operation performance after we apply one or more elements of the EPRI practices. Because the baseline of a plant is an important factor that determines how the plant will behave, and because baselines are different across different plants, it should always be kept in mind that the conclusion regarding the benefit of a practice is not universal, and that every piece of the study should be reexamined for each different plant.

Given a baseline of a plant, how shall we study the effect of a practice on this plant using ORSIM? There are three steps.

The first step in a practice study is to understand the practice itself. Ask ourselves what the nature of the practice is, what aspects of the plant operations are affected by this practice, and what are the pros and cons if we apply this practice? Answering these questions often requires discussion with plant managers who are familiar with the issues.

The second step is to quantify these effects as either numbers, such as resources required, or as a function, for example how productivity is affected by technologies as a function of time. ORSIM users generally have to consult with experienced plant managers as well as the plant database administrator for these quantifications.

The third step is to run simulations in ORSIM and analyze the results. Sometimes the results do not make sense at first. Sometimes this is because of errors made while making changes, while other times these seemingly unreasonable results actually make sense because of feedbacks. These feedbacks are often overlooked but turn out to be significant.

6.4 Studies of EPRI Practices

Two examples are presented in this section to demonstrate the framework of how to use ORSIM to study EPRI practices (and any other practices). The first concerns EPRI practice 1.6.4 A7, which says “craft perform peer field observation”. The second is EPRI practice 1.8.5 A7, which says "employees at all levels are encouraged to identify and report problems in accordance with Corrective Action Program criteria".

6.4.1 Practice: 1.6.4 A7

Content: Craft perform peer field observation

Pros: higher quality

Cons: lower production time

Quantification: Suppose in the baseline case that we do not perform peer field observations. Further assume that employing this practice starting at t=260 can improve quality by 5%, while productivity decreases to 1/1.05 of its initial value due to time spent on peer field observation rather than production. Notice that the product of productivity and quality remains unchanged.

Expected results: Since the product of productivity and quality remains the same, the net outflows from the system (productivity*quality) are the same in both cases. Also, since net inputs or defect generation rates are the same in both cases, work backlog should be the same in both cases.

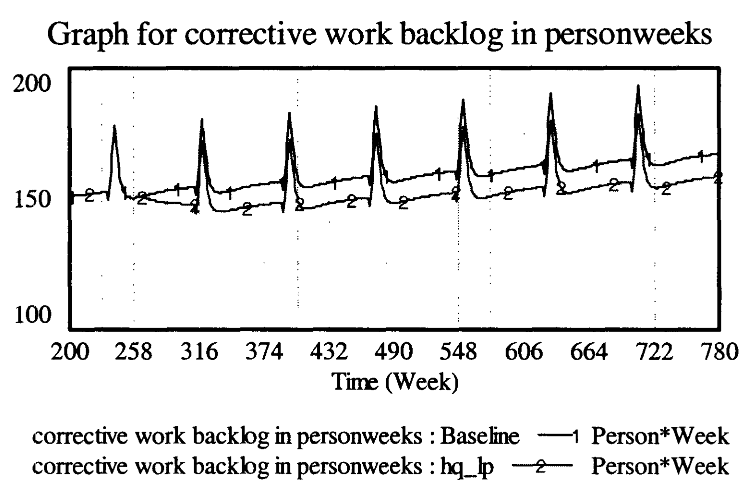


Figure 6-2: Corrective work backlog under alternative work inspection policies: The case with higher quality and lower productivity as a result of employing practice 1.6.4.A7 has a lower work backlog, even though the product of productivity and quality are the same in both cases. (hq_lp: higher quality, lower productivity)

Actual results: See Figure 6-2, the 'perform peer field observation' case with higher quality and lower productivity has a lower work backlog.

The results look counterintuitive at first sight. It looks as if quality matters, while productivity does not because the change is in the same direction as better quality. In order to see if this is the case, a case with higher quality but unchanged productivity was simulated. The results are presented in Figure 6-3. Indeed, from Figure 6-3, two cases with the same improvement on quality but different productivities have a very close work backlog, even though the case with higher productivity has a little smaller work backlog.

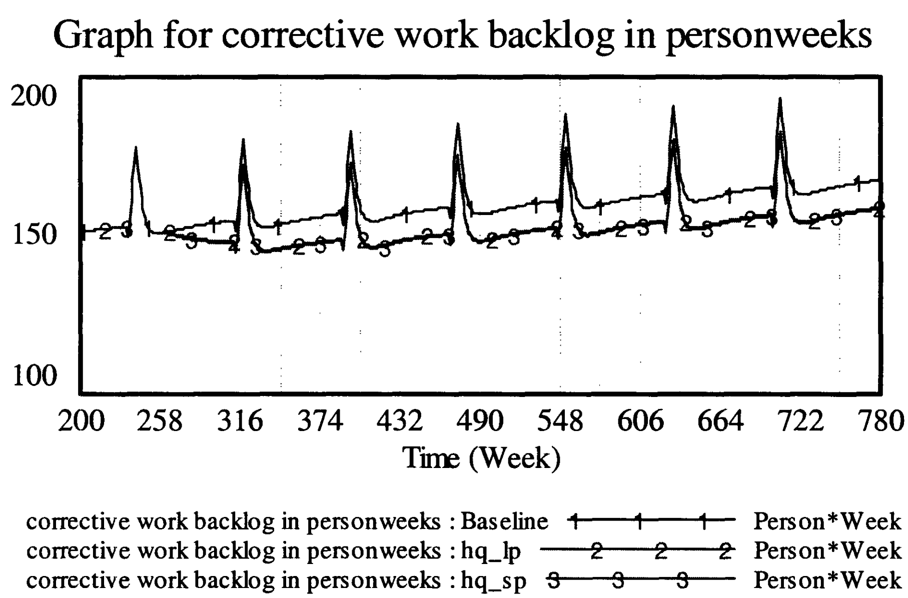


Figure 6-3: Corrective work backlog under alternative work inspection policies and differing productivity levels: With a change in quality, higher or lower productivity does not matter! (hq_sp: higher quality, same productivity)

Why does quality matter while productivity seems not to?

