**THE EFFECT OF MAINTENANCE POLICY ON SYSTEM MAINTENANCE AND SYSTEM LIFE-CYCLE COST**

by

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**(ABSTRACT)**

This research presents a framework system dynamics (simulation) model that evaluates the effect of maintenance policies on system performance and life-cycle cost. The model highlights factors such as learning, aging and the technological upgrades that occur during the life-cycle of a system. The metrics used to measure the effectiveness of maintenance policies are the system life-cycle cost and cumulative breakdowns. In this research, a varying maintenance policy has been modeled using system dynamics methodology to determine the future performance of the system that is dependent upon its past performance when breakdowns occur randomly. The main objective of this modeling approach is to balance the cost of preventive maintenance actions with the opportunity losses due to system breakdowns. The approach used in this research primarily involves forecasting future breakdowns using an average of accumulated opportunity losses.

This research effort was mainly aimed at developing a (framework) model to determine effective maintenance policy for a system and evaluating the effect on the life-cycle cost for various scenarios. This model could further form the basis of a decision support system for maintenance modeling.

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life = study period or expected service life.

investment = initial investment or acquisition cost.

avg bd1 = average breakdown in year 1.

avgbd = average breakdown in any year.

learning = % learning curve.

pm = cost of a preventive maintenance action.

bdm = cost of a breakdown maintenance or repair.

oper cost = annual operational cost of the system.

avg loss per breakdown = opportunity loss per breakdown.

repl = replenishment per breakdown.

fprbd = factor by which preventive maintenance reduces breakdowns.

ftebd = factor by which time affects breakdowns.

premium = market premium for risk.

w1 = fraction of equity financing in the capital structure.

w2 = fraction of debt financing in the capital structure.

# Chapter 1 Introduction

## 1.0 Introduction and Background

This chapter is divided into five sections. The first section presents an introduction to the problem and the research methodology, the second presents the research objectives, the third deals with the motivation and challenges in the research, the fourth gives an overview of the research methodology developed and the fifth deals with the organization of this thesis.

## 1.1 Introduction

Life-cycle cost management has gained paramount importance in the decision making process for new technology, design and procurements. The emphasis on the computation of life cycle cost for analysis of alternatives is increasing. This reduces the chances of errors in investment. It is believed that decisions made in the early phases of a system's life-cycle have significant cost impact during the operational phase of a system [18]. There is a need for management to have a life-cycle perspective in order to make rational decisions [see Glossary]. Often, managers make operational and tactical decisions that are "myopic" or short term in nature. For example, purchasing decisions may be based only on acquisition cost and preventive maintenance may be ignored. This strategy will help reduce expenses in the short term but repercussions may be experienced later in the form of increased breakdowns and unavailability. The use of the life-cycle cost concept forces management to consider the future cash flows during the procurement and design phases of the system under consideration. A logical goal for management is to balance the life-cycle costs with system effectiveness [see Glossary] or availability.

A significant amount of the annual operational costs are attributed to maintenance costs. An effective and efficient [see Glossary] maintenance policy would operate a system to achieve operational objectives successfully, considering that the systems are getting complex with the advancement of technology. When one considers systems required during emergency or which are required perennially, for example, aircraft carriers, airplanes, printing presses and many other systems, maintenance policies determine the ongoing availability of the system. Additionally, it may not be in the interest of management to invest in redundant capacity or in excessive maintenance efforts. For example, one of the biggest operational challenges faced by a plant manager is to reduce maintenance costs, capital investment in maintenance resources and redundant capacity without reducing system reliability. In the United States, the estimated cost of maintenance increased from $200 billion in 1979 to $600 billion in 1989. Maintenance activities account for, on an average, 28% of the total cost of finished goods [2]. In short, maintenance costs are important and need to be considered in the early phase of the product life-cycle, i.e., during design or procurement. This would help reduce maintenance costs substantially during the service life of the system.

The motivation of this research is to provide a (framework [see Glossary]) model by which an effective maintenance policy can be formulated for large systems with long service lives and limited initial knowledge of breakdowns. Also different policies can be tested using this framework. It is a decision support tool for the maintenance manager to systematically consider many issues such as future technologies, learning and aging to compute the life-cycle cost of the system.

A large system is a conglomerate of several small subsystems. The interaction between these numerous subsystems leads to a very dynamic and complex system. In a dynamic technological environment, it is imperative to consider the effect of future technological changes, as much as possible, on all the subsystems not only before the system construction but also during the lifetime of the system. The technological changes will have impact on the procurement and operational costs of the system. Furthermore, the initial investment can affect the operation, i.e., the number of breakdowns of the system during its service life. These relationships, i.e., the effects of technological developments, learning and the initial investment costs on system life cycle costs, may be studied using system dynamics principles. System dynamics is an approach that investigates the information feedback characteristics of dynamic systems and shows how structure, policies, decisions and delays interact to influence system growth and stability [10].

If employed properly, system dynamics modeling brings the following benefits [25]:
- policies and actions that are effective and efficient (See Glossary);
- explicit considerations of assumptions, uncertainties, costs, consequences, spillovers etc.;
- a logical framework for considering and setting policy goals;
- improved understanding of the issues and hence better insights on the part of the decision-makers;
- new options, new goals, and new horizons that expand people's perceptions of what might offer them the chance of improving system performance.

## 1.2 Research Objectives

The goal of this thesis is to develop a system dynamics modeling framework to evaluate flexible system maintenance policies and to simulate the impact of all critical maintenance parameters on system life-cycle cost (LCC). The critical system maintenance parameters include technological upgrade of subsystems, the effect of preventive maintenance actions on future breakdowns, and the effect of age on breakdowns. The organization interested in this research has many complex mechanical and electronic systems that need to be maintained. The organization is interested in reducing the costs involved keeping the effectiveness of the systems at their present level. In one of the meetings with the maintenance personnel of the concerned organization, it was claimed that they have a "fixed" preventive maintenance policy throughout the life cycle of a system. But in chapter 4, from the data available for two systems, the data reveals that the number of preventive maintenance actions per period is not fixed. This thesis attempts to develop a framework model for a "flexible" preventive maintenance policy philosophy. The preventive maintenance policy is initially set with the support of the supplier (if purchased) or the designer (if built in-house). But over the system life cycle, it may be advisable to change the preventive maintenance policy to account for deterioration of the system with time, technological improvements, breakdown patterns, actual maintenance costs, changes in mission criticality and various other operational issues. This modeling framework evaluates the impact of flexible maintenance policy depending upon the past record of the system. It may not be very logical to follow a fixed policy throughout a system's life-cycle.

Therefore, the null hypothesis being considered in this thesis is that there is a difference between fixed and flexible preventive maintenance policy, in terms of its impact on the system life-cycle cost and operational effectiveness.

Other supporting research objectives are:

- To develop relationships among certain variables, such as life-cycle cost and cumulative breakdowns.
- To evaluate the relationship between the overall system and its important subsystems in terms of a maintenance policy.
- To suggest a suitable methodology to evaluate both fixed and flexible maintenance policies.

## 1.3 Motivation and Challenges

### 1.3.1 Motivation

As mentioned earlier, maintenance plays a very vital role throughout a system's life-cycle. It is widely accepted that it contributes to a major portion of the life cycle costs of a system. Besides, an effective maintenance policy leads to better operational availability and reliability of a system. It is important to obtain a proper balance among system performance, effectiveness and logistics support. Logistics support includes maintenance crew organization and spares requirements [see Glossary].

Adequate maintenance is essential to ensure the effective and economical support of a system [39]. The term "adequate" refers to effective maintenance and would be system specific. It is an art to define the adequacy of maintenance for any system. It would not be advisable to use similar parameter values for different systems. For example, values for the parameter indicating mission criticality may differ for different systems. It requires one to acquire a thorough knowledge of the operations and requirements of the system and would also require one to experiment with several values of the model parameters.

The literature review, in Chapter 2, points out that not many models contain a comprehensive list of factors affecting maintenance policies. Besides, a general framework that helps set a maintenance policy based on the effect of various factors and activities associated with the system throughout its life cycle would be useful. Usually the models in the literature tend to concentrate only on a few issues in their approaches, such as balancing the costs of breakdowns and preventive maintenance actions, neglecting many other significant issues, such as learning and technological effects. There is a need to develop some tool that a manager can use for analyzing any system; a tool that would allow the manager to consider as many variables as possible so that the realism of the model increases.

The system dynamics model, developed in Chapter 3, is an attempt to develop a framework that will direct a manager to incorporate many life-cycle parameters to analyze any system. The model has many of the advantages of system dynamics. It considers the interaction among various parameters of the life-cycle cost of the system. In the model developed in Chapter 3, an attempt has been made to consider the impact of preventive maintenance actions on breakdowns. Additionally, most of the models dealing with maintenance do not address issues such as the effect of technological upgrades on breakdowns, the effect of the initial investment on operational costs and breakdowns and the effect of learning on breakdowns. In the model developed, provision has been made to incorporate these parameters in the system analysis.

Very few authors have employed system dynamics to decision-making regarding maintenance policies. System dynamics can be a powerful tool in analyzing the association among various factors on the life-cycle cost of the system. It adds insights and complements the existing models by considering a holistic [see Glossary] view of the system. Most of the models employ linear or nonlinear programming, some use Markov chains and a few use dynamic programming. The traditional Operations Research models suffer from the disadvantage that they do not consider feedback loops. The hard (traditional) Operations Research models incorporate many details while the system dynamics modeling can be effectively used when tactical decision-making is involved, when the aggregate system level is considered and when one is not concerned with intricate system details.

Simulation results, in Chapter 4, indicate that this model would be particularly useful when the breakdown rate of a system is not accurately known. It is also useful when the system is likely to be operational for a long time. Changes in failure rates due to deterioration with time, learning and technological upgrades or even replacement of certain parts are more likely to occur in this long-term situation. The model gives an estimate of the tradeoffs associated with preventive maintenance actions. The model is a decision-support and tradeoff tool that could be used by the managers to check the economic and operational impact of their policies, even though the breakdown rate is not accurately known. The feedback loop in the system dynamics model helps correct the preventive maintenance policy errors due to the initial lack of knowledge of the system. In the traditional Operations Research models, the preventive maintenance policy is fixed based upon the data and there is no formal provision to correct any possible errors in the estimates made initially. In case of the system dynamics model, the data made available every period is used to plan the preventive maintenance actions for the next year.

### 1.3.2 Challenges

The subjectivity involved in the modeling is the biggest challenge in the acquisition and maintenance analyses of a system. In the framework model presented in Chapter 3, an attempt has been made to incorporate as many life cycle parameters as possible in the maintenance policy analysis of a system in order to get more accurate estimates of the system life-cycle cost. There are ways suggested to quantify qualitative data but it is worth noting that such techniques are not perfect. The handling of subjectivity is the key to the success of such models. The policy parameters would be set as per the requirements of management while the operational parameters would be set based on the experience of the maintenance personnel.

## 1.4 Overview of the Research Methodology

The model developed in this research captures the impact of various factors on breakdowns like technological upgrades, preventive maintenance actions and age in computing the life-cycle cost of the system. This model helps management define a basis for deciding the maintenance policy for any system. The model involves certain parameters to describe the system under consideration. Some of the parameters are subjective and may be estimated by expert judgement or from past data for similar systems. There are some parameters that may be set based on the policies of management. All these parameters may be a function (of time or any other variable) or a constant. This model may be used for systems with long service life [see Glossary] as it requires some time to stabilize, i.e., errors introduced by the initial preventive maintenance policy require some time to correct and to balance the preventive and corrective maintenance actions. This model is useful for operational managers in setting maintenance policies and for tactical managers in determining the budget for a system and impact of different policies on the cost. The model can perform the functions of operational and tactical decision-making at the same time.

The model developed here stimulates the thinking process in terms of studying the relationships among various parameters and variables. For example, this model requires that management study and estimate the effect of technological upgrades on breakdowns. This would force them to study their previous technological upgrades to make a realistic estimate for the model parameter with respect to upgrades.

The model has been developed on the principle that the objective of any maintenance problem is to balance the cost of breakdowns and opportunity loss [see Glossary] associated with the cost of preventive maintenance. Such an objective also depends upon the mission criticality [see Glossary] of the system under consideration. For a system with a (relatively) high mission criticality factor, more preventive maintenance may be preferred to breakdowns while for systems with (relatively) lower mission criticality factors, less preventive maintenance may be acceptable to keep the operational costs within the budget. System breakdowns involve opportunity loss in the form of reduced output or risk due to non-availability of the system. The average of the cumulative opportunity loss is used to determine the preventive maintenance actions for the next period and in turn the preventive maintenance actions have their effect on the breakdowns. This is how the feedback loop has been modeled. The impact of other parameters on breakdowns, such as, technological upgrades, learning and aging, have been added. The rest of the model incorporates accounting formulas that compute the system life-cycle cost.

The model closely resembles the logic used to insure automobiles. The insurance premium depends upon the individual's driving record (past few periods) apart from his age and the type of automobile (e.g., sports utility vehicle, luxury car, economy car etc.). The insurance premium changes according to the driving record of the driver. It is increased if the record is not good at any point of time, again decreased if there are no driving violations added to the record for certain period of time and decreased with an increase in the age of a driver. The insurance premium is dynamic and is directly related to the driving record (especially the recent past periods) and other factors (such as, age).

In the model developed, we can compare the insurance premium to the preventive maintenance schedule. The mission criticality and the age of the system are similar to that of the type of the automobile and the age of the driver. As the production rate of the system increases the number of failures also would increase, assuming the mean time to failure is constant. The production (or service) rate (i.e., usage rate in case of automobile insurance) would determine the preventive maintenance actions required for the system every period. It can be seen that the preventive maintenance policy suggested by this model is similar to an insurance premium.

It may be noted that this model is more reactive than proactive. The preventive maintenance actions in any time period depend upon the cumulative breakdowns up until the previous time period. It may be noted that for the first period the maintenance policy is to be decided depending upon the manufacturer's recommendation.

Depending upon the policies and the expected performance of the system, the parameters of the model may be set and the simulation runs may be taken for a range of parameter values. This output is a set of values that are subject to user's judgement, advocated by system dynamics practitioners, or statistical tests, preferred by mathematicians. The model is programmed using VENSIM version 1.62 (a System Dynamics simulation software) and C++. The C++ program has been attached in Appendix [G].

## 1.5 Organization of the Document

The first chapter gave a brief overview of the research objectives, the problems and issues addressed in the research and motivation for the research. The second chapter contains a literature review of the research work performed in the areas of system dynamics modeling, technological forecasting, maintenance modeling, followed by a brief note on life-cycle costing and learning. The third chapter deals with the framework model developed as a part of this thesis. The fourth chapter presents with the validation, simulation and application of the model to a hypothetical system (parameter values have been assumed for simulation) and to a mechanical and electronic systems (data supplied by the organization). The fifth chapter provides the conclusions and recommendations for future research.

# Chapter 2 Literature Review

## 2.1 Introduction

This chapter is devoted to the literature review on the topics of system dynamics, maintenance modeling and technological forecasting. A brief note on learning and life-cycle costing has been added.

## 2.2 System Dynamics (SD)

System dynamics, as defined by Drew in [10], "is an approach that investigates the information feedback characteristics of dynamic systems to show how structure, policies, decisions and delays interact to influence growth and stability". It is a method of dealing with questions about the dynamic behavioral patterns of complex systems. It is a methodology developed by Prof. Jay Forrester of M.I.T. It deals with dynamic, non-linear, closed boundary systems.