First, let us use ORSIM to explain why productivity does not matter. See Figure 6-4. Even though the two cases have different productivity, they have the same repair rates! The only reason is that they have a different number of maintenance workers. This is also true if we look at Figure 6-5, which shows how many maintenance workers are 'idle', or not working on production. The lower productivity case has less idle workers, or more workers working on production, so that the product of productivity and workforce is the same for both cases. This is true because our allocation of workforce is based upon workload and productivity. As long as there is enough workforce, productivity changes will not affect the production rate since we can always step up the workforce dedicated to working on production.

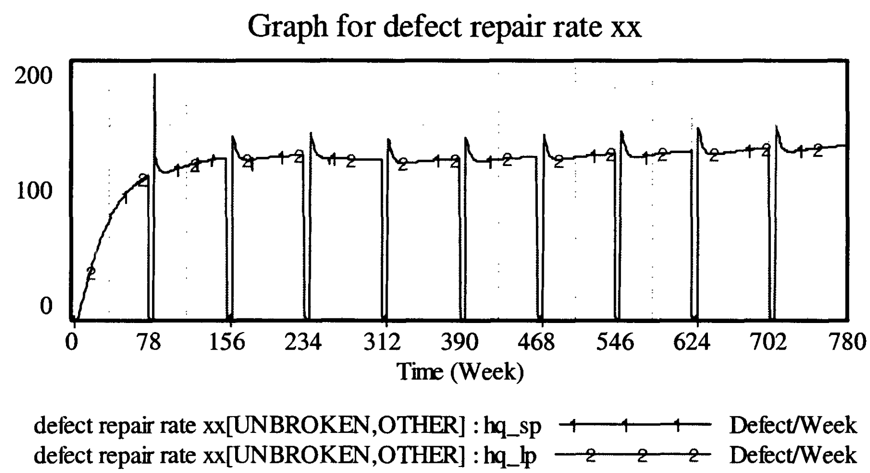


Figure 6-4: Defect repair rate for increased maintenance inspections with different productivity values: In both cases, repairing rates are the same, even though productivities are different

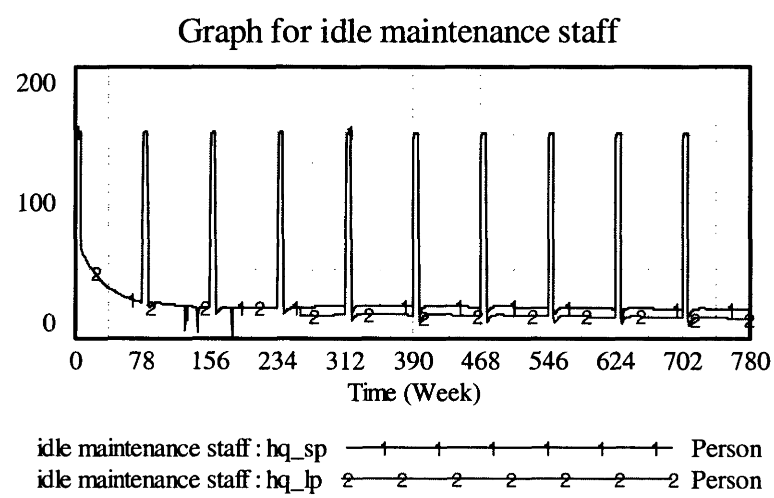


Figure 6-5: Idle maintenance staff for increased maintenance inspections with different productivity values: It makes sense if we look at how many maintenance staff are working on production.

This does not mean productivity does not matter in ANY case. Because first of all, lower productivity means more workforce is required to keep up with the production rate, and when there is no more workforce to use, lower productivity then means a lower production rate. Even though we have enough workforce, lower productivity still implies that we have less in reserve to respond to surprises, and higher productivity may increase this reserve to a point that we can reduce the size of the workforce and cut down salary expenses.

Next let us examine why quality matters. When quality is not perfect, it is possible to introduce new defects or leave defects uncorrected. These defects, if not spotted in work closeout, will remain in the system.

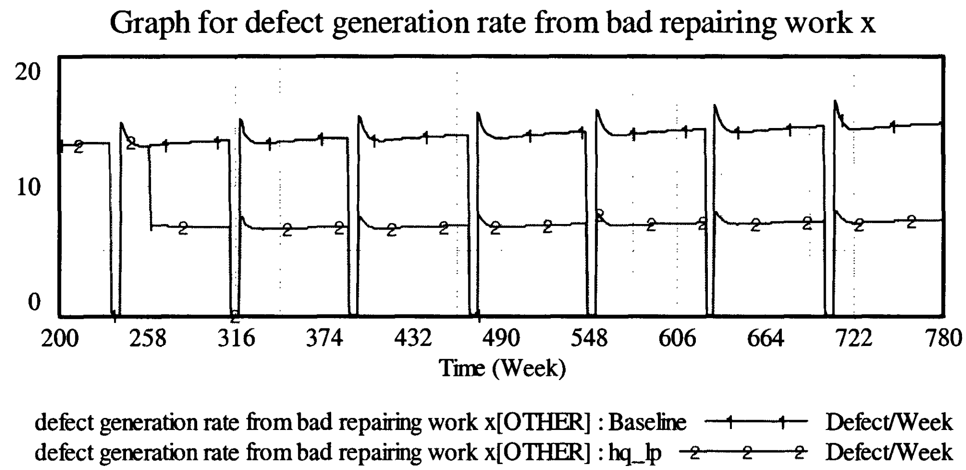


Figure 6-6: Defect generation rate under alternative maintenance quality cases: In the higher quality case, rework rate is less than the baseline case

See Figure 6-6: as quality improves, the inventory of newly introduced defects and uncorrected defects decrease, which is represented by the variable 'defect generation rate from bad repairing work' in Figure 6-6. For the time being let us assume 'defect growth rate' remains constant. In steady state, it must be true that:

Defect discovery rate = defect growth rate + defect generation rate from bad repairing work.

The 'defect generation rate from bad repairing work' decreases as quality improves while defect growth rate is constant, the 'defect discovery rate' must decrease, and so does the 'defect repair rate' (Figure 6-7).

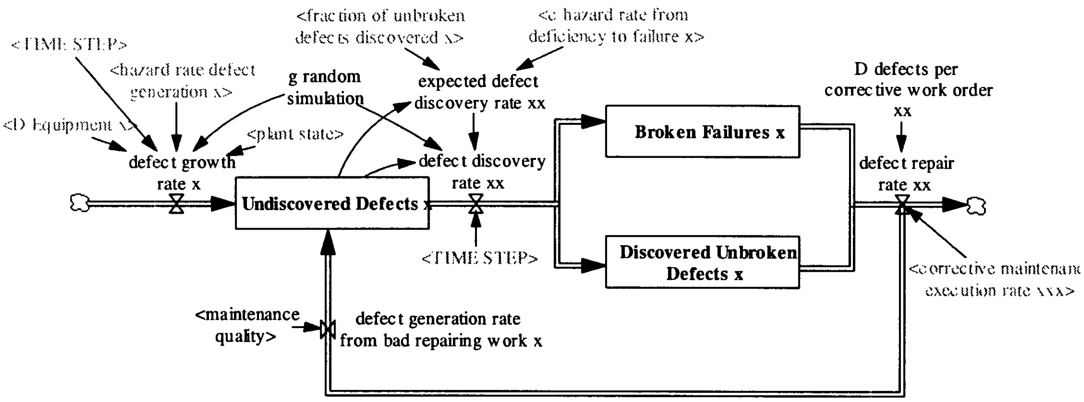


Figure 6-7: Defect discovery process diagram: In steady state, defect discover rate equals the sum of defect generation rate and rework rate; therefore in the higher quality case, defect discovery rate is less.

The total time that 'Broken Failures' and 'Discovered Unbroken Defects' stay in the system are mainly caused by delays and are approximately the same in both cases. Given this fact and the decreases in defect discovery rate, the backlogs of broken failures and discovered unbroken defects will both reach lower equilibrium levels (see Figures 6-8 and 6-9), since in steady state:

Broken Failures = defects discovery rate [broken] x time in system, and

Discovered Unbroken Defects = defects discovery rate [unbroken] x time in system.

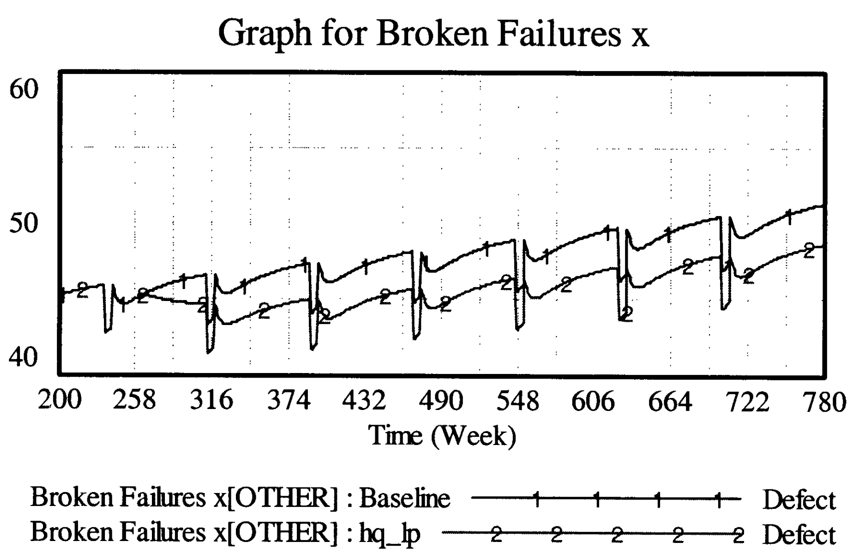


Figure 6-8: Broken failures under alternative inspection quality policies: Smaller defect discovery rate implies higher broken failures and discovered defects in stock, given that they stay in the system for the same amount of time

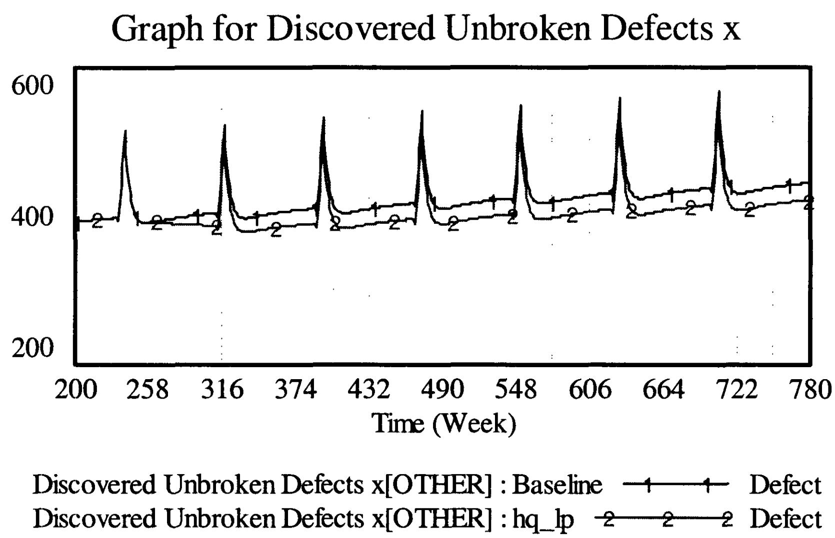


Figure 6-9: Discovered unbroken defects under alternative inspection quality policies: Smaller defect discovery rate implies higher broken failures and discovered defects in stock, given that they stay in the system for the same amount of time