System dynamics is based on feedback concepts and makes it possible to represent decision policies and information flows. Decision rules (called policies) control system activities. A *policy* describes how available information is used to generate a decision. It is the rationale that influences how decisions are reached related to organizational laws, natural processes, rules of thumb, etc.[11]. The policy determines how goals are set, what information sources are used for making decisions and the nature of the response to available information about past and present conditions of the system and to various personal and political pressures[11].

System dynamics attempts to put the system structure in mathematical form. The feedback loops are the basic building blocks of a system. System dynamics modeling requires feedback loops in the model. A *simple feedback loop* is a closed path connecting two or more variables and/or parameters. There are two types of feedback loops- positive and negative feedback loops. *Positive feedback loops* represent either continuous growth or decline whereas *negative feedback loops* deal with loops that try to approach a given goal or desired value for the level variable (explained later) by adjusting the rate of growth or decline.

System dynamics is based on the foundations of decision making, feedback system analysis and simulation [11]. System Dynamics is useful in applications where a holistic view of the system is important and feedback loops are involved [31]. System Dynamics does not necessarily concentrate on the finer details of the system. Traditional methods like statistical analysis do not consider the interrelationships among the system variables, instead require finer details. This has a potential danger of overlooking important policy aspects. System Dynamics modeling is a useful technique to test implications of policies on various systems.

The modeling procedure involves the following steps [11]:

(1) formulate a mental model in the form of a verbal description,

(2) construct of a visual diagram,

(3) form differential equations to describe the visual model.

The verbal model is the description of the system in words. The visual diagram is a causal diagram and shows cause and effect relationships among the system variables and parameters. The differential equations are the most precise representation of the system for analysis [10]. It permits the quantitative analysis and evaluation of alternative solutions to a problem. It is a laboratory tool and helps analyze the system for various management policies. The modeling procedure is sequential and iterative as long as the model is proven useful.

### 2.2.1 Causal diagram

This is an important tool for displaying the cause-and-effect interactions among key variables when developing the model of a dynamic system. The first step when developing a causal diagram is to identify the key variables that describe the problem. Causal relationships are indicated using arrows. For example,

$$\text{Breakdowns} \xrightarrow[-]{\qquad\qquad} \text{Output}$$

This indicates that an increase in the number of breakdowns results in the decrease in the output. Output has a negative association with breakdowns. The direction of the arrow indicates the direction of causation for a pair of variables. The variable at the head of the arrow is the dependent variable; the variable at the tail is the independent variable for the given pair of variables. A plus (+) sign indicates a positive association between the variables while a minus (-) sign indicates a negative association. A positive association means that an increase in the value of the independent variable leads to an increase in the value of the dependent variable. A negative association means that an increase in the value of the independent variable leads to a decrease in the value of the dependent variable. The strength of the relationship is indicated by a factor. For example, consider the relationship shown above. The strength of the negative relationship between breakdowns and output could be represented as a factor (say 20 units), i.e., every breakdown reduces the actual output by 20 units from the ideal output.

### 2.2.2 Classification of system variables

There are two basic components of the structure of a system. They are rates and levels. Levels are state variables that represent the accumulation of resources in the system. They denote the state of the system at specific points in time. *For example,* population and level of liquid in a tank are state or level variables. Rate variables represent the change of a variable per unit time. *For example,* births and deaths and fluid flow rate are rate variables. Rate variables effect changes in the level variables. A generalized level equation is given as follows in equation (2.1) [11].

$$L(t) = L(t-1) + \int_{t-1}^{t} R.dt \qquad (2.1)$$

L(t) = Value of the level variable at time 't'.

R = Value of the rate variable during the time interval (t-1, t).

The number of level variables in a feedback loop determines the order of the differential equations describing the feedback loop, i.e., if there are *n* level variables in a feedback loop then the mathematical model for that feedback loop would be an $n^{th}$ order differential equation.

Auxiliary variables are the variables used in the feedback loop that are a function of time, other than the level and rate variables. They are used to simplify the model by avoiding complex level equations. The absence of auxiliary variables may increase the complexity of the rate equation and obscure the meaning of the model. Refer Appendix [E] for an example.

### 2.2.3 Some Applications of System Dynamics

System dynamics (SD) modeling has been used in variety of areas to model complex systems. One of the advantages of using system dynamics is that it can take into consideration even certain "soft" issues like sociological, environmental, psychological factors [10,31]. System Dynamics can take into account the effect of feedback loops which regression models or operation research models like linear programming (LP), dynamic programming (DP) or critical path method (CPM) models cannot [10]. SD is useful for managing processes having two major characteristics: (a) they must change over time, and (b) they allow for feedback. SD allows management to experiment with possible scenarios. It can uncover flaws in myopic practice [28].

Professor Jay Forrester built the "industrial dynamics" model to study the short-term dynamics between inventory and the production rate. He also built "world models" using his system dynamics approach to model the problem of unchecked growth in the world. Further, he modeled the "urban crisis" (unplanned growth of the US cities) which is called "urban dynamics". He used SD to model complex social systems, mainly in the industrial context [31].

Drew, Garza, Kim [9] developed a simulation model to move toward a sustainable development decision support system (DSS) for planning, construction, maintenance and management of an infrastructure (highway system) throughout its life-cycle. They have presented the modeling of: (1) infrastructure deterioration, (2) infrastructure rehabilitation, and (3) a highway management system. Sustainable development means the economic development coupled with the protection of the environment and infrastructure development.

Ogunlana et al. [28] have applied system dynamics to a civil engineering (construction) project management application. Their model integrates four subsystems: human resources, design production, controlling and planning. It interrelates the four subsystems and gives the management some insights into the model behavior and seeks alternatives for better management strategies or policies. The effectiveness of the policies in terms of meeting scheduled time and man-days expended or cost reduction are determined. Also a comparison of the model output and actual project completion results has been made and it was found that the SD model gave a good picture of actual scenarios.

Kivijarvi and Soismaa [21] have developed a SD model to solve problems when the terminal (end of simulation period) conditions of certain level variables are known (or fixed) while the initial condition of other level variables are known (or fixed). These types of problems are called two-point boundary value (TPBV) problems. Such problems are often encountered in areas of economics and finance. To solve this, they have selected the Newton-Raphson shooting method (instead of trial-and-error method) due to its simplicity and strong convergence properties. Shooting methods in numerical analysis are formal methods that require an initial value to be input manually by the user. The deviation from the required terminal value for the given initial value is used to change the initial values toward the ones that lead to the required final states. This process is iterative and the initial input values (for the variables with known terminal conditions) required for the SD model is obtained.

Rodrigues and Bowers [31] have applied SD modeling to project management. This application has been motivated by factors such as the need for considering the whole project (a holistic approach) rather than the sum of individual elements, a need to examine major non-linear aspects typically described by feedback loops, a need for a flexible project model to experiment for different management policies and failure of traditional models to incorporate intra-project forces, that lead to overruns and overspending in practice.

SD is used in high budget, high risk application areas, e.g., software developments, aerospace, R&D etc. Three main issues addressed by many authors are monitoring and control, rework generation and staff hiring (human resource management) policies. The focus of management is usually to concentrate on resource levels and productivity as the most important for project success. But Richardson and Bowers [31] have demonstrated with experiments that the quality and error discovery rates are more important factors. They have demonstrated that SD gives a deeper understanding of the problems and hence a greater possibility that these problems will be taken more seriously by the project team. Also the hiring and firing policy of management so as to meet the target completion date can be evaluated. The authors demonstrate that merely increasing the project workforce may not increase (might even decrease) project progress rate owing to learning and the error generation effects. Thus SD can model many important, though difficult, factors explicitly.

Optimization in SD has been incorporated by many authors to substitute the traditional reliance on intuition and experience. Models like DYSMAP (Dynamic Simulation Modeling Analysis and Program), developed by Cavana and Coyle, and DYSMOD, (Dynamic Simulation Model Optimizer and Developer) developed by Keloharju[20], are examples of such work. In [20], Keloharju has developed a search decision rule (SDR), called DYSMOD, to determine heuristically the optimum values for any number of model parameters relative to predefined objective functions or performance measures. The search decision rule involved uses a "hill climbing" routine. The iterative method gives optimal or near optimal values of parameters.

### 2.2.4 Comparison of System Dynamics and Traditional approaches

Rodrigues and Bowers [31] have presented a comprehensive comparison between traditional and system dynamics approaches for project management. This comparison may be extended to other applications. This paper gives a good understanding of the underlying principles of the two approaches.

Traditional approaches to project management have many shortcomings inherent in them, which has lead to quite a few project failures. These approaches fail to cope with strategic issues. SD can handle the strategic issues. Though both the approaches are based on a "system perspective", the level of detail considered is different. The system approach comprises of identifying a cycle of planning, implementation and control. Traditional approaches are useful for detailed operational problems within the process, while SD models provide more strategic insights and the effect of different managerial policies. The two approaches are complementary and could be very useful if the advantages of both approaches were integrated. Both approaches provide estimates for project cost and duration.

Traditional approaches are based on the premise that every project, though unique, has many of its constituent elements or activities that have been experienced before. The project is decomposed into elements as well as its corresponding cost, duration and resource requirements. Traditional approaches focus on a detailed view of the project work. In evaluating possible alternatives they only assess the direct impacts on time and cost, while other important effects, such as, organizational culture are ignored. This could lead to project over-runs.

The SD approach is based on a holistic view of the project management process and focuses on the feedback processes that take place within the project system. It offers a rigorous method for the description, exploration and analysis of complex project systems comprised of organizational elements, the project work packages and the environmental influences. SD models may not show in detail the direct causes of the estimated project cost and duration, but they consider explicitly the indirect causes that result from the feedback processes that usually result in project over-runs and over-expenditure.

Factors explicitly considered by the traditional models are the logic of the work structure, the cost of resources, indirect costs, constraints on resources, resource requirements whereas SD models consider the quality of work performance, staff productivity, experience level, learning, rework generation and progress status.

Managerial decisions in traditional models include the trade-off between cost and time, changes in the schedule of activities, the scheduling of resources among activities, changes in the logic of the project work structure. The issues addressed in SD models include hiring versus delaying the project completion date, the incorporation of new technologies, changes in the schedule of project life-cycle phases and other strategic decisions.

It would be useful to adopt an integrated methodology, i.e., a combination of both traditional and system dynamics methodology, for various applications because this would give us an opportunity to combine the advantages of both techniques. Both approaches should be considered as complimentary approaches and can be used effectively for various applications.

### 2.2.5 System Dynamics Model Validation

Many analysts, including Forrester, prefer SD models to be subjective, comparing the intuitions, opinions, and judgements of experts with the policies generated by the system dynamics models. This would make the models more realistic and practical. Forrester advocates that statistical tests not be used to validate SD models. Shreckengost [36] has quoted Johnson 1980, Mass and Senge 1978 to substantiate his argument that statistical tests (e.g., t-tests) can only be of little help or may even be misleading. But many analysts use the statistical tests as they feel that these tests give objective information.

Shreckengost [36] has described some tests to validate the SD models. There are mainly two types of tests:

1. Model structure tests: These tests check the validity of the structure of the model compared to the real system being modeled. They depend upon experience, intuition, and judgement as opposed to data. There are three model structure tests:

   (a) *Model parameter test:* The model parameters are tested against historical data.

   (b) *Boundary adequacy test:* This is a subjective test and depends upon the purpose of the model. As the purpose changes, the model's boundaries shift.

   (c) *Extreme conditions test:* The ability of the model to function properly under extreme conditions contributes to its utility as a policy evaluation tool and also boosts user confidence. These tests may expose structural faults or inadequacies and incomplete or erroneous parameter values.

2. Model behavior tests: These tests are less technical and more appealing to the user.

   (a) *Behavior replication test:* Model behavior is compared to system behavior. When quantitative data is not available, the test may be one of reasonableness.

   (b) *Anomalous behavior test:* This test is particularly useful when a model behaves well except for a particular period. In such cases, the model structure or parameter values may not be incorrect but the error may lie in the data. This test helps in resolving discrepancies and bolsters validity.

(c) *Behavior sensitivity test:* Small, reasonable changes in the model parameters should not produce unreasonable, radical changes in model behavior, unless expected.

(d) *Behavior prediction test:* Confidence in the model is reinforced if the model not only replicates long-term historical behavior but also responds similarly to existing systems in which various policies have been implemented.

(e) *Family member test:* When SD models are generic (applicable to family of similar situations), it may be validated for similar systems.

(f) *Behavioral boundary test:* By the previous tests, the boundary conditions may be modified. This test helps check if the model includes the necessary modifications.

3. <u>Other tests</u>:

(a) *Policy implication test:* This includes system improvement, changed behavior prediction, boundary adequacy, and policy sensitivity tests. These deal with whether the real system's response to a policy change would replicate the response to that policy change as predicted by a model, i.e., whether perturbations given to parameters bring about output changes that are expected out of the system.

(b) *Dimensional consistency:* Errors in dimensional consistency [see Glossary] might be introduced due to adjustments during other tests.

(c) *Surprise behavior test:* There are certain unknown facts revealed by the model about the system. Such discoveries help reinforce confidence in the model.

Some of these tests would be used to validate the model developed. These tests will be adapted for the maintenance model in the next chapter.

### 2.3 Maintenance Policies

In the previous section, there was a discussion of the literature published in the area of system dynamics. System dynamics can be used to determine effective maintenance policies since it allows one to address the effect of different issues, such as, learning, technological upgrades and age, on the system operations. Before employing this technique, a literature review of the various maintenance models that have been developed is presented in this section.

Maintenance involves planned and unplanned actions carried out to retain a system in or restore it to an acceptable condition. Optimal maintenance policies aim to minimize downtime and the cost of operations. Many practitioners and academicians have tried to address the problem of maintenance policies.

The two basic types of maintenance are:

(1) <u>Corrective:</u> Unscheduled maintenance required as a result of failure to restore a system to acceptable performance level.

(2) <u>Preventive:</u> Scheduled maintenance required in order to operate a system at an acceptable level of performance.

For complex systems comprised of many different components, the actual maintenance problem may be the organization of preventive maintenance work that depends on the critical ages of components, rather than searching for some optimal solution in terms of some precise criterion. This would help reduce the complexity of the problem and help develop heuristics. Often sufficient data may not be available for complex models; if they are available then the maintenance policies may not be pragmatic. It is very difficult in practice to develop maintenance models where suitable data is available and adopted policies are realistic [32].

The literature related to optimal maintenance models is classified as follows [34]:

(i) Deterministic models

(ii) Stochastic models

- (a) under risk
- (b) under uncertainty

The model developed in this thesis may be classified as a stochastic model since the breakdowns are assumed to be random in nature. The different approaches for determining effective maintenance policies are presented subsequently.

### 2.3.1 The Subjective Approach

This approach is useful in situations where objective data is not available or difficult to obtain. The validity of such approaches is always debatable as it is based on expert opinion, which may be influenced by current maintenance practice rather than being based on the understanding of the actual maintenance process. Various models have been proposed that incorporate expert judgement to determine maintenance policies. Scarf [32] has developed a model that uses subjective data but works like a quantitative model. The model developed in this thesis also employs a similar technique. An integrated approach to maintenance modeling involves the following steps:

1. problem recognition
2. design of data collection
3. design of systems for future data collection

4. effective (mathematical) modeling using data collected
5. comparison with competitive techniques
6. formulation of revised maintenance policy
7. imparting ownership of models and policy on maintenance managers
8. economic considerations of new policy

The author advocates that through such a comprehensive approach mathematical modeling can be considered successful from a scientific (i.e., modeling) point of view.