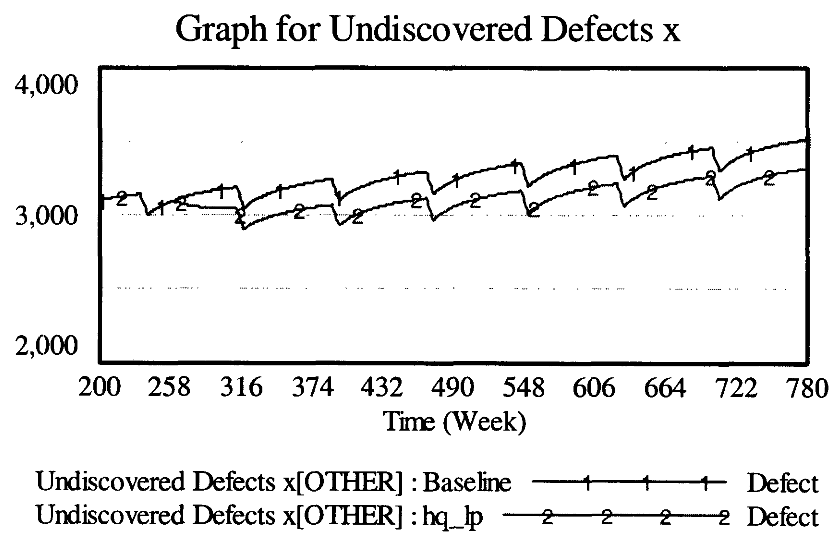


Figure 6-10: Undiscovered defects under alternative inspection quality policies: Smaller defect generation rate as well as smaller defect generation rate from bad repairing work imply fewer undiscovered defects

We have assumed earlier that the defect generation rate remains unchanged. In fact, it does change. It becomes smaller due to better material conditions (lower backlogs of defects). Since the defect generation rate from bad repairing work also decreases, the sum of these two, which are equal to the defect discovery rate in steady state, also decreases. Given that inspection and field observation rates do not change, the average time for a defect to be discovered remains the same, and so 'Undiscovered Defects' will decrease (see Figure 6-10), since in steady state:

Undiscovered Defects = defect discovery rate x time to discover a defect.

So far we have not looked at numbers but only relative comparisons. If we take a look at how much work the backlog is decreased after employing this practice, we see that in steady state the backlog decreases by more than 5% (see Figure 6-11). Remember, we only improved our quality by 5% and at the same time the productivity is lower!

The explanation for this is that the feedback within the system that amplifies the result. As quality improves, material conditions improve because we have a lower defect inventory, which causes the defect generation rate to decrease. It is this favorable feedback that gives us better results.

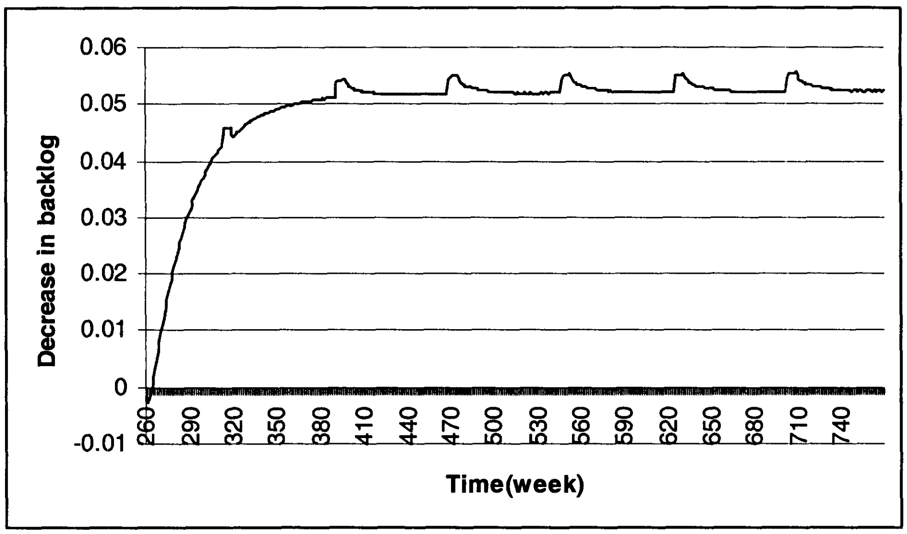


Figure 6-11: Actual decrease in corrective work backlog is more than 5% even though the peer field observation practice only improved quality by 5%

Note: Decrease in backlog = (Baseline – Practice) / Baseline.

The lesson is as long as we have enough workforce, improving productivity does not lead to a lower backlog of defects. It can help with a workforce cutback, though. On the other hand, improving quality is one of the ways to work down the backlog. And because of the feedbacks from defect generation rate, improving quality can bring better than expected results.