### 2.3.2 Condition Based Maintenance

Recently, condition monitoring techniques are being adopted by many practitioners [32]. The competitive market conditions have forced plant management to reduce downtime for routine preventive maintenance. In such cases, the maintenance department inspects the condition of all parts that are due for replacement. If the condition-related variable is below a preset (critical) value (which is determined by subjective opinion), then the component is replaced, else it is allowed to operate. Thus a routine preventive maintenance shut down can be avoided. This also has a psychological effect on the workers working in the plant, who would, otherwise, feel uncertain about the state of the plant.

But this technique requires a database of all the components replaced on all the machines and their preset value. Also a systematic plan must be developed to check and recheck regularly if the state of any of the component has crossed its preset value (beyond safe usage conditions). This would increase the maintenance cost. The fundamental question for condition monitoring of a particular component should be whether this approach will reduce costs in the long run by giving a policy very close to the true optimal. Since condition-based maintenance helps use all the components for a longer period than fixed maintenance policy, lesser replacements would be required reducing the long-term maintenance costs.

### 2.3.3 System Dynamics Model for Maintenance Schedules

Coyle and Gardiner [8] have proposed a discrete (integer) system dynamics model of maintenance schedules for submarine operations. System dynamics models are usually continuous models but the authors have developed a discrete model since the ships are discrete objects. The model addresses the issues of fleet availability and usage during the service life of a submarine. The model computes the number of submarines to be commissioned so that the minimum number of submarines is in service. The feedback system used for the model captures how well a force of a given size is likely to meet its operational needs and what policies might guide decision makers to cope with difficulties as and when they arise. The model considers three types of decisions: short term, medium term, long term decisions. The discrepancy between the operational needs (goal) and actual availability is used to drive the decisions of the model.

The short-term decisions deal with the number of submarines in operations, the medium-term decisions deal with the maintenance program while the long-term decisions deal with the construction of submarines.

This thesis considers the cumulative opportunity loss per unit time as discrepancy (deviation from the goal) and this variable is used to drive the model, i.e., to determine maintenance policy. The main objective is to minimize life-cycle cost, subject to mission readiness. The main objective may also be to minimize opportunity loss.

The integer and random characteristics of this model have been incorporated in the model developed in chapter 3.

### 2.3.4 General Failure Model and Maintenance Policies

Beichelt [1] has presented a general model for a system. Any system has two types of failures: Type 1 that can be removed by minimal repairs and type 2 that can be removed by replacements. Beichelt [1] has considered both failure types. Minimal repairs do not alter the failure rate (memoryless), but put the system back in operation. In case of replacements, the failure rate is altered. It may be noted that the model in Chapter 3 also treats preventive maintenance and breakdown maintenance or repairs in a similar manner.

Beichelt's model has been solved for various policies mentioned below.

1. The system is maintained according to the failure type. In this policy, the cycle length (i.e. the time between successive replacements) is random and the expected number of failures of type 1 is computed. This is the simplest of all policies.
2. The system is replaced at system age 't'.
3. The system is replaced after n-1 minimal repairs, i.e., at the $n^{th}$ failure.
4. On failure the system is replaced if the random repair cost exceeds a given repair cost limit.
5. In policy 4, in addition, there is a preventive replacement made at system age 't'.

### 2.3.5 Gamma Approximation for Preventive Maintenance Scheduling

Park [29] has developed a gamma approximation model to determine minimum cost preventive maintenance schedules where accurate failure data are not available except the mean and the mode of component lifetimes. This model is particularly useful since it is usually difficult to get useful data on maintenance, *i.e.*, data on the lifetimes of components, probability distribution of lifetimes etc. The model in Chapter 3 also is useful when accurate data on the breakdown rate is not available.

From historical accounting data, we can calculate the average cost of scheduled preventive maintenance, $c_p$, and the average cost of breakdowns, $c_f$, (including costs of downtime and possible lost sales, idle direct and indirect labor, delays in dependent processes, increased scrap and cost of repairs).

When accurate data is not available, a Gamma distribution is considered to be useful since it only requires estimates of average and most likely (or mode) lifetimes of a component to describe the specific failure distribution. Also in case of the gamma distribution, it captures increasing failure rates, which has been observed to be the case with most components. The gamma function may be represented as:

$$f(t) = z/\Gamma(\alpha).\ (zt)^{\alpha-1}\ e^{-zt} \tag{2.2}$$

where $t$ = age of unit $\geq 0$

$z$ = scale parameter = 1/ (mean - mode)

$\alpha$ = shape parameter = $z$ * mean $\geq 1$

This model has no economic value if mean/ mode $\geq c_f/c_p$ [29], where the average cost of scheduled preventive maintenance is denoted by $c_p$ and the average cost of breakdowns (including costs of downtime and possible lost sales, idle direct and indirect labor, delays in dependent processes, increased scrap and cost of repairs) is denoted by $c_f$.

The expected cost of maintenance per unit time (with preventive maintenance at age T),

$c_T$ = Expected cost per maintenance/ expected inter-maintenance time (2.3)

= Expected cost per maintenance * expected maintenance frequency (2.4)

This model has been shown to be robust against underlying lifetime distributions, i.e., with other distributions like the Weibull, and with respect to errors in estimating the mean and modal values of lifetimes.

Ntuen [27] has also used a truncated gamma failure distribution. The hypothesis of his model is that an optimal maintenance policy should balance the cost of failure of a system during operation against the cost of planned maintenance. This hypothesis also forms the basis of the modeling approach in this thesis.

### 2.3.6 Simulation and Economic Analysis to Determine Corrective Maintenance Policy

Sheu and Krajewski [35] have developed a decision making approach for corrective maintenance management. It consists of a simulation and is complemented by economic analysis. The simulation model predicts the inventory costs and effectiveness of a corrective maintenance policy. The simulation results feed into an economic analysis, comprising a net present worth (NPW) and breakeven analysis model, that determines the economic worth of various maintenance policies. The authors have presented an example to evaluate the options of machine redundancy and worker flexibility. Machine redundancy refers to the use of standby machine or extra capacity in some other machine while worker flexibility refers to the number of operations each worker can perform. The benefits of worker flexibility include the use cross trained workers that release the load at bottlenecks during machine breakdowns. The two forms of redundancy mentioned above need not be mutually exclusive, i.e., a combination of the two may be preferred.

To analyze the economic worth of maintenance policies, the model requires information on:

a. the manufacturing performance of alternative maintenance policies regarding customer service (backlogs) and inventory cost that can be provided by a simulation model.
b. the costs of implementing each maintenance policy, e.g., the cost of cross training workers and the capital cost of machine redundancy.

This information is then used to perform NPW calculations and breakeven analyses for the various maintenance options. In the given example, the author has carried out breakeven analyses to determine the effect of certain variables like the cost of capital and training costs. The model provides useful information for a manager in determining an effective maintenance schedule. The comparison of various maintenance policies is analogous to that of comparing project alternatives. According to the authors, the above model can be extended to preventive maintenance policy making.

The research methodology of this thesis uses life-cycle cost along with opportunity loss as the metrics that determine optimum maintenance policy for a system. This model uses NPW and breakeven analysis for the same purpose. In the future, it may be worth using other metrics like a cost-benefit ratio to determine optimal preventive maintenance policies.

### 2.3.7 Other Models

Various other models have been developed using techniques like linear programming, non-linear programming, dynamic programming, mixed integer programming, decision theory, search techniques and heuristic approaches [34]. The following models are briefly described in this section to give the reader information about other techniques used for maintenance modeling.

Hariga [17] has developed a general model to determine a periodic inspection schedule as part of a preventive maintenance policy for a single machine subject to random failure. The problem has been formulated as a profit maximization model with a general failure time distribution. A heuristic approach has been developed to obtain an approximate inspection schedule, when the failure times are exponentially distributed.

Menipaz [24] introduced the concept of a discounting factor to bring all future cash expenses to time, t = 0. The objective function considered is the expected cost per cycle when some or all cost components are variables and a discount rate is assumed. The objective function is solved using a differentiation method and a dynamic programming approach.

Zuckerman [39] developed a stochastic model to determine the optimal maintenance schedule under the following criteria: long run average cost and total expected discounted cost over an infinite horizon. The system is subject to shocks causing a random amount of damage to the system components. The research methodology uses the average opportunity loss as a driver to determine the maintenance policy.

Inozu and Karabakal [19] have formulated a model that is marine industry specific. According to the authors, the maintenance schedule in the marine industry is very complicated owing to conflicting objectives. Here a new approach to perform group (multi-item) replacement has been proposed under budget constraints (capital rationing). It considers all replacement decisions of an entire ship fleet (or all component replacements for a single ship) simultaneously. The problem has been formulated as an integer linear program. A Lagrangian methodology for the replacement problem is also presented. This has been introduced to find the dual of one of the constraints, namely, the capital rationing constraints, and incorporate it into the objective function in order to solve the integer program easily.

Sim and Endrenyi [37] have developed a minimal preventive maintenance model for repairable, continuously- operating devices whose conditions deteriorate with time in service. This model is useful for devices like coal pulverizers, circuit breakers, and transformers. The preventive maintenance times are assumed to have an Erlang distribution while the failures are Poisson distributed. Deterioration failures have been considered in the model. The objective function used by the model is to minimize the unavailability of the system.

Sherif [33] has developed an optimal maintenance model for life-cycle costing analysis that determines a schedule that minimizes the system's future total expected maintenance cost. This may be added to other costs like acquisition, salvage, operation costs to obtain the life-cycle cost. The equations for optimal maintenance schedule and minimum expected future cost of the system, developed in the model, are solved recursively using dynamic programming principles.

### 2.3.8 Distribution for Maintenance Task Times

The normal distribution applies to relatively straightforward maintenance tasks and repair actions. The log-normal distribution applies to more sophisticated tasks where times and frequencies vary. Exponential and Poisson distributions apply to electronic components with sudden failures [18].

### 2.3.9 Maintenance Metrics

Availability is the fraction of time a plant facility is capable of being used for production during the period it is needed [18].

In the model in Chapter 3, "availability" could be used instead of "opportunity loss". Depending upon the data available in terms of the details, such as, repair times, logistics delay time and administrative delay time, any of the following metric could be used.

#### 2.3.9.1 Inherent Availability ($A_i$)

It is the ratio of mean time between failures (MTBF) and the sum of MTBF and mean time to repair (MTTR).

$$A_i = MBTF / (MBTF + MTTR) \qquad (2.5)$$

This metric assumes an ideal support environment. It does not include preventive maintenance, logistics or administrative delay time. This metric indicates "as designed" or "ideal" availability.

#### 2.3.9.2 Achieved Availability ($A_a$)

This metric also assumes an ideal support environment but includes preventive maintenance.

$$A_a = MTBM/ (MTBM + M) \qquad (2.6)$$

where, MBTM = mean time between maintenance

M = mean maintenance time

#### 2.3.9.3 Operational Availability ($A_o$)

It considers actual operational environment and includes all maintenance actions, the administrative and logistics delay. It is a useful operational assessment metric.

$$A_o = MTBM/ (MBTM + M + ADT + LDT) \qquad (2.7)$$

where, ADT and LDT are administrative and logistics delay times respectively.

## 2.4 Technological Forecasting

When a large, complex system is being conceptualized, it is necessary to forecast the technology that would be available during its entire life cycle. A change in technology may invalidate a particular decision with respect to allocating resources.

Technological forecasting may be useful in giving direction to research and exploratory development efforts. It must be used in a controlled fashion as one of the inputs, together with others. A technological forecast attempts to predict the direction of technological growth and should not be considered as absolute. A forecast is considered to be good if it gives a fair picture of the future trend, but accurate future values should not be expected from a model.

In the model developed in Chapter 3, technological forecasting has been considered as an important input to the system dynamics model. Any technological forecasting model described in this chapter would be suitable for use in the system dynamics model. Apart from forecasting technology, the cost of technology also needs to be predicted for the model developed in Chapter 3.

Technological forecasting can be defined as a prediction of the future characteristics of machines, procedures, or techniques. A technological forecast deals with characteristics, such as levels of performance (e.g., speed, power etc.) and does not indicate how these characteristics are achieved. Technological forecasting deals with machines, procedures, or techniques and excludes those items intended for luxury or amusement, that depend more on popular tastes than on technological capability. Technological forecasting has been considered in the model developed in chapter 3 since it effects the operations of a system. This would enhance the accuracy of the model.

Technological forecasting has four elements: the technology being forecast, the time frame of the forecast, a statement of the characteristics of the technology in terms of functional capability which is a quantitative measure of the ability of the system to perform the function, and the probability associated with attaining a given level of functional capability by a certain time or a distribution of the levels that might be achieved by a specific time period.

Technological forecasting can be exploratory or normative. An “exploratory” forecast starts with past and present conditions and projects these to estimate future conditions, while a "normative" forecast starts with future needs and identifies the technological performance necessary to meet these required needs. Exploratory looks ahead and identifies likely technological progress from the present [5]. Normative technological forecasting is needs oriented. It is based in societal requirements of the technology in the future. Its foundation is based on systems analysis (see Glossary).

There are different methods of exploratory forecasting, i.e., extrapolation, leading indicators, causal models, probabilistic models and combination (of the above) methods [23]. It should be noted that forecasting is not a precise science in its present state. In [5] the author has advocated that one should use exploratory forecasting for certain functional parameters and then cross check the results using normative forecasting for other functional parameters.

Technological upgrades are changes in the system technology made whenever there is a change in technology. Technological upgrades are sought whenever certain technology leads to a failure rate that is greater than the maximum tolerable rate. In the chapter 3, technological upgrades are assumed to affect the performance (in terms of breakdowns) of the system by a certain multiplier.

Any of the following methods can be used as an input to the system dynamics model developed in Chapter 3. The choice of any particular method would depend upon the availability of data and the system under consideration.

### 2.4.1 The Delphi Approach

There are three conditions under which subjective opinion can be useful as opposed to formal forecasting methods. They are: the non-availability of historical data, the impact of external factors that are different than the factors that governed the previous development of the technology and ethical and social factors that dominate the economic and technical considerations related to the development of the technology [23]. The Delphi process, originally developed by the Rand Corporation, consists of extracting the opinions from a group of experts, making a consolidated list of opinions, circulating the consolidated opinion among all the group members to get a revised opinion list and continue the iteration with controlled feedback. Controlled feedback helps avoid repetitive questioning on issues where consensus already exists or it helps delete controversial comments. The group is then analyzed statistically, using regression methods, graphs and other techniques to obtain the mean and deviation of opinions [23].

### 2.4.2 Forecasting with Analogy

In forecasting with analogy, a historical model situation is compared with another situation in order to determine whether the two are "analogous". The following factors may be used as the basis for technological forecasting [23]: technological, economic, managerial, political, social, cultural, intellectual, religious-ethical and ecological factors.

The issue associated with this method is to identify a similar technology that can be used as the basis for forecasting. Analogous technologies should be selected from a wide range of candidates. An imaginative and exhaustive search will enable the analyst to find good analogous technologies, which at first sight may seem to be irrelevant [23].

Often, historical situations can be a good starting point for forecasts. A combination of historical situations and expert opinion can form a meaningful and useful forecast. The use of analogies is the basis of inductive inference. For example, forecasts of solar energy technology (heliostats) could be prepared by using similar parts used in the manufacture of automobiles. Also radio telescope, aircraft windshields, personal calculators were found to have parts that were analogous to that of heliostats. This method has several pitfalls. The assumption made by this method is that "history repeats itself". However, historical situations may not repeat themselves in the same manner in future.

### 2.4.3 Growth Curves

Many experts feel that the growth of technology is comparable to the growth of living organisms. The growth curves or S-shaped curves have been used to indicate a pattern of technological change.

The growth curves most frequently used by forecasters are the Gompertz and Pearl curves. Both of these curves empirical curves can be applied to various technologies by changing their parameters. These curves have been developed by considering the trajectories of various technologies [4,23].

The Pearl (or logistic) curve equation is $y = L/(1 + a*e^{-bt})$. (2.8)

The Gompertz curve equation is $y = L*e^{-bd}$ (2.9)

where $d = e^{-kt}$

where L is the upper limit of the growth of the variable 'y' (which represents a technical parameter) determined by certain physical, economic or social limit that may be known or can be defined by expert judgement. This limit may be based on historical data on analogous technologies. a, b, k are coefficients obtained by fitting the curve to the data (using the least squares method).

The "goodness of fit" (least square estimates) should not be used to extrapolate the forecast as it may not represent the future appropriately. Instead, the underlying dynamics must be considered that produced the past data and will affect the future. Both curves differ in the underlying dynamics. The Pearl curve is recommended to forecast technologies that depend not only upon their present state but also their progress to the upper limit. The Pearl curve was mainly developed to describe the growth of an albino rat, a tadpole's tail, the number of yeast cells in a nutritive solution, number of fruit flies in a bottle, and the population growth in a geographical area.

The Gompertz curve is useful when the technology in consideration will depend only on the path remaining from the present state to the upper limit. The selection of the appropriate curve requires the study of the factors that affect the growth of the technology. Eschenbach [12] prefers the Gompertz curve to the Pearl curve since the

Pearl curve assumes symmetry about the inflection point whereas Gompertz curve doesn't.

Fisher-Pry [14] have defined another growth curve that is a variation of the Pearl curve. This curve is useful when the technological growth is proportional to both the fraction of the market penetrated, the fraction remaining and the diffusion of the technology. The diffusion is given by the number of users for which the technology is applied and the number to which it is yet to be applied [4].

Many of these trend models are of a specific form of the more general equation developed by Lotka-Volterra [4]. The equations that represent the interaction between two technologies (x and y) are given by:

$$dx/dt = x(a_1 - b_1x - c_1y) \tag{2.10}$$

$$dy/dt = y(a_2 - b_2x - c_2y) \tag{2.11}$$

where $a_1$, $a_2$, $b_1$, $b_2$, $c_1$, $c_2$ are parameters that describe the technologies.

This model assumes that technology develops within a larger market system in which technologies compete. This model was developed to explain the competitive-resource chain such as the population changes of sharks and the fish upon which they feed. This model is based on the assumption that the existence of technologies in the market can be compared to the existence of sharks and fish in a sea.

### 2.4.4 Trend Extrapolation

In this methodology, the future progress is predicted beyond the upper limit, determined by certain physical, economic or other factors believed to constrain growth that may be subjective in nature. Also in the absence of any upper limit, the trend may be a useful tool for forecasting. The most common long term trend is that of exponential growth.

Empirically many technologies grow exponentially. Martino has demonstrated, as an example, the exponential growth of electric power production in the US over a period of 40 years in [23].

### 2.4.5 Correlation Methods

In some cases, direct forecasting may not be a good means for making a decision. Some functional parameter may be highly correlated with some other factor that can be measured directly or can be forecasted easily. For example, a reduction in the weight of an airplane may result in an increase in the speed of the airplane. Some of these correlation methods are described below.

#### 2.4.5.1 Lag Lead Correlation

Some technologies have a tendency to follow other technologies. For example, the technology in commercial jets lags that of fighter jets by a certain time period. Another example is that of the replacement of metal components in airplanes by composites (plastics). The forecaster has estimated a 10-year lag between the first demonstration in an experimental aircraft and application in an operational aircraft [23]. There are many more areas where the lead-lag correlation holds true.

In using the concept of the transfer of technology from a leader to a follower technology, it is imperative to consider the different levels of functional capability in order to determine the lag. There may be many pairs of technology transfers involved with varying correlation. Therefore, this method may give ambiguous results in the form of multiple forecasts. Validation is done with the help of growth curves or any other method.

### 2.4.5.2 Technological Progress Function

The dependence of a technical value upon production quantities is defined as the "technological progress function". This function is similar to the industrial learning and the psychological learning curves [16]. The need for progress function arises since the commonly used technological forecasting techniques do not handle the environmental factors easily. Industrial progress relationships are functions, such as production costs per unit, maintenance costs per unit, and manufacturing costs per unit, that can be written as a function of the costs associated with unit number one, the cumulative unit number and a learning constant. They are termed "technological progress functions" because a reduction in costs indicates a gain in efficiency. The development of the technological progress function, $T_i$, which is the value of the function for the $i^{th}$ unit, characteristic of technological improvement, evolved from a consideration of:

(1) problems and background factors (dynamics) inherent in industrial progress relationships,

(2) indications from psychology that general phenomena of learning are present, and

(3) difficulties in existing techniques of forecasting.

The general equation given is:

$$T_i = a*i^b \tag{2.12}$$

where $T_i$ = value of the parameter at the $i^{th}$ unit

$i$ = cumulative production quantity

$a$ = a constant associated with unit number one

$b$ = the rate of progress which is dependent on the external environment

When plotted on a log-log paper, this equation gives a straight line with a slope equal to the rate of progress (b). The changes in the rate of progress (i.e., the slope) are not random but are a function of critical parameters forming part of the external environment like personnel motivation, changes in the demand for the product and other such issues. One of the problems associated with this equation is defining the values for the constant, which is subjective. Some basic mathematics on technological progress:

$$T_i = a * i^b \qquad (2.13)$$

$$\log T_i = b* \log i + \log a \qquad (2.14)$$

$$dT_i/ T_i = b* di/i \qquad (2.15)$$

Equation (2.15) indicates that percentage change in a technical parameter is a linear function of the percentage in cumulative production considering the constant 'b'.
Also if cumulative production quantity can be expressed in the form mentioned below:

$$i = constant* \exp(Kt) \qquad (2.16)$$

$$\log i = Kt + \log (constant) \qquad (2.17)$$

$$di/i = k\ dt \qquad (2.18)$$

Equation (2.18) indicates a linear change in production as a linear function of time, referred to as the "substitution effect".

$$dT_i/T_i = b\ k\ dt \qquad (2.19)$$

Equation (2.19) is the traditional trend-forecasting relationship.

### 2.4.6 Causal Methods

One of the shortcomings of the techniques mentioned above is that they do not consider the causal factors involved in technological growth. The assumption made is that the factors that affected the technological growth would continue in the future. Martino [23] has discussed three types of causal models. The first attempts to forecast technological change on the basis of internal system factors that produce technological change (technology-only models). The second attempts to forecast technological change on the basis of economic factors. The third type includes some social and economic factors by which the technology is being developed. These models are hypothetical models attempting to describe the transfer of knowledge in a mathematical form. They have certain terms that cannot be quantified easily.

Causal models are of two categories:

(a) closed-form analytical models that express the cause-effect relations in an equation form or as a set of equations,

(b) simulation models, that may be expressed as a set of differential equations but cannot be solved (or difficult to solve) analytically due to random variable(s).

*Technology-only* models assume the technology to be "autonomous" or "out-of-control", that is the effect of external factors are reflected in factors internal to the technology-producing system. The two growth curves known are:

(i) The growth of scientific knowledge: This model explains that the growth of scientific knowledge or information on the basis of factors within the science and technology. It explains that the rate of increase of scientific knowledge is a function of information already known, the maximum that can be known in that field, the number of people working in the field, and the interaction between the researchers. The equation is:

$$I_t = L - (L-I_0) \exp(-KmfN^2t/2L) \quad (2.20)$$

where $I_t$ = information available at time 't'

$I_0$ = information available at time '0'

L = Maximum amount of information possible

N = number of researchers involved

K = constant of proportionality

m = average relative productivity resulting from a transfer of knowledge as compared to a researcher working alone, that is, the average increase in knowledge of a researcher during interaction with another researcher in the same area.

f = fraction of the possible information-transferring transactions per unit time that actually take place.

There are certain terms used in this model that are very subjective in nature.

(ii) A universal growth curve: This model attempts to explain growth toward an upper limit on the basis of effort made by researchers. The equation obtained is

$$P(f,t) = 1 - \exp - [-\ln(2)\ (c_1 t + c_2)/\ (\ln(Y-1) + Y + c_2)] \qquad (2.21)$$

$$Y = (F-f_c)/(F-f) \qquad (2.22)$$

where P(f,t) = probability of achieving level 'f' by time 't'.

F = upper limit of 'f'.

$f_c$ = functional capability of the competitive technology.

$c_1,c_2$ = constants

*Techno-economic models* have been developed to forecast the substitution among firms that adopted the new technology. The hypothesis is that the more profitable an innovation, the more rapidly it would be adopted. On the other hand, the more costly it is to adopt the innovation, the more slowly it would be adopted. The measure of profitability through a specific innovation is regressed on the measure of cost of adopting the innovation and the number of firms that adopted the innovation. Ayres (1985) developed a model for the market share captured by an innovation. The growth rate for market penetration is given by [23]:

$$kF = q\ (r-x) \qquad (2.23)$$

The price trajectory is given by:

$$P= P_0.\exp -((r-x).f) \qquad (2.24)$$

where k = rate coefficient of the Pearl curve

F = upper limit of the Pearl curve

f = fractional market penetration for the innovation

q = price elasticity of demand for the innovation

r = minimum expected rate of return

x = adopter's time discount rate (approximated to the interest rate of bonds in the adopting industry).

*Economic and social models* include economic, technological and environmental factors.

### 2.4.7 Probabilistic Methods

The previous techniques generated point estimates of future states and they were all deterministic in nature. Uncertainty comes from various sources, e.g., the timing of research breakthroughs, speed and nature of a competitor's response to a new product, cost of manufacture etc. Some uncertainty could be reduced by gathering more data, some can be controlled by careful implementation, and some must be allowed for in decision making [12]. A probabilistic forecast gives a range of values and a probability distribution over that range. One type of probabilistic forecast might give a range of possible future values and the probability distribution over that range. Another possible type of probabilistic forecast might be based on the probability distribution of input factors to a Monte Carlo simulation. Eschenbach has used probability metric to analyze the effects and relative importance of individual variables. The use of probability as a common metric allows the effects of different variables to be presented on the same graph, and facilitates comparisons among them. By using explicit probability density functions for each variable, stochastic sensitivity analysis minimizes the misleading results obtained from the deterministic sensitivity analysis that assumes a uniform distribution.

### 2.4.8 Combining Forecasts

It is possible to improve a forecast by combining several techniques. This alleviates the problem of selecting the best technique for a particular application. The techniques being combined may complement each other and yield a better forecast. Martino [23] has illustrated a few examples to demonstrate the effectiveness of combining forecasts such as trend and growth curves and trend and analogy curves.

The trend and growth curves have been combined, for example, to illustrate the fastest aircraft speed records as a succession of growth curves involving previous technologies (e.g., wood and fabric structure, all metal structure, subsonic jets, supersonic jets) used in the constructing a airplane. The prediction of aircraft speed is complemented with an exponential curve trend [23]. To forecast the technology in which successive trends produce long-term trends, it is necessary to project both the overall trend and the relevant growth curves.

The trend and analogy curves have been combined to illustrate the growth in efficiency of coal-burning electric plants and also the use of inanimate nonautomotive horsepower (like prime movers, factory machinery). The use of this technique is to forecast the magnitude and timing of the deviation from a trend that would have been caused by some external event.

Cross- Impact models are useful when a large number of related forecasts are to be combined. These models take into account the dependence of some forecasts on other forecasts. They consist of a set of events, each assigned a time and a probability. They are a collection or a network of interconnected events. If there are 'N' events in a cross impact model then the number of cross-impacts may be as much as N(N-1). For example, if event E2 is subject to the occurrence of a previous event E1 then E1 has cross-impact on E2. The outcome for E2 would be based on the forecast of outcome of E1. Now, if the actual outcome of E1 works out to be different from that of the forecast then the forecast for outcome of E2 would have to updated for timing or probability or both. The critical issue is that the starting point of a cross-impact model is a decision that needs to be made. Martino [23] has used a program MAXIM to carry out a cross-impact analysis to forecast space exploration. Sullivan [38] has used cross-impact analysis to study the impact of using solar technology for cooling and heating of buildings in the US. The Delphi method has been used to quantify the impact of various events on one another. The impact of the change in technology on various events has been measured in terms of the change in probabilities of occurrence before and after the change.

### 2.4.9 Normative Forecasting

"Normative" forecasting starts with future needs and identifies the technological performance necessary to meet these required needs. It is based on the societal requirements of the technology in future. Its foundation is based on systems analysis. Systems analysis involves a systematic breakdown of associated activities, events and issues in a technology. Normative forecasting is widely used by the Japanese companies. In some instances, the normative approach can be viewed as a "planning" tool. Normative forecasting techniques are [4]:

(1) Decision matrices

(a) Horizontal

(b) Vertical

(2) Relevance Trees

(3) Morphological analysis

(4) Network techniques (like CPM, PERT)

(5) Mission Flow diagrams

(6) Other emerging techniques like game theory and complexity theory.

### 2.4.10 Adaptive Forecasting

Kang et al [22] propose a new model as a framework for forecasting demand and technological substitution, that can accommodate different patterns of technological change. This model is called the "Adaptive Diffusion Model" and is formalized from a conceptual framework. It incorporates several underlying factors that determine the market demand for technological products. This model has been developed to overcome the limitations of the existing mathematical and 'S' shaped models that generally do not consider the decreasing phase of the aggregate diffusion rate along the product life cycle (PLC). Every product is considered to have four phases in its life cycle. The decreasing phase of a PLC is the "death" or "decline" phase of a product after which the product becomes obsolete. This also explains the dynamics of major factors determining market demand. The static formulation of demand has been shown to be:

$$Q_i = r_i + b_i/p_i\ (Y - E\ p_i.r_i) \qquad (2.25)$$

where $Q_i$ = demanded quantity for product 'i'

$r_i$ = minimum necessary quantity of product 'i'

$b_i$ = marginal budget share (propensity to consume) for product 'i'

$p_i$ = market price for product 'i'

Y = consumer's income (or funds available)

The dynamic model developed is as follows:

Purchased quantity at time 't', $Q_t = f(r_t, Y_t, P_t, S_t, T_t)$

$Q_t = r_t + b_1Y_t + b_2P_t + b_3S_t + b_4T_t$ (2.26)

$Q_t = Q_{t-1} + r_t + b_1 Y_t + b_2 P_t + b_3 S_t + b_4 T_t$ (2.27)

where $S_t$ = stock level at time 't'

$T_t$ = tastes or preferences at time 't'

This is the level equation for $Q_t$. Similarly, the level equation for stock level has been developed.