6.4.2 Practices 1.8.5 A7

Content: Employees at all levels are encouraged to identify and report problems in accordance with Corrective Action Program criteria

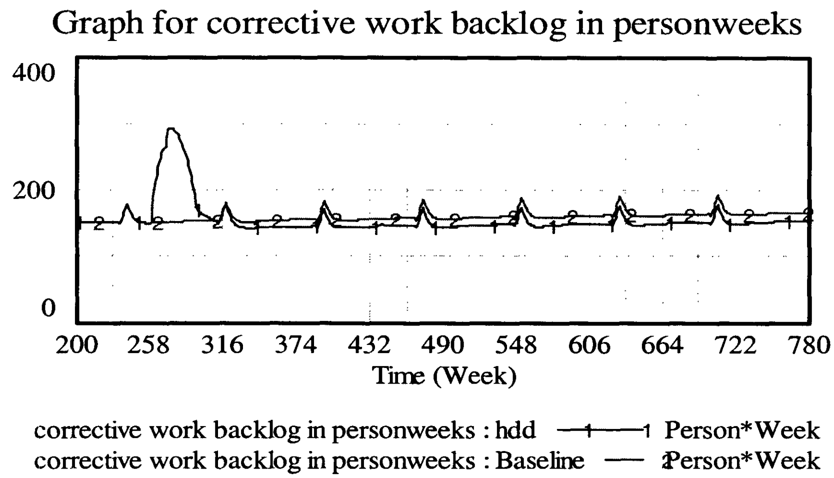
Pros: higher defect detection probability

Cons: time spent on defect discovery

Quantification: Assume that in the baseline case, we do not have this practice. By employing this practice starting at week 260, we expect the defect discovery probability to increase by 100%. At the same time, 5% of everyone's time in the maintenance department is spent, on this task, which is modeled by moving 5% of total workforce to 'workforce on other tasks'.

Notice that defect discovery probability means if there is a defect, what is the likelihood that it is discovered within a period of one week. This is different from the defect discovery rate, which is actually a product of defect discovery probability and defects undiscovered. The defect discovery probability is linearly dependent upon frequencies at which SSCs are inspected and observed, and so it is linearly dependent upon the person-hours spent on inspections and observations. Our quantification here implicitly assumes that in the baseline case, inspections and observations take 5% of the total person-hours, so if we spend 5% more, we can double our defect discovery probability.

Results: The practice starts at week 260. Work backlog increases for a continuous 6 months to a maximum of 80% and then turns back down for another 6 months, eventually reaching baseline level. There is an outage at this point. Starting just at the beginning of the next re-start, the backlog reaches a steady state level at about 7~8% below that of baseline. The practice works, but it takes one year to see a lower steady state backlog. During this one year, the backlog is actually higher than the baseline case due to the higher defect discovery rate.



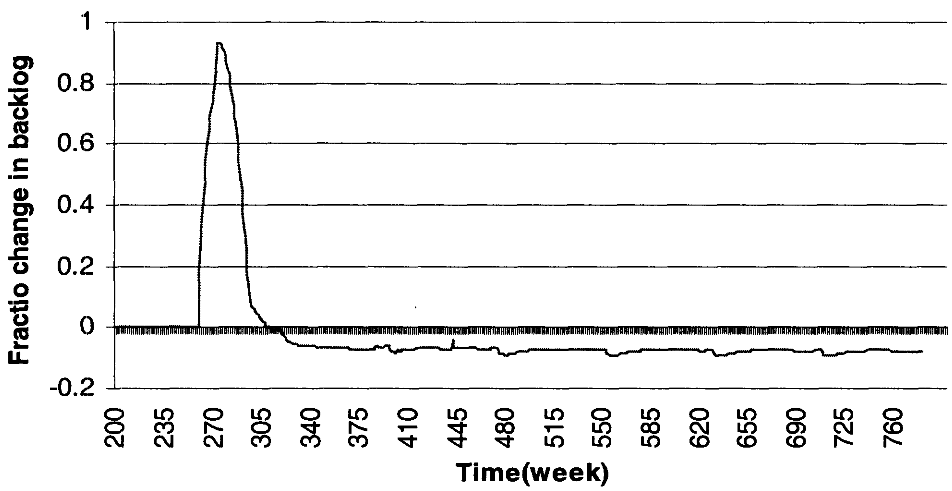


Figure 6-12: Corrective work order backlog under alternative defect discovery policies: After employing defects report practice (hdd - higher defect discovery probability) at t=260 week, corrective work backlog first increases and then decrease to reach a steady state level lower than that of the baseline.

Explanation: In the beginning, defect discovery probability increases by 100%. This increase leads to an increase in the defect discovery rate, as can be seen in Figure 6-13:

Defect discovery rate = Undiscovered Defects x defect discovery probability.

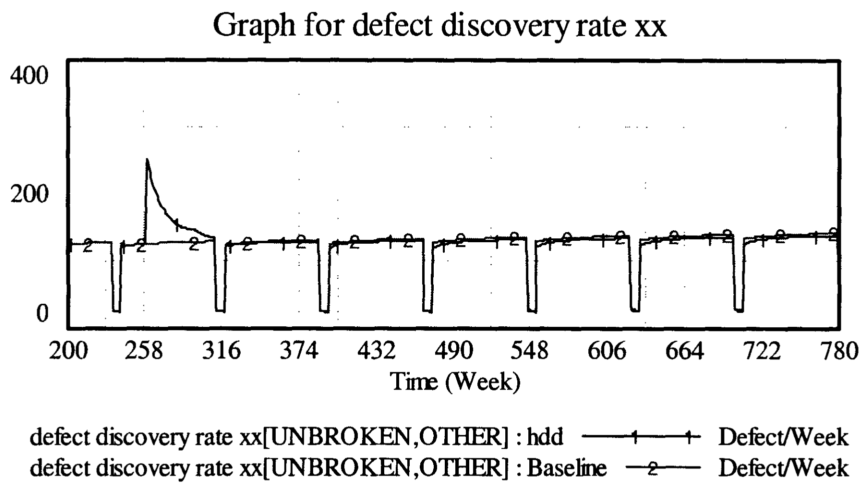


Figure 6-13: Defect discovery rate under alternative defect discovery policies: Defect discovery rate increase suddenly when practice is employed, and then decreases to reach a steady state level lower than that of the baseline.

Assume for now that inflows to Undiscovered Defects remain unchanged. Before we reach the next steady state, outflows from Undiscovered Defects are greater than inflows, making Undiscovered Defects smaller; the smaller level of Undiscovered Defects has a feedback effect upon the defect generation rate and makes it smaller until we reach steady state, in which case inflow equals outflow. This process is represented in Figure 6-13.