$S_t = S_{t-1} + Q_t - d\, EQ_j$, where $1 \leq j \leq n$ (2.28)

where d = mean value of depreciation over time in existing stocks for the same product.

n = the number of years.

The aggregate diffusion rate equation of current stock relative to potential purchases in the continuous form has been derived. The authors claim that their model can provide a framework that is sufficiently robust in forecasting demand and innovation diffusion for various technological products.

Technological forecasting is not a precise science. For any system, various models are to be considered and the one that explains the trend most appropriately needs to be selected. There are plenty of factors that affect technological growth. In general, the most widely curves used by forecasters are the Pearl and Gompertz curves.

As mentioned earlier, any of the above mentioned methods may be used in the research methodology of Chapter 3 as an input to the technological upgrade variable depending upon the technology being considered. The approach used however, for simplicity, is a pulse input of $x every ‘y’ years.

## 2.5 Life Cycle Cost (LCC)

The life-cycle cost (also referred to as "ownership cost") may be defined as the total cost of a system or product to be incurred over its anticipated useful life in research and development, construction, production, operation, maintenance and support, retirement and disposal. It is total cost of ownership of a system. This is not a new concept, but it is an updated version of the capitalized cost analysis that uses NPW to evaluate a system [27]. LCC problems are quite complicated and hence can be considered as a computational technique for studying design and operational alternatives [27]. In general, LCC is the sum of acquisition cost (which is the sum of purchase, R&D, commissioning costs), the present worth of annual maintenance cost over the intended period of service, the disposal cost and all other costs expected to be incurred discounted to the present time.

The life cycle cost is considered during the analysis of alternatives (AoA) since decisions made early in the system life cycle have significant cost impact downstream, i.e., in the future. There's a need to extend planning and decision-making to address system requirements from a total life-cycle perspective. The use of the LCC can influence system design and assist in producing low cost systems. For existing systems, it can form the basis of a continuous improvement process. In both the cases, the LCC creates awareness among the designers to produce an effective system with not only a low acquisition cost but also low operation, support and disposal costs. LCC models vary in scope and form. There is no standard LCC model. Most of the models developed are case-specific rather than universal [33].

From a management standpoint, LCC is an integral part of the ultimate goal- to achieve desired system performance (and readiness) at an affordable cost. The desired level may be a subjective or objective. In the model developed in the next chapter, the life-cycle cost is calculated to determine the effectiveness of various maintenance policies.

### 2.5.1 Basic Steps in LCC Analysis

The basic steps involved in a life-cycle cost analysis are [2]:

1. Describe the system configuration being evaluated in functional terms and identify the appropriate technical performance measures or applicable "metrics" for the system.
2. Describe the system life cycle and identify the major activities in each phase as applicable (e.g., system design and development, construction/ production, utilization, maintenance and support, retirement/ disposal).
3. Develop a work breakdown structure (WBS) or cost breakdown structure (CBS), covering all activities and work packages throughout the life cycle. The work breakdown structure involves a breakdown of all the necessary activities involved throughout the life-cycle. Cost breakdown structure involves the following:
   - (i) includes all costs- direct, indirect, supplier, consumer, contractor etc.;
   - (ii) provides insight to management regarding design and decision making;
   - (iii) a structure for initial cost allocation and the subsequent collection and summarization of costs;
   - (iv) complete description of cost categories, methods of cost determination, and cost-input factors;
   - (v) a functional breakdown of costs (i.e., costs of R&D, production, operations, disposal).

   The cost breakdown structure must be tailored for each system application.
4. Estimate the appropriate costs for each category in the cost or work breakdown structure, using activity-based costing (ABC) methods [3], or the equivalent. Activity-based costing gives a more accurate cost since it does not apportion the overhead on a company-wide basis, instead activity costs are directly linked to the product or system that causes it.

5. Develop a model to facilitate the life-cycle cost analysis process. Considering the complexities involved it may be advisable to develop a computer-based model.
6. Develop a cost profile for the "baseline" system configuration being evaluated. The initial cost estimate becomes the baseline and other configurations are compared to this baseline.
7. Develop a cost summary, identifying the high cost contributors (i.e. high-cost "drivers").
8. Determine the "cause-and-effect" relationships and identify the causes for the high-cost areas.
9. Conduct a sensitivity analysis to determine the effects of input factors on the results, and identify the high-risk areas, areas that could lead to substantial increases in cost.
10. Construct a Pareto diagram, which is a non-increasing order of the relative ranking of importance of major problem areas. Rank the high-cost areas in terms of their relative importance that require immediate management attention.
11. Identify feasible alternatives (potential areas for improvement), construct a life-cycle cost profile (graph of annual cost) for each, and construct a breakeven analysis showing the point in time when a given alternative assumes a point of preference.
12. Recommend a preferred approach and develop a plan for system modification and improvement (equipment or software or process). This constitutes an on-going iterative approach for continuous process improvement.

The model developed in this thesis involves steps 1 through 5. The steps 6 through 12 are also essential and may be used in conjunction with the model by the decision-maker.

### 2.5.2 Applications of LCC Analysis

Applications of the life-cycle cost concept has taken place in various areas like evaluating alternative supplier proposals, design configurations, production profiles, logistics and maintenance support policies, identification of high-risk contributors (issues that are expected to have a significant effect on the life-cycle cost of the system), long-range budgeting and allocation of resources, project management and control, and replacement policies of existing systems.

In the “alternatives identification” stage, LCC may be used to compare alternatives using simple parametric cost estimating relationships (CER). After selecting a particular configuration or system, design tradeoffs may be evaluated based on LCC calculations. After construction of the system, LCC may be used for engineering change evaluations using more detailed analytical CERs.

When the concept of LCC is applied to new systems then it could influence design for lower life-cycle cost. When it is applied to existing systems then it could be used to assist the "continuous improvement process" to lower life-cycle cost, and redesign of costly items, policies and other tactical decisions.

### 2.5.3 Benefits of LCC Analysis

There are various benefits of life-cycle costing [2]. Some of them are:

1. Fosters long-range considerations and helps avoid myopic or short-term decisions.
2. Necessitates total cost visibility.
3. Establishes relationships between different system components and elements of cost.
4. Causes a reduction in risk by identifying potential "high-risk" areas.
5. Allows for better overall resource management.

As mentioned earlier, the research methodology of chapter 3 uses the life-cycle cost as a metric, along with opportunity loss, to determine an optimum maintenance policy.

## 2.6 The Learning Effect

It is commonly believed that the average time to complete any repetitive work decreases with time (or repetitions) due to a learning effect. A learning (or improvement) curve expresses the decreasing time it takes to perform a repetitive task as one continues from cycle to cycle of the task. As a general rule, when the production or service doubles the total time required per output reduces by x% [3, 13].

For example, if the hours for making the $n^{th}$ unit (on an 80% learning curve) were 100 then the hours for making the $2n^{th}$ unit would be 80.

Academicians and practitioners have tried to model the learning effect. In the model developed in Chapter 3, provision has been made to account for the learning effect. The learning effect may be considered from any of the models available in the literature. By including the learning effect, the realism of the modeling is enhanced.

The learning theory, developed by T.P. Wright in 1936 [13], is used in the model developed in Chapter 3 and is given by [3]:

$$y_i = y_1 * i^b \tag{2.29}$$

where $y_i$ = direct labor hours for the $i^{th}$ production unit

$y_1$ = direct labor hours for the first production unit

$i$ = cumulative unit count

$b$ = the learning curve exponent

$$b = \log(x) / \log(2) \tag{2.30}$$

where x = fraction by which time required to produce per unit reduces with learning when the production doubles. This parameter is subjective in nature and needs some experience to be estimated.

Fauber [13] has developed a model for estimating the time requirement to produce future units and the cost of learning. The steps involved in the model are as follows:

Step 1: Calculate cycle time for the first unit.

$U_1 = ES/(LC)^{\log N/\log 2} = ES/(LC)^{3.322* \log N}$ {base of log is 10} (2.31)

where ES = estimated standard time

LC = learning curve factor

$U_1$ = cycle time for the first unit made

N = number of units by which the standard time will be reached.

Step 2: Calculate cycle time for 2 to N-1 units.

$U_n = U_1 * (LC)^{3.322* \log n}$ {base of log is 10, n = 2 to N-1} (2.32)

This would yield the learning (or improvement) curve.

Step 3: Calculate the total time on the learning curve. The total (cumulative) time, TU, on the learning curve is calculated by adding all the $U_n$, n=1 to N-1.

Step 4: Calculate the learning hours and cost of learning.

The extra hours required for learning = TU - N * ES (2.33)

Multiplying the extra hours calculated above by the cost of labor gives an estimate of the cost of learning.

In general, the learning curve models require three estimates:

(i) An estimate of the standard time to perform the operation after learning is complete using time studies or historical data from similar processes.

(ii) An estimate of the learning curve factor from similar items previously manufactured.

(iii) An estimate of the unit number at which standard will be reached; usually this would be soon after the production rate target is reached.

It may be noted that both papers mentioned above consider the learning curve factor as the ratio of the time required for the $n^{th}$ unit to that required for the $2n^{th}$ unit. The difference between the two models is that Wright's model requires an estimate (or measurement) of the time required for the first unit while Fauber's model requires an estimate of the standard cycle time after learning is complete.

In the model developed in Chapter 3, Wright's model has been used since it requires the time required for maintenance which may be easier to estimate than the standard time required for maintenance after learning is complete. It may be noted that the learning effect on maintenance actions is a major contribution of this research methodology, apart from the effects of technological upgrades and age.

# Chapter 3 The Framework Model

This chapter contains the model developed for maintenance management. It is a System Dynamics model with life-cycle cost [refer to Chapter 2], opportunity loss [see Glossary], cumulative preventive maintenance actions and cumulative breakdowns as level variables [refer to Chapter 2]. The rate variables are annual total cost, breakdowns in a period and preventive maintenance actions in a year. The chapter has been divided into five sections. The first section deals with a general description of the model. The second section lists the assumptions made by the model. The third section explains the feedback loops incorporated in the model. The fourth section discusses the parameters, variables and potential sources of data for the various parameters. The fifth section gives a brief note on inter-subsystem influences, dependent and independent subsystems, and introduces a budget constraint for the life-cycle cost of the aggregate system.

## 3.1 General Description of the Model

As mentioned in chapter 1, the model captures the impact of various factors like technological upgrades, learning and preventive maintenance. These factors impact breakdowns and the life-cycle of a system including disposal, annual operational cost and initial investment. This model helps management by defining a decision-making framework for a system with high maintenance costs. The model is generic and involves critical system parameters, such as, the breakdown rate, effectiveness of preventive maintenance, learning factor etc. This model may be used for systems with long service life as it would work effectively when the breakdown rate has an upward (or downward) trend. This model is useful for operational managers in setting maintenance policies, for tactical managers in determining the maintenance budget for a system and for policy makers in determining the impact of different policies on the system's life-cycle cost.

The model uses the principle that the main objective of any maintenance problem is to balance the cost of breakdowns and opportunity costs with the cost of preventive maintenance. As explained in Chapter 2, the model resembles the logic used for automobile insurance.

In general, the idea is to forecast the opportunity loss based on past records and determine preventive maintenance policy based on it. In the first period, the maintenance policy is set depending upon the manufacturer's recommendation. The number of periods for which one may have to rely on the manufacturer's recommendation depends upon the behavior of the system in the initial periods and till sufficient data has been collected. The model can be made more proactive by incorporating more sophisticated forecasting models. In this case, the simple average of the previous periods is used as the forecast for expected opportunity losses in the next period. Forecasting techniques that can make better estimates of the breakdowns in the next period can make the model more proactive. Here, the simple average method has been used since the focus is more on the development of a methodology for a flexible maintenance policy than on forecasting future breakdowns.

Table 3.1 gives a brief idea of the similarities between the maintenance modeling methodology and the automobile insurance. The important aspects considered by the maintenance model have been mapped with the equivalent automobile insurance aspects. For example, the type of the car influences the premium. Luxury cars and sports car have higher insurance premiums than standard cars. Similarly, mission critical defense equipment needs more maintenance than non-mission critical equipment.

**Table 3.1** Comparison between automobile insurance and framework model

| **Automobile insurance** | **Framework model** |
|---|---|
| Age of the driver | Age of the system |
| Type of the automobile (e.g., luxury car, sports car) | Type of the system (mission criticality) |
| Distance to be traveled | Usage (Production rate) |
| Driving record in the recent past (e.g., 2 years) | Opportunity loss due to breakdowns (cumulative- from installation) |
| Driver experience (more than 1 year of driving record) | Maintenance crew learning |
| Technological improvements like automatic seat belt fastening when the automobile is started | Technological upgrades (both incremental and radical) that occur from time to time. |

Figures 3.1 and 3.2 are simplified and detailed sketches of the system dynamics model. Figure 3.1 shows the overall concept or flow of the model. The feedback loop (breakdowns- opportunity loss- preventive maintenance- breakdowns) is shown. Also it can be seen that learning and technological upgrades effect breakdown rate. The annual cost of breakdowns and the annual cost of preventive maintenance actions are calculated, which along with the technological upgrade cost and the operational cost constitute the annual total cost. When the total cost is accumulated over the entire life of the system, along with the initial investment and any disposal costs at the end of the life-cycle, it gives the life-cycle cost. Figure 3.2 is a detailed sketch showing all the relationships considered in the model. All the variables and parameters used in the model have been

shown here. For example, annual total cost for any system is equal to the sum of the annual total costs of preventive and corrective maintenance actions, technological upgrades (if any in that year) and the operational costs. Inflation is multiplied to the sum to give the annual total cost per year. A positive sign on the arrow between two variables indicates a positive effect of one variable on the other, i.e., an increase in one variable increases the other.

The variables used have been presented in the "List of Variables" and the symbols have been put in Appendix [F].