During this transient process, the higher defect discovery rate (which increases inflows to the work backlog level) leads to a higher corrective work backlog because we do not have enough workers to match the sudden increase in inflows to the corrective work backlog inventory. This result can be derived from Figure 6-14. The maintenance program stability index is below zero for some period of time, indicating that we are not able to produce as much work as is generated. As the defect discovery rate decreases, the maintenance program stability index increases, but never comes back to the same level because 5% of the time is now being used for defect detection, making the time resources available to work down backlogs less than that of the baseline case.

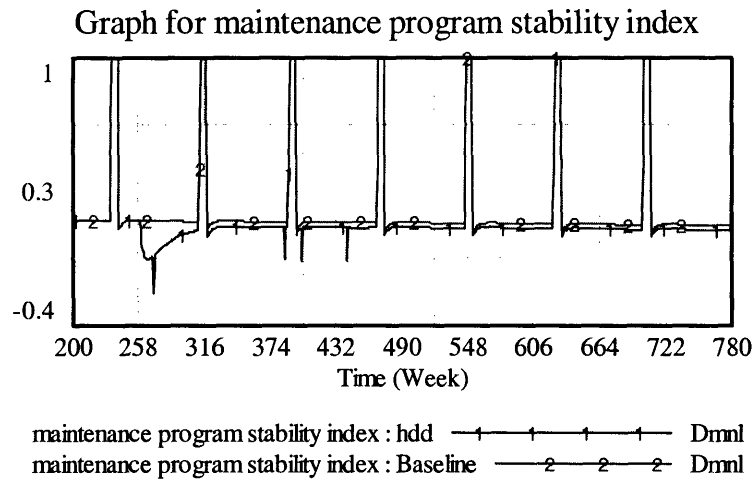


Figure 6-14: Maintenance program stability index: Maintenance program stability index is less than zero for a period of time, then comes back and reaches a steady state level lower than that of the baseline case.

When it reaches a steady state, it must be true that inflows to Undiscovered Defects equals outflows, or defect discovery rate, the steady state defect discovery rate in both the baseline case and practice case should be the same:

Baseline defect discovery rate = Practice defect discovery rate, or

Baseline Undiscovered Defects × baseline defect discovery probability =

Practice Undiscovered Defects × practice defect discovery probability.

Because the defect discovery probability increases by 100%, Undiscovered Defects should decrease by 50%:

$$\begin{cases} \text{Baseline Undiscovered Defects} \times \text{baseline defect discovery probability} = \\ \text{Practice Undiscovered Defects} \times \text{practice defect discovery probability.} \\ \text{practice defect discovery probability} = (1+100\%) \times \text{baseline defect discovery probability} \end{cases}$$

$$\Rightarrow \text{Practice Undiscovered Defects} = 50\% \times \text{Baseline Undiscovered Defects}$$

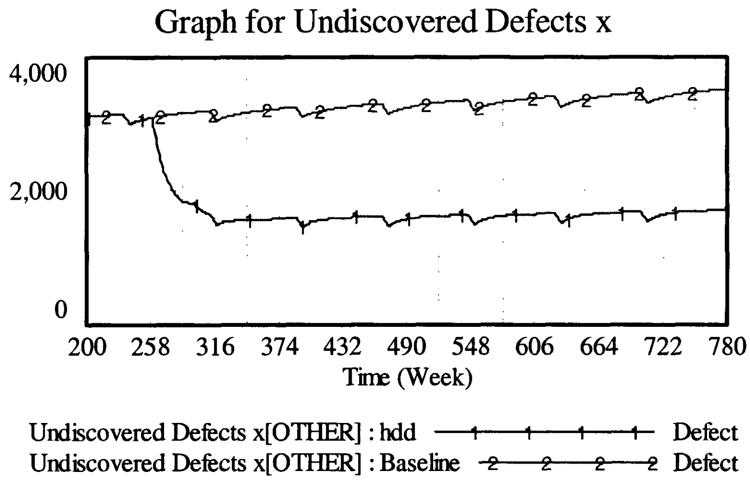


Figure 6-15: Inventory of undiscovered defects under alternative defect discovery policies: Practice case has a lower inventory of undiscovered defects

Of course inflow to Undiscovered Defects does not remain the same. It actually becomes smaller because we have better material conditions with less Undiscovered Defects in the inventory (see Figure 6-16). Therefore when we reach steady state, the defect discovery rate will be smaller than that of the baseline case due to the smaller inflow to Undiscovered Defects (see Figure 6-13). At the end of the day it seems quite strange that after taking measures to improve our defect detection, we are detecting fewer and fewer defects. As is pointed out previously, the main reason for this result is that we have a smaller defects inventory.

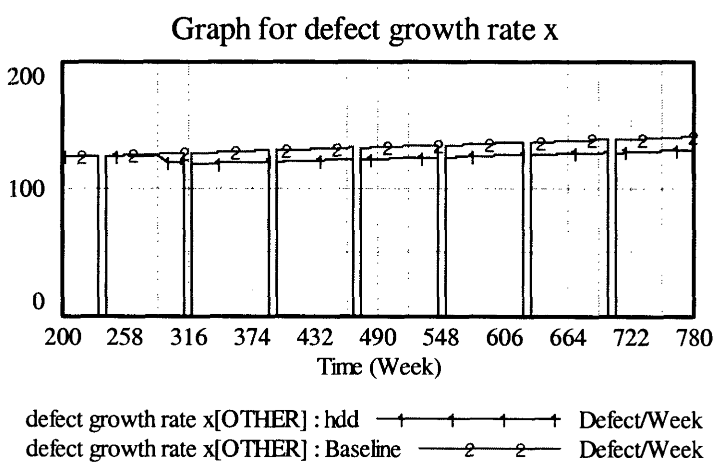


Figure 6-16: Defect growth rate under alternative defect discovery policies: Material conditions are better in practice case. This is reflected by a lower defect generation rate as compared to the baseline case.