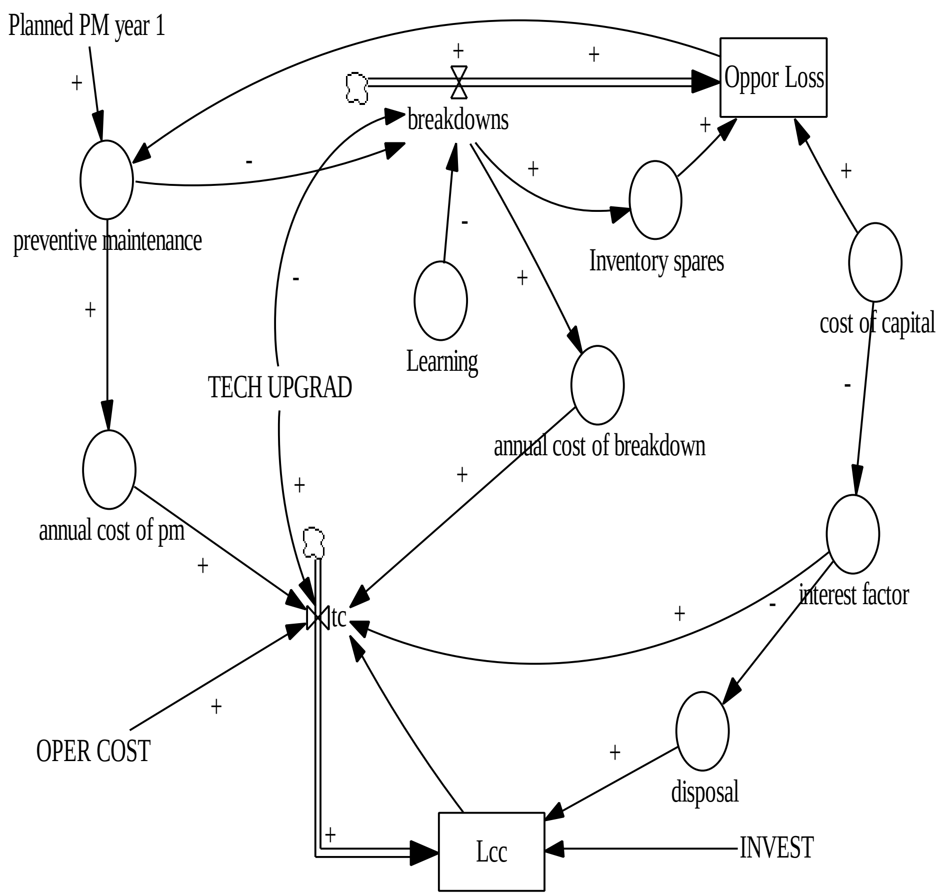



**Figure 3.1** Simplified Sketch of the Model

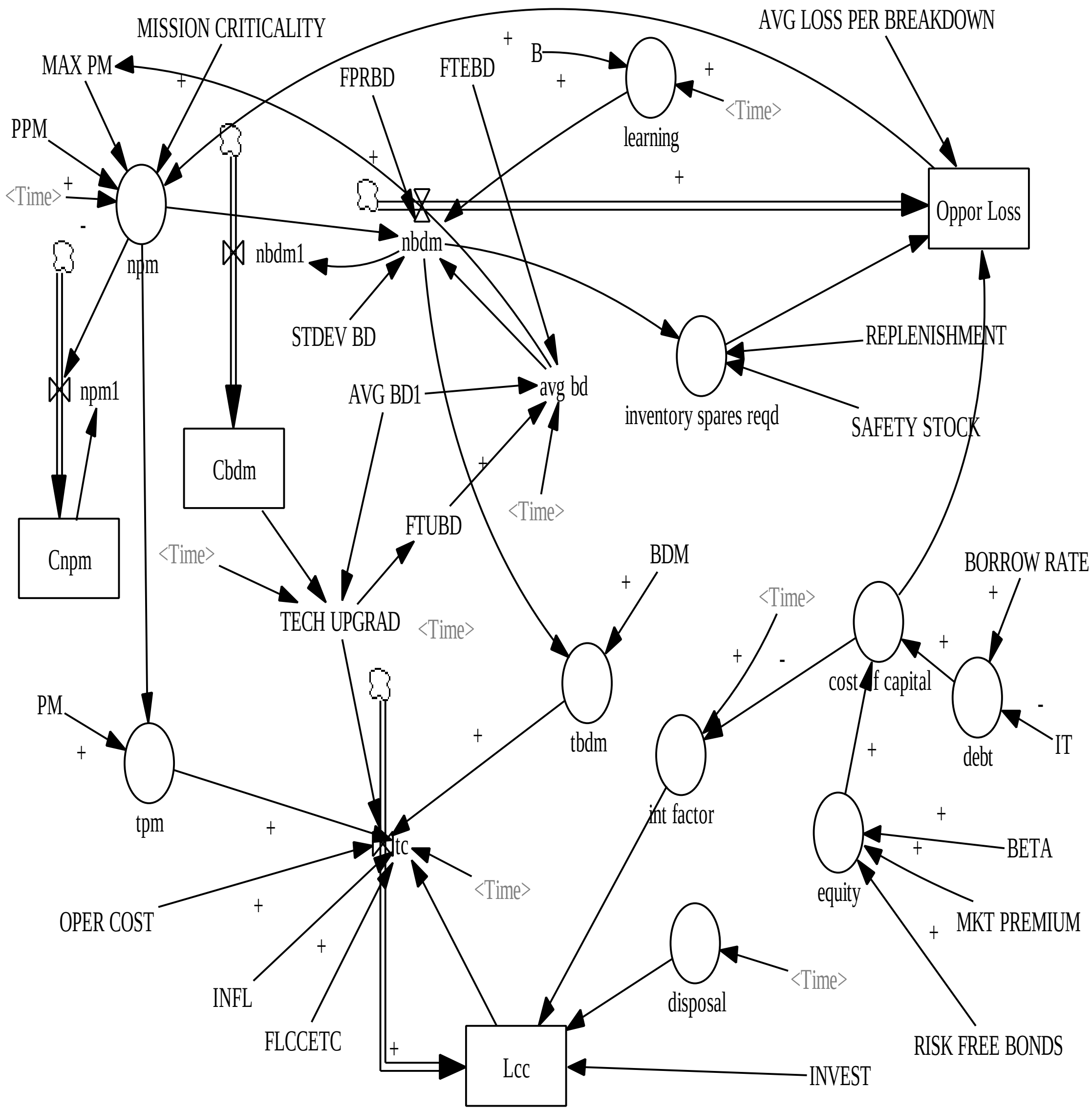



**Figure 3.2** Full Sketch of the Model

### 3.2 Assumptions

1. Breakdowns during any period 't' are affected by the number of preventive maintenance actions carried out in the previous period (t-1). However, beyond the preceding period the preventive maintenance actions are ignored since the process is considered memoryless. Consideration of periods beyond the preceding period would increase the subjectivity of the model by introducing additional parameters as well as their quantification. Breakdown maintenance or repairs do not affect the breakdowns in the next period, i.e., breakdown maintenance only puts the system back in operation without affecting its breakdown rate unlike preventive maintenance actions.
2. The breakdowns are random in nature. An exponential distribution is assumed for simulation purposes.
3. Technological upgrades and time (aging) influence breakdowns by known factors.
4. Learning affects the number of breakdowns. As the maintenance personnel deals with a system, they undergo the process of learning thereby reducing imperfect maintenance actions. Labor turnover is negligible and hence its effect on the learning process is also negligible.
5. The number of preventive maintenance actions during any period 't' is affected by the average opportunity loss (or the average number of breakdowns) up to the previous period. The preventive maintenance policy is a function of the mission criticality of the system. In other words, the number of preventive maintenance actions changes from period to period. It may be noted that the model can also be used to test for fixed preventive maintenance actions policy as illustrated in Chapter 4.
6. There is no opportunity loss involved with preventive maintenance actions as these are considered to be scheduled shutdowns, i.e., the preventive maintenance actions are taken into consideration at the production planning stage.
7. The effect of breakdowns on operational cost (direct costs) other than the loss in production (opportunity loss) is not significant and may be ignored.

### 3.3 The Feedback Loops

The feedback loops are the most important feature of a system dynamics (SD) model. This is the feature that differentiates the applications of SD from traditional Operations Research (OR) techniques like linear programming (LP), nonlinear programming (NLP), dynamic programming (DP), etc.

There are three feedback loops associated with the model. The first involves the variables: number of preventive maintenance actions (npm), number of breakdowns (nbdm) and opportunity loss (Oppor loss).

The second loop involves all the variables in the loop mentioned above and inventory spares. Because data regarding inventory level for spares can be gathered from accounting, this loop has been considered separately. This loop considers the inventory cost that is usually high for large systems. Inventory costs include all expenses related to inventory, such as, interest lost on the capital tied up in spares, storage costs and labor involved in inventory handling.

The third loop is a dummy loop and has been considered in order to define the variable *life-cycle cost (lcc)* as a level variable. Without this loop, it is not possible to calculate the value of *lcc* as the accumulation of the annual total costs beginning with the system investment. The first two loops mentioned above are shown in Figure 3.3. Other loops that have been introduced are the ones that calculate the cumulative number of breakdowns and preventive maintenance actions. These loops have been introduced to collect data from the simulation. For example, the cumulative breakdowns influence technological upgrades.

It may be noted that when a variable has a *positive impact* on another variable, an increase in the variable results in an increase in the other, i.e., positive association between variables.

In the first loop, breakdowns have a positive impact on (association with) opportunity loss. Opportunity loss has a positive impact on preventive maintenance actions. Preventive maintenance actions have a negative impact on breakdowns.

In the second loop, breakdowns have a positive impact on inventory spares required which has a positive impact on the opportunity loss. The second loop captures the impact of higher inventory levels required when the system undergoes many breakdowns. Since management may have a policy or constraint regarding inventory levels, this loop has to be considered to help management decide on an inventory policy depending upon the maintenance required.

Both the loops are negative feedback loops that help keep the entire system in control even when the random number of breakdowns takes a large value.

The feedback loops were constructed on the following basis:

(1) the need to balance the number of breakdowns with the number of preventive maintenance actions,
(2) the effect of breakdowns on the number of preventive maintenance actions due to opportunity loss
(3) the effect of preventive maintenance actions on breakdowns.

The model was further constructed to encompass the effect of many other possible effects of learning and technological upgrades on the preventive maintenance actions and breakdowns. The compounded annual total cost is calculated to give the life cycle cost of the system.

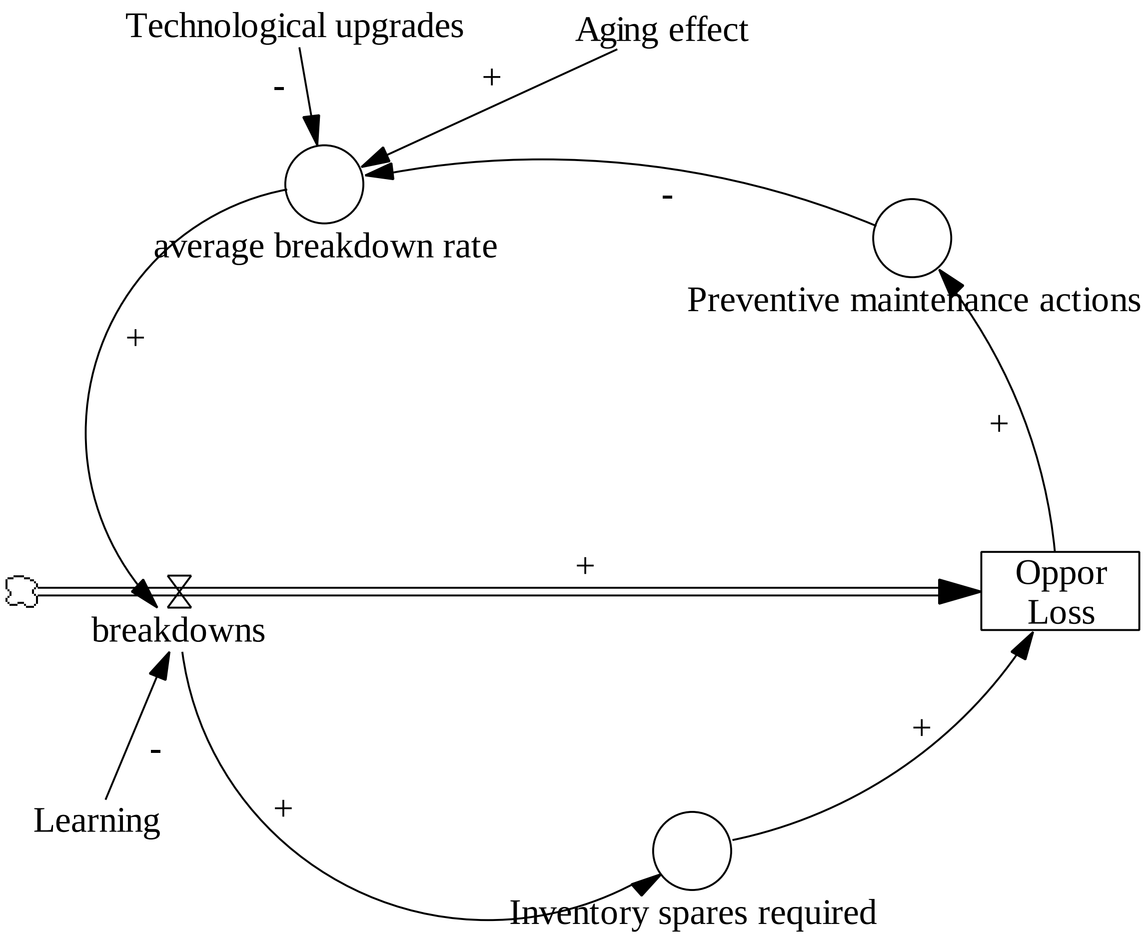



**Figure 3.3** The Basic Feedback Loop

## 3.4 Variables, Parameters and Sources of Data

The variables and parameters used in the model have been explained in sections 3.4.1, 3.4.2 and 3.4.3.

### 3.4.1 Parameters

Parameters are certain values, obtained from previous records or past experience, used to describe the system. Parameters describe characteristics of the system. However, it may be noted that any of the parameters mentioned below may be functions in order to test different policies and various scenarios. The terms in the parenthesis are the abbreviations used in the figures.

*Mission criticality (MC)* - It may also be referred to as the factor by which opportunity loss affects preventive maintenance. This is a policy parameter and could be set depending upon the required level of readiness (or availability) of the system. It indicates the level of tolerance for the non-availability of the system.

*Factor by which preventive maintenance reduces breakdowns (FPRBD)*- This parameter could be defined using expert judgement if historical data are not available. It could be calculated by determining the coefficient of correlation between the preventive maintenance actions in a period and the number of breakdowns in the next period for all periods for which data are available and the system did not undergo any major production or service rate change or any major technological upgrades.

*Factor by which time (age) affects breakdowns (FTEBD)*- This parameter could be set as per the recommendation of the Design or the Engineering Department. If historical data were available, this factor can be set using the slope of the trend line between the number of breakdowns and time between periods which did not involve any major technological change or any change in the production rate. This factor may be a constant or a function of time [see Glossary].

*Average loss per breakdown (AVG LOSS PER BREAKDOWN)*- This is a penalty parameter that quantifies the loss incurred due to breakdowns in terms of revenue, backorders and lack of service readiness. These may be expressed in dollars or any other convenient unit. If the average loss per breakdown is to be expressed in terms of dollars, it would be the product of mean-time-to-repair (MTTR) and profit earned per unit time. If the average loss per breakdown is expressed in terms of time lost, the mean-time-to-repair (MTTR) may be used. MTTR may be a random variable or a constant. This parameter can be estimated from historical data.

*Planned preventive maintenance for year 1 (PPM)*- This parameter is set based on the designer's (or supplier's) recommendation. This parameter sets the value of preventive maintenance actions required in the first period of operation after installation of the system. It is an input to the model initially. Beyond the first period, the model takes care of the annual preventive actions depending upon the past performance and the mission criticality of the system.

*Maximum allowable preventive maintenance (MAX PM)*- It is the upper limit or the maximum number of preventive maintenance actions allowed per period. This may be due to the maintenance budget constraint, manpower availability or production targets. For the hypothetical system considered in chapter 4, it has been set equal to the average breakdown rate in that period.