If anyone in the management team later finds out that with extra time resources being spent on defect detection and yet only a few defects being detected, and a decision is therefore made to reverse the practice, he will be happy to see what he wants to see: time resources are saved, defect detection increases – looks like a winning strategy. But wait, he does not realize that the increase in defect detection is not because of more effective inspections, but because of an increase in the inventory of defects! The consequence will be very bad, indeed. This result illustrates the value of being able to identify fundamental causes of what is observed rather than mere symptoms.

6.5 Summary

Two practices were selected from the EPRI Excellence matrix to demonstrate how to use ORSIM to investigate the implications of practices upon plant performance. Each study began with understanding the practice in terms of its effect on the ORSIM model variables and quantifications of these effects. A matrix of performance indices, especially stability indices, helps pinpoint improvements as well as unfavorable impacts, and the tracking capability of ORSIM leads us quickly to the root causes.

For the two sample studies conducted, the first one shows that improved productivity is far less efficient in reducing work backlog than improved quality, given that enough workforce is available. The reason is because improved productivity only reduces the time a work order remains in the system by a small amount, with most of the delays coming from stages prior to execution, while improved quality reduces the flow rates between maintenance processes significantly. The backlog, which is a product of flow rates and delay times, is therefore far less in the improved quality case than in the improved productivity case.

The second sample study demonstrates that a good safety culture, even if it requires some resources to maintain, can improve the operational performance of the plant, as more efficient defect discovery helps reduce the unobservable backlog of undiscovered defects, which improves the material conditions and reduces the defect generation rate.

CHAPTER 7 – CONCLUSION

7.1 Recapitulation

The work reported here has developed an approach to diagnose problems and to identify good practices in the operation of nuclear power plants using system dynamics technique. The underlying problem surveyed in this research is the fact that NPPs have yet to fully recognize and utilize the dynamic interactions between organizational and physical systems, which often drive plant performances. The objectives of this work include:

- Creation of a computer model that represents these interdependent systems in a quantitative way;
- Development of a matrix of performance indices to measure plant performances in terms of stability, reliability, and economic performance;
- Work with utilities to demonstrate how ORSIM is applied in practice.

The research began with construction of the ORSIM model, with its operational component modified from an existing model OPSIM, and its risk component newly created in this research. For its operational part, the ORSIM model replicates the organizational structure of a typical utility and the activities carried on in the course of plant operations. The organizational structure is represented by sectors that include management, operations, engineering, maintenance, and planning, all of which interact with plant physical systems and themselves. Within a typical sector there is a work generation rate governed by specific mechanisms, an inventory or backlog of work to be done, and a work accomplishment rate. Work creation occurs during operation and is unique for each sector. These rates accumulate into backlogs. The backlogs are reduced by the rate at which work is accomplished, which is determined by the number of people assigned to the tasks and the productivity at which they perform their work. In each sector, workforce is allocated to different tasks based upon work priority algorithms. Workforce productivity and quality are represented as dynamic variables that change continuously throughout simulations. For its risk component, ORSIM uses the transient, trip event, and core damage probabilities to represent the reliability aspect of NPP operations. The plant material conditions and human performance together determine the reliability performance of a plant.

A matrix of high-level performance indices was created to measure plant performance as a function of continuous operation. The matrix includes a corrective work backlog, a reliability index, an economic performance index, and operational stability indices. The corrective work backlog is the weighted sum of all types of maintenance work accumulating in all stages (assessing, planning, execution etc.). And the economic performance index is simply represented by electricity loss due to outages – both expected and unexpected. The reliability index is actually the conditional core damage frequency index, or 'CCDF index'. It measures how conditional CDF compares to a nominal design-based CDF and the reflects effects of materials conditions, broken failures, and human reliabilities:

$$\text{CCDF index} = \frac{E[CDF]}{CDF_0} = \prod_g \left(\overline{\text{RAW}_g}^{\,n_g} \right) \times \exp\left(\sum_g \delta_g FV_g \right) \quad (7\text{-}1)$$

Where $\overline{\text{RAW}}$ is the average of all components' RAW, weighted by components' failure probabilities; n_g is modeled in ORSIM as "equipment with broken failure", and δ_g is modeled as "materials condition factor" minus one. Both of these two variables are functions of continuous operations in ORSIM. FV is sum of component Fussell-Vesely values in each group.

The stability index indicates whether the work backlog in a sector is able to approach a steady state level. It is determined by the capability to match net output with net work generation, or, the workforce in place as compared to the workforce required to match work inflows – given productivity and quality:

$$\text{Stability index} = 1 - \frac{\text{expected workers required}\,[person]}{\text{available workers}\,[person]} \quad (7\text{-}2)$$

The work continued with development of an interface program to provide a user-friendly environment. There are two major components in ORSIM interfaces: ORSIM Simulator and ORSIM Inputs. ORSIM Simulator is a standard Windows program where the user can load the ORSIM model, load ORSIM inputs, run simulations, and perform post-simulation analysis such as root-cause analysis. ORSIM Inputs is an Excel spreadsheet written in Visual Basic for

Applications, where users can load the ORSIM model, view definition and values of ORSIM parameters, and change them to reflect their actual plant data.

In order to show how ORSIM is used in practice, a pilot study was conducted with a Canadian power plant, and two sample studies were performed to investigate an EPRI Excellence matrix. In the pilot project, ORSIM was first customized and tuned to the baseline of the plant. This pilot project demonstrated that customization of the ORSIM model is not difficult. Once customized, ORSIM is a helpful tool in identifying existing problems and investigating practices and policy changes. For this pilot plant, we found that the assessing department was the weakest link in the maintenance process. We also found inefficient use of planning staff and overloaded plant modification work for engineers. In order to solve the problem in the assessing department, a proposed policy change was studied. The policy under consideration was found to be capable of solving the problem.