*Factor by which technological upgrades affect breakdowns (FTUBD)*- It is the factor by which technological upgrades of the system affect breakdowns. It may not be easy to quantify this factor. Past records for similar systems may indicate improvement in performance after technological upgrades. An approximate method to estimate this factor is to consider the average breakdown pattern before and after every major technological upgrade and to determine the ratio by dividing the average breakdown level before upgrade by the average breakdown level after upgrade. If long periods are considered, the learning effect and the preventive maintenance actions may reduce breakdowns and lead to distorted results. In such cases, corrections for the learning effect and preventive maintenance actions may be necessary. The value of this factor would depend upon the nature of technological upgrade expected in the system. Technological upgrades can be classified as *radical* or *incremental*. Radical technological changes are changes that have substantial effect in the operations (and breakdowns) of the system. For example, changing over from a mechanical subsystem to an electronic one. Incremental technological changes are changes that do not have substantial effect on the operations (and breakdowns) of the system. For example, changing an old electronic system to a new one involving minor changes. Radical technological upgrades would have a larger impact on breakdowns than the incremental ones. For any system, it is first necessary to forecast the nature of changes expected and then decide on the factor by which technological upgrades affects breakdowns.

*Maximum tolerable rate of breakdowns (MAXTOL)*- This is the maximum cumulative breakdown rate (cumulative breakdowns per unit of time) that can be tolerated for a system. This parameter is a matter of management policy. If this limit is crossed, i.e., the cumulative breakdowns per unit of time exceed the maximum tolerable rate, a technological upgrade would be necessary. This would reduce the failure rate. An assumption has been made implicitly that a better technology would be available then. For the hypothetical model in chapter 3, this parameter has been assumed equal to twice the number of average breakdown rate of the system. This has been introduced as a loop in the C++ program.

*Cost per breakdown maintenance (BDM)*- This is the average cost of breakdown computed from historical data of the system or similar system. This is an accounting parameter.

*Cost per preventive maintenance (PM)*- This is the average cost of preventive maintenance and includes material, labor and other indirect costs. This is also an accounting parameter.

*Annual operating costs (OPER COST)*- This is the sum of direct and indirect costs and overhead (excluding maintenance costs). This parameter may be affected by the initial investment. For example, if additional investment is made initially in automation then it might result in reduced operational cost in the form of reduced direct labor cost. This adjustment may be made and the adjusted value of operational cost may be used in the model. Care must be taken during evaluation of various alternatives to enter the corresponding value of operational costs.

*Inflation (INFL)*- This is the average inflation level or a inflation level as a function of time that would prevail through the service life of the system. This parameter may be obtained from the Finance Department.

*Borrowing rate (BORROW RATE)*- This is the average borrowing interest rate (constant or a function of time) that the company expects from financial institutions. This parameter may be obtained from the Finance Department.

*Income tax rate (IT)*- This again would be the input from the Finance Department.

*Beta*- This parameter indicates the volatility of the company stock. This parameter may be obtained from the Finance Department.

*Market Premium (MKT PREMIUM)*- This is the premium the shareholders expect in return for the risk they undertake by investing in the company which again would be from the Finance Department.

*Risk-Free bond rate (RISK FREE BONDS)*- This is the return expected from the long-term (30-year) government bonds.

*Factor by which life-cycle cost affects annual total cost (FLCCETC)*- This is a factor introduced to nullify the effect of the dummy loop, explained in section 3.3, in the model. It has a value of 'zero'. It is necessary to compute life-cycle cost. System Dynamics requires feedback loop to accumulate (compute) the level variable, in this case, the life-cycle cost (LCC).

*Cost of disposal (DISPOSAL)*- This is the cost of the system disposal that occurs at the end of its service life.

*Initial investment (INVEST)*- This is the initial investment required for the system that includes the initial purchase, initial training and commissioning expenses, initial research and modifications (if any).

*Learning curve exponent (b)*- This would be set depending upon the skill level of the labor force.

$$b = \log_{10}(\text{learning})/\log_{10}(2) \tag{3.1}$$

where learning = Learning curve being used for the model and $\log_{10}$ = logarithm to the base 10.

*Replenishment*- This is the average value of spares replenishment in dollars. Any inventory model can be used to compute the replenishment of spares. The model of this thesis was tested for a constant value of replenishment after every breakdown.

*Safety stock*- This is the dollar value of minimum level of spares that need to be maintained. It would be a policy issue based on the mission criticality. Inventory models could be used to compute this parameter. In the model considered in chapter 4, it has been assumed to be constant over the entire study period.

*Learning effect parameter*- This helps in accounting for the learning effect. It would be the ratio of resources (time, money) required for the $i^{th}$ action to that of the first action. The number of imperfect repairs reduces with time. As the number of imperfect maintenance actions decreases, the number of system breakdowns also decreases.
learning effect parameter = pow(t,b) (i.e., t to the power of b). (3.2)

### 3.4.2 Variables

The variables are functions of time (or some other variable). Their value changes with time or with some other variable.

*Number of preventive maintenance actions every period (npm)*- This is a very important variable in the model and indicates the number of preventive maintenance actions required in the next period. An upper limit and a lower limit on the number of preventive maintenance actions may be introduced in the equation for this variable. It is calculated by considering the mission criticality and past opportunity loss incurred due to breakdowns.
npm[t+1] = oppor loss/t * mission criticality, where t = time elapsed or clock time in simulation. (3.3)

*Number of breakdowns followed by breakdown (or corrective) maintenance or repairs (nbdm)*- This is the rate variable in the system dynamics model for the level variable, opportunity loss. It is also a random variable. The assumption here is that every breakdown has an opportunity loss associated with it. The number of breakdowns, though random, is affected by other factors such as preventive maintenance actions in the preceding period and the learning effect. For the hypothetical example in chapter 4, the breakdowns have been assumed to follow an exponential distribution. It may be noted that the model assumes that the corrective (or breakdown) maintenance does not reduce the future breakdowns. It only puts the system back into operation. Only preventive maintenance actions help reduce future breakdowns. Additionally, the learning factor also helps increase the effectiveness of preventive maintenance. This factor (with a value less than or equal to 1) has been used in the equation to increase the factor by which preventive maintenance reduces breakdowns with time.

nbdm[t+1] = rn- npm[t] * fprbd/l (3.4)

where rn = random number generated using exponential distribution for a mean value of "average breakdown rate" (avg bd)

*Average breakdown rate (avg bd)*- This is the average breakdown rate the system is expected to undergo in any period. Technological upgrades and age of the system affect this parameter. The expected breakdown rate in the first period (or initial periods) is a characteristic of the system and needs to be specified by the manufacturer. This is represented as AVG BD1 in the sketch.

avg bd = avg bd1 * (1 + ftebd * t) * (1 - ftubd); (3.5)

*Inventory spares required (inventory spares reqd)*- It is the dollar value of the average inventory level required to be maintained. Historical data or estimates based on the knowledge of breakdowns and mission criticality of the components of a subsystem may be used to define this parameter. The model does not consider the effect of unavailability of spares. Inventory models may be used to estimate this variable in this model.

inventory spares reqd = nbdm[t] * replenishment + safety stock. (3.6)

*Technological upgrades (TECH UPGRAD)*- This model has been designed for systems with long service life. Such systems would undergo major (radical) and minor (incremental) technological changes during the life-cycle. It is important to consider these changes at the procurement stage in order to get a more realistic estimate of the life-cycle cost. The output of a technological forecasting model would be the input to the system dynamics model. The output of this variable should be the dollar value of the upgrade. The cost of future technologies should be forecast along with the attributes of the technology. Technological forecasting curves like the Pearl curve or Gompertz curve or any function described in chapter 2 may be used. This variable may also be a pulse function [see Glossary] of $x every 'y' years, which has been used in the thesis model, i.e., $x is invested every ‘y’ years to upgrade technology.

*Total equivalent annual cost (tc)*- This is the annual cost of operation including operational cost, cost of maintenance and technological upgrades (if any) of the system under consideration. The effect of inflation is also considered. The interest rate is a multiplier in the equation that computes the equivalent present value of total annual cost.

tc[t] = (oper cost + tbdm[t] + tpm[t] + tech upgrad[t] + (nbdm[t] * average loss per breakdown + inventory * cost of capital))* (1+ infl/100*t) * interest factor. (3.7)

*Total annual cost of preventive maintenance (tpm)*- This is the annual expenses incurred by preventive maintenance actions.

tpm[t] = npm[t] * pm. (3.8)

*Total annual cost of breakdowns (tbdm)*- This is the annual expenses incurred by the repairs following breakdowns.

tbdm[t] = nbdm[t]*bdm. (3.9)

*Cost of capital*- This is the total of the cost of equity and cost of debt, in general, the cost of funds for the organization. Cost of capital is the sum of costs of debt and equity. It may also be referred to as the minimum rate of acceptable return (MARR) for the organization.

Cost of capital = w1 * cost of equity + w2 * after tax cost of debt, (3.10)

where w1 = proportion of equity in the capital structure, w2 = proportion of debt in the capital structure and w1 + w2 = 1.

*Cost of debt (debt)*- This is true cost of debt after deducting the tax shield available due the debt financing of the system.

debt = borrow/100 * (1- it/100); (3.11)

*Cost of equity (equity)*- This is the cost of raising funds from the shareholders.

equity = (risk free bonds + mkt premium * beta)/100. (3.12)

*Interest factor or discounting factor*- This is calculated from the cost of capital. This is the multiplier used to determine the present worth of all future cash flows. The continuous compounding formula has been employed since system dynamics uses continuous simulation.

interest factor = exp(-cost of capital * t) (3.13)

where t = time elapsed or simulation clock time.

### 3.4.3 Level (or State) Variables

The following four variables are the level variables used in the system dynamics model. As mentioned in chapter 2, these variables represent the accumulation that occurs at a certain rate over a certain period of time.

*Opportunity loss (Oppor loss)*- This is the loss due to breakdowns and represents lost sales, loss of direct expenses during breakdown time (wages are paid even during the breakdown period), loss of readiness and other losses, such as, loss of goodwill perceived by the customers or the community.

oppor loss[t] = oppor loss[t-1] + (nbdm[t] * average loss per breakdown + inventory * cost of capital). (3.14)

*Cumulative breakdown maintenance (cbdm)*- This denotes the total number of breakdown that occurred during the service life of the system. In the hypothetical system used in chapter 4, this variable triggers technological upgrades whenever the breakdown rate exceeds the maximum tolerable rate of breakdowns.

cbdm[t] = cbdm[t-1] + nbdm[t]. (3.15)

*Cumulative preventive maintenance (cnpm)*- This is the cumulative preventive maintenance actions that are performed throughout the service period.

cnpm[t] = cnpm[t-1] + npm[t]. (3.16)

*Life cycle cost (Lcc)*- This is the sum of all the cash outflows incurred in operating the system. It includes initial investment, annual cost of operations and maintenance, disposal cost at the end of the service life. This is the metric used to determine the preventive maintenance policy for a system.

$$Lcc[t] = Lcc[t-1] + tc[t] + disposal * interest\ factor. \quad (3.17)$$

This model can be referred to as an "adaptive" maintenance model as it tries to change the preventive maintenance actions in the succeeding period depending upon the breakdowns that occurred in the preceding period. The model has been programmed in VENSIM (a System Dynamics simulation software) and C++.

## 3.5 Dependent and Independent Subsystems

If in a system the subsystems are independent of each other, i.e., they do not impact each other's operations, then the subsystems are referred to as "independent subsystems". A system wherein the subsystems are all dependent on each other, i.e., impact each other's operations, are referred to as "dependent subsystems".

Any large system (see Glossary) can be considered to be a combination of many subsystems. For independent subsystems, this model may be applied to each subsystem independently and the life-cycle cost of each subsystem can be added to obtain the life-cycle cost of the aggregate system. In such cases, inter-subsystem influences would be ignored. For dependent subsystems, the inter-subsystem influences are substantial and so it is necessary to define the parameters by which one can quantify these influences.

The model should be simulated for all the subsystems at the same time along with the inter-subsystem factors. The model should be adapted to all the subsystems separately and the inter-subsystem parameters should be used to interface the various subsystems. The inter-subsystem parameters may affect the breakdown patterns among subsystems or may relate to the preventive maintenance action required. For example, in a machine, when a shaft is changed the bearings at the end may be affected and may have to be changed as well. This represents a negative inter-subsystem effect. But by changing the bearings, there may be some other part or equipment, e.g. the cutting tool, that may require less maintenance (re-grinding) due to reduced vibrations. This represents a positive inter-subsystem effect.

In practice, one may find dependent subsystems more often. There may be cases where the system may be a combination of dependent and independent subsystems, i.e., some of the inter-subsystem parameters may have value of zero or there may be subsystems that may not affect other subsystems. For example, the mechanical subsystems may have no effect on the operations of electrical subsystems.

Consider a system comprising *n* subsystems. Let $S_iS_j$ = factor by which subsystem *i* affects the number of breakdowns or preventive maintenance of subsystem *j*; i = 1,2,3,…,n; j = 1,2,3….,n.

$S_iS_i = 1$ for all i = 1,2,…,n, if $S_iS_i$ is a multiplier. (3.18)

Figure 3.4 and 3.5 explains both these types of subsystems.

The maintenance policy followed by different subsystems can be very complex, especially for dependent systems. For ease of understanding, we divide the maintenance policy into two types:

(i) Group replacement: In this case, the preventive maintenance actions would involve a group of subsystems at a time. This type of policy could be applied to both independent and dependent subsystems. Each group would be comprised of subsystems with similar (within certain range) individual maintenance policies. An extreme case of group replacement is that the entire system is out of operation for maintenance and preventive maintenance actions would be carried out on all the subsystems at the same time. A group preventive maintenance would be useful for large systems.

Consider a system comprised of many subsystems. Different subsystems may require different preventive maintenance actions every period. In such cases, the subsystems should be grouped according to the number of maintenance actions. For example, subsystems requiring 1 preventive maintenance action should be grouped together, subsystems requiring 2 preventive maintenance actions should be grouped together and so on. In general, subsystems requiring 'm' preventive maintenance actions should be grouped together. Preventive maintenance actions may be performed on all the subsystems of a group at the same time.

(ii) Individual replacement: The preventive actions would involve maintenance of individual subsystems at a time. This type is possible mainly for independent subsystems or for any subsystem that has an alternative subsystem which could be used during its maintenance. The model could be run for each subsystem and the maintenance policy could set. Individual preventive maintenance philosophy may be useful for small systems.

A budget constraint may be introduced in the model to ensure that the life-cycle cost is within a budget limit or the investment required is within the budget limit.

i.e., $Lcc_1 + Lcc_2 + Lcc_3 + \ldots.. + Lcc_n \leq$ Target Lcc or budget. (3.19)

where, $Lcc_i$ = life-cycle cost of subsystem 'i', for all i = 1,2,….n.

Similarly, $Invest_1 + Invest_2 + \ldots.. Invest_n \leq$ Investment budget. (3.20)

where, $Invest_i$ = initial investment required for subsystem 'i', for all i = 1,2,…n.

Figure 3.4 is a block diagram of dependent subsystems. Consider a system comprising *n* subsystems. The effect on the breakdowns of subsystem 1 by changes in subsystem 2 due to maintenance actions or technological upgrades is denoted by S2S1. In general, the effect of the changes in $m^{th}$ subsystem on the breakdowns of the $n^{th}$ subsystem is denoted as SmSn. Variables of the subsystems interact with each other and the magnitude of the same is given by the factor SmSn. Figure 3.5 is a block diagram of independent subsystems. Here the inter-subsystem parameters are absent. The preventive maintenance actions on one subsystem do not have any effect on the other subsystems. In these systems, the subsystems do not interact much with each other.

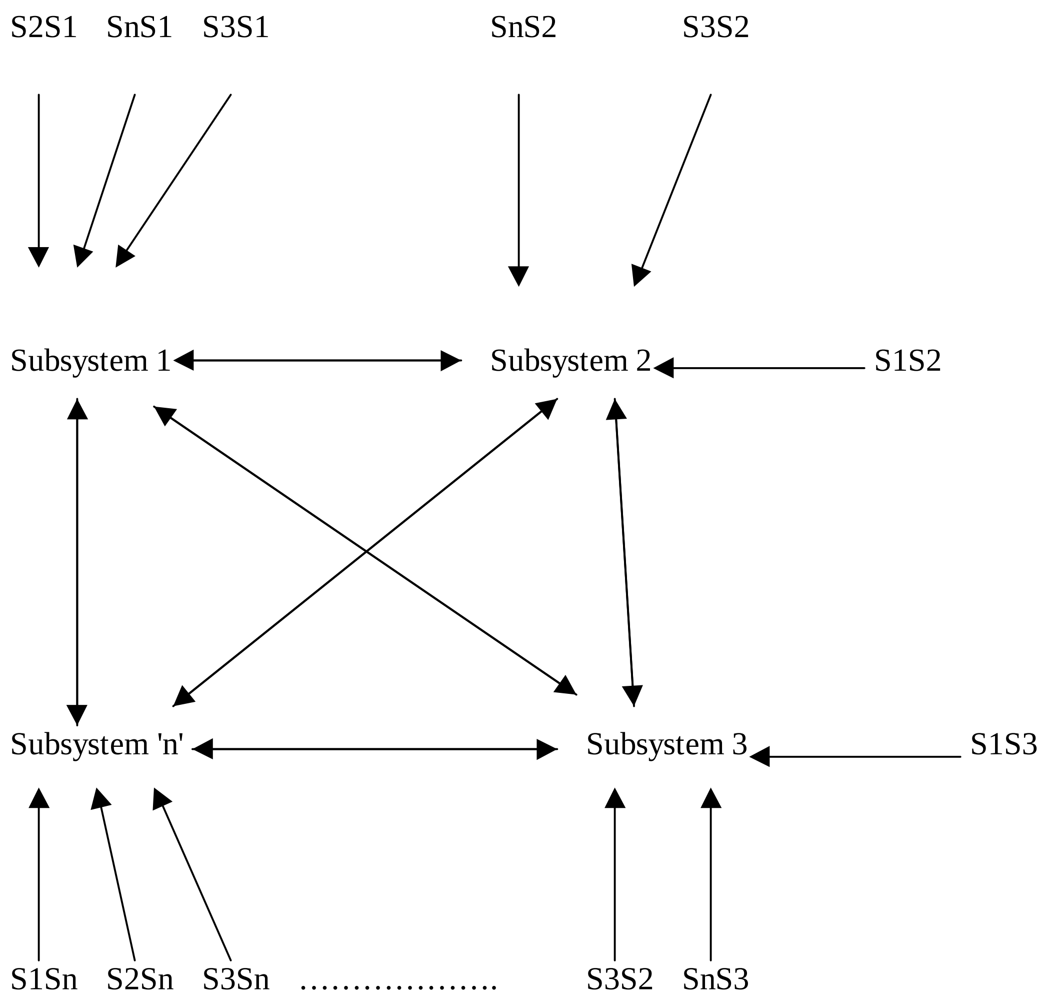



**Figure 3.4** Block diagram of a dependent subsystem.

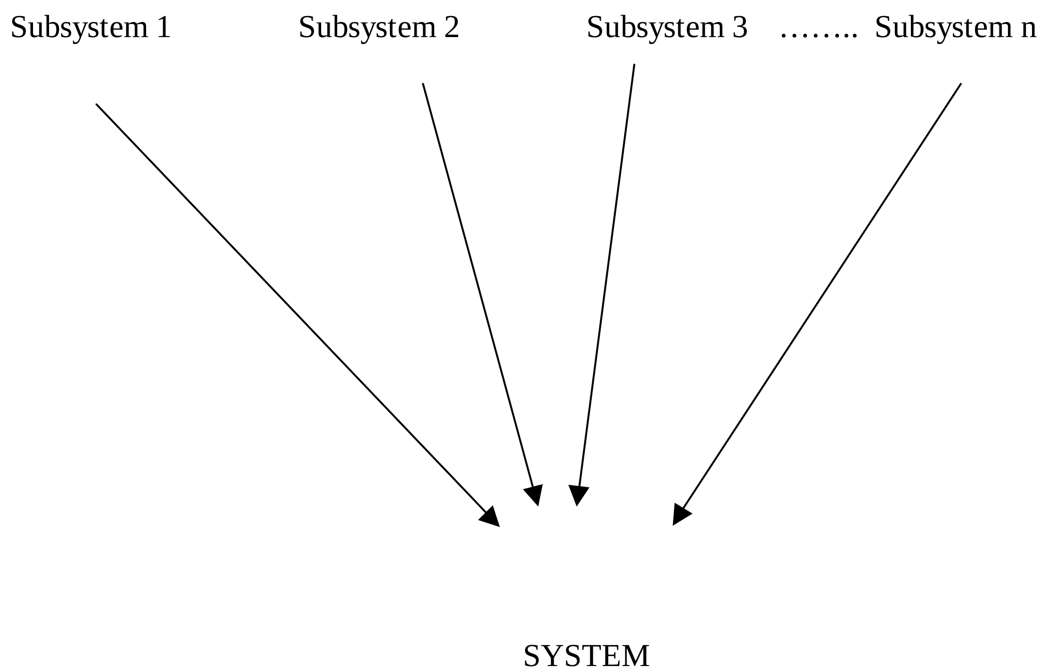



**Figure 3.5** Block diagram of an independent subsystem

# Chapter 4 Simulation, Application and Results

## 4.0 Introduction

This chapter presents a comparison with other models found in the literature, examines the scope of the model and provides the hypothetical data set used to validate the model. The model has been applied to an electronic and a mechanical system to validate its results.

## 4.1 Comparison with Other Models

The literature review discusses many maintenance models developed for theoretical and practical purposes. Many of them employ traditional Operations Research techniques while some use the System Dynamics methodology to evaluate alternative maintenance strategies.

The model developed in this thesis is a system dynamics model that is discrete and stochastic in nature. This is explained in the ensuing discussion. As mentioned in Chapter 2, Coyle and Gardiner [8] have proposed a discrete (integer) system dynamics model of submarine operations and maintenance schedules. Their model addresses the issues of fleet availability and usage during the service life. Their model computes the number of submarines to be commissioned so as to have minimum number of submarines in service. The feedback system used for their model helps analyze its dynamic behavior and studies how well a force of a given size is likely to meet its operational needs. Furthermore their model evaluates the policies might guide decision making that cope with difficulties, such as the delay of the maintenance process for submarines in order to have them in service, as and when the need arises. The model considers three types of decisions: short term, medium term, long term decisions. The discrepancy between the operational needs (goal) and actual availability is used to drive the decisions of the model.

The short-term decision deals with the number of submarines in operations, the medium-term decisions deal with the maintenance program while the long-term decisions deal with the construction of submarines.

In [8], a discrepancy is defined as the difference between the actual number of submarines required and the actual number available. A discrepancy gives rise to control actions categorized as short, medium and long term decisions. The model developed in this thesis considers the discrepancy as the cumulative opportunity loss per unit time and this variable is used to drive the model, i.e., to evaluate the maintenance policy. The main objective may be to minimize life-cycle cost, subject to the constraint of mission readiness or opportunity loss or the objective may be to minimize opportunity loss (or cumulative breakdowns) subject to the constraint of an upper limit on the life cycle cost. By adjusting the value of the mission criticality factor, the main objective of the model may still be to minimize life-cycle cost, though the user may also want to minimize opportunity loss.

The thesis model as well as [8] can be called stochastic and discrete system dynamics modeling. In this model, the number of breakdowns per period is considered to be discrete, i.e., a system can have only integer number of breakdowns, and is stochastic in nature or the number of breakdowns in future periods is unknown. In [8], the number of submarines have been considered to be discrete (integer) and the breakdowns of submarines have been considered to be stochastic. The discrete and random nature of the thesis model has been inspired by Coyle and Gardiner [8] that indicates that system dynamics modeling can be used when continuous simulation may be discrete or random.

Other linear models, as described in Chapter 2, usually attempt to estimate an optimum fixed maintenance policy that is performed at regular intervals throughout the life cycle of the system.

However, it may not be suitable to have a fixed preventive maintenance policy in case of systems with long service periods. When the preventive maintenance policy is initially set for any system, certain issues may not be considered such as the increase in the breakdown rate with time, technological upgrades made to the system and the learning effect of the maintenance team leading to better maintenance practices with time. These issues have been considered in the model developed in Chapter 3.

### 4.2 Data Set for the Simulation of the Model

The model of Chapter 3 was simulated for a hypothetical system with certain parameter values. The hypothetical system was simulated for fixed and varying maintenance policies and the results have been tabulated in Appendix 1.

The system considered here has an expected service life of 15 years. The initial investment (acquisition cost) is $1000. The breakdown rate expected is 100 in the first year and the maintenance actions are assumed to follow a 95% learning rate. The average cost of a preventive maintenance action is $15, the average cost of breakdown maintenance action or repair is $12, the operational cost (direct and indirect expenses excluding maintenance expenses) is $100 per year. The opportunity loss per breakdown has been set at $20. This may also be defined in terms of hours lost during breakdown maintenance or repairs commonly referred to as mean-time-to-repair (MTTR) in the maintenance literature multiplied by the rate of profit lost per unit of time. This parameter may also be multiplied by some weight depending upon the management's tolerance toward breakdowns. The inventory safety stock required for spares has been valued at $15 and the average replenishment after every breakdown repair, i.e., the average material consumed by a repair, is $5. An exponential distribution is assumed for the number of breakdowns each year. An exponential distribution has been assumed in [17]. This is a widely used distribution for failure rates.

For this system, it is assumed that the factor by which preventive maintenance reduces breakdowns is 0.7, i.e., preventive maintenance in any period would reduce the chances of breakdowns in the next period by 70% in the initial period. This parameter will be adjusted by the learning effect in future. It is further assumed that the factor by which time affects breakdowns is 0.1, i.e., the average breakdown rate increases by 10% every year.

The mission criticality of this system has been set at 0.3, i.e., one preventive maintenance action would be conducted in the next period when the average cumulative opportunity loss is 3 units. The management has a policy of upgrading any system that has a cumulative breakdown rate of more than the maximum tolerable cumulative breakdown rate, which for this system has been defined as twice the average expected breakdown rate. The maximum tolerable breakdown rate depends on management's discretion. It may be noted that the breakdown history affects preventive maintenance actions in the current period while preventive maintenance actions performed only in the previous period affect breakdowns. Here, a technological upgrade is supposed to occur whenever the average breakdown rate increases beyond the maximum tolerable rate apart from the technological upgrade that would occur every 5 years. This is the control measure taken by management if any technology is observed to be adversely affect the operation of the system.

Thus the following data is assumed:

life = study period or expected service life = 15 years

investment = initial investment or acquisition cost = $1000

avg bd1 = average breakdown in year 1 = 100

learning = % learning curve = 95%

pm = cost of a preventive maintenance action = $15

bdm = cost of a breakdown maintenance or repair = $12

oper cost = annual operational cost of the system = $100

avg loss per breakdown = opportunity loss per breakdown = $20

safety stock = $15

replenishment per breakdown = $5

fprbd = factor by which preventive maintenance reduces breakdowns = 0.7

ftebd = factor by which time affects breakdowns = 0.1

mission criticality = 0.3

The financial parameters assumed are as follows:

borrowing interest rate = 10%

income tax rate = 40%

volatility of the company's stock, beta = 1, indicating that the stock price moves along with the market index and in the same magnitude.

premium = 6%

risk free bond rate = 6.2% (Source: Walls Street Journal, 10/15/1997)

inflation = 4%

w1 = fraction of equity financing in the capital structure = 0

w2 = fraction of debt financing in the capital structure = 1

Only debt financing has been considered for easy handling of the cost of capital parameter in the sensitivity analyses. In Section 4.7, sensitivity analysis has been performed to evaluate the impact of borrowing rate on system life-cycle cost. The sensitivity analysis with respect to the cost of capital will be equivalent to that of performing sensitivity analysis on the borrowing rate since only the debt financing option has been considered.

These parameters are assumed to be constant over the entire service period. However, these parameters may vary with time.

It is further assumed that the maximum number of preventive maintenance actions allowed in a year is equal to the average breakdown rate of the system during that period. Since a limit on the maximum number of preventive maintenance actions has been defined and the cost per preventive maintenance action is assumed constant, this constraint can be regarded as the budget constraint on the preventive maintenance actions in a period. It could also be expressed as a monetary budget constraint. The monetary constraint should be divided by the average cost per preventive maintenance to determine the maximum number of preventive maintenance actions in a period.

The model has been tested for its sensitivity with respect to specific model parameters and results have been presented in Section 4.6. The sensitivity analysis has been performed to determine the tolerance of the model output to variability in parameter estimates. It is important to study these parameters since they are subjective in nature.

The sensitivity analyses have been carried for the following parameter values:

factor by which preventive maintenance reduces breakdowns = 0.5, 1, 1.5, 2.
factor by which time affects breakdowns = 0.1, 0.2, 0.3, 0.4.
loss per breakdown = 5, 20, 35, 50, 65, 80, 95.

borrowing rate (%) = 0, 5, 10, 15, 20, 25.

learning (%) = 50%, 70%, 90%.

planned preventive maintenance policy for year 1 = 0 (corrective) to expected breakdown rate in year 1.

These values were changed one at a time from the original values mentioned above without changing other parameter values. The results obtained have been tabulated later in Section 4.7.

The model can be calibrated by adjusting the system parameters, i.e. by adjusting the parameter values different systems can be represented. The process of quantifying the model parameters forces management to consider various aspects of the maintenance policies, study the maintenance processes in terms of cause and effect relationships and to consider the long term effects of such polices. This model helps generate a set (an efficient frontier of maintenance policies) of dominant maintenance policies in terms of lower life-cycle cost and lower cumulative breakdowns from which various tradeoffs between the opportunity loss and life cycle cost can be made. The dominance concept of maintenance policies has been explained in Section 4.4. It may be noted that, as advocated by leading system dynamics practitioners, the output of the model does not incorporate any statistical analysis. The output of the model would be a valuable input for the decision-maker to make decisions based on his/her judgement.

The simulation was performed using VENSIM and C++. VENSIM (version 1.62) poses a problem of running the simulation with different starting seeds. This problem has been solved by programming the model in C++ which allows simulation runs with different starting seeds. The C++ program is attached in Appendix [G].

## 4.3 Scope of the model

This model has been designed for systems with long service periods. A long service period would be one in which the system undergoes a significant change in its breakdown rate and where technology could play a vital part in changing the breakdown rate apart from the learning effect. Practically, this period may be about 10 years or more. Usually the maintenance policy for any system is decided based on the initial operating conditions. The effects of learning, aging and technological upgrades on preventive maintenance action requirements may be overlooked. The feedback loop in the model (Figure 3.1) keeps track of the trend (upward or downward) of the breakdown rate