Two practices were selected from the EPRI Excellence matrix to demonstrate how to use ORSIM to investigate the implications of practices upon plant performances. Each study began with understanding the practice in terms of its effect on ORSIM model variables and quantifications of these effects. A matrix of performance indices, especially stability indices, helps pinpoint improvements as well as unfavorable impacts, and the tracking capability of ORSIM leads us quickly to the root causes.

In the EPRI practice studies, two practices were chosen as samples to show how ORSIM can be used to investigate practices. For the two sample studies conducted, the first one shows that improved productivity is far less efficient in reducing work backlog than improved quality, given that enough workforce is available. The reason is because improved productivity only reduced the time a work order remains in the system by a small amount, with most of the delays coming from stages prior to execution, while improved quality reduced the flow rates between maintenance processes significantly. The backlog, which is a product of flow rates and delay times, is therefore far less in the improved quality case than in the improved productivity case.

The second sample study demonstrates that a good safety culture, even if it requires some resources to maintain, can improve the operational performance of a plant, as more efficient defect discovery helps reduce the unobservable backlog of undiscovered defects, which improves materials conditions and reduces the defect generation rate.

7.2 Conclusions

This work shows that ORSIM is a good tool that assists nuclear plant managers to understand the current state of the plant and to make informed decisions regarding policy changes. With system dynamics technique, ORSIM takes into account many coupled and non-linear relationships among various aspects of plant operations, and provides insights into improvements as well as decays of performance as a function of continuous, changing plant operations.

The matrix of performance indices developed in this research is able to measure stability, reliability, and economic performance in a concise and clear way. With this matrix, ORSIM is able to pinpoint bottlenecks of current operations and to project into the future what would be the implications of various policy changes. Together with the tracking capability built into ORSIM, it is rather easy to locate root causes of problems and to identify circumstances in which operational improvements can be implemented.

The pilot project with a Canadian nuclear power plant and the studies on EPRI practices further demonstrated that in practice, ORSIM is capable of identifying existing problems and investigating corresponding practice changes regarding whether they work or not and why. It therefore can help improve the quality of decision-making and help achieve more stable, reliable, and economic operations of nuclear power plants.

7.3 Comments

It looks quite intriguing that the System Dynamics model can capture so many hidden feedbacks in the systems. However, as John D. Sterman pointed out: “All decisions are based on models ...and all models are wrong!”

Human perception and knowledge are limited. We operate from the basis of mental models, and we can never place our mental models on a solid foundation of Truth because a model is always a simplification, an abstraction, and a selection; our models are inevitably incomplete, incorrect, and wrong.

Meadows in her book wrote [14]: “...that [system dynamics] field is persisting in its own perverse behavior:

a. It concentrates on easily quantifiable parts of the system, not important parts;

b. It devotes tremendous labor ...to achieving small increases in precision, meanwhile doing little effective testing for general accuracy;

c. It assumes and reinforces the social structure that is the cause of the destructive behaviors, rather than raising questions of long-term goals, meaningful social indicators, or system redesign;

d. It produces complicated black boxes that outsiders must take on faith—it does not share its learning effectively with users;

e. It rarely sets its sights high enough to demonstrate its most unique contribution—its ability to focus attention on systems as wholes (not parts) and on long-term evolution;

f. Many of its efforts are not credible, not used, and not even documented so that others can learn from mistakes."

But shall these inevitable defects stop us from using the technique? There was a joke about a bear. Two men are sitting outside their tent in a forest campsite when they see a huge angry bear charging toward them. One starts lacing up his running shoes. The other says, "are you crazy? You'll never outrun that bear!" The first says, "I don't have to outrun the bear. I only have to outrun you."

Yes, we do not have to reach the truth; we only have to understand better than our competitors in order to succeed. In this sense, ORSIM is a good tool because it helps us understand better what happened and what will happen to our plants.

7.4 Future Work

The current version of ORSIM should be seen as a first-generation tool that hopefully will improve in the future. For example, the current version represents managers of only two types: experienced or inexperienced. It should be possible to segregate further into a profile of management skills such as quickness in understanding an issue, quality of response or decision-making, and ability to function with an overload of work.

The current version of ORSIM does not contain any cost analyses. The model merely calculates expected capacity losses for each simulation. It would be relatively straightforward to include cost parameters for materials and manpower and produce estimates of the cost for each scenario studied, as well as capacity losses. It would also be possible to include an income calculation if the sale price of kWh's can be identified. It is likely that owners will face many complicated decisions in the future involving alternative investments, policy changes, or personnel changes. The ORSIM model could help in analyzing the costs and benefits of each alternative.

In the human resource sector, the current version of ORSIM does not consider internal rotations/promotions, for example, from maintenance to operation. However, it is generally true that a certain internal rotation/promotion mechanism exists in most plants. For example, in some plants operators are selected from excellent maintenance workers, and in some plants, because of the salary difference across different functional organizations, people are leaving low-paid positions to join high-paid ones.

Finally, the number of sectors in the model can be expanded to include more elements of the organization, and the processes in each sector can be expanded to include more detailed stages. This could be particularly important as the ownership pattern of nuclear power plants is changing. If an entity owns and operates one or more plants and subsequently acquires a new plant, an issue of integrating operations and processes arises. The ORSIM model could be used to study what changes are most effective and which changes are least important on subsequent performance.

Going beyond such specific applications, the greatest benefit of using a complex simulation model such as ORSIM is the stimulation of its user, provoking new understanding and changes in the manner in which a problem is viewed. For this reason alone, ORSIM is likely to be valuable to the future managers who have the vision to explore their potential.

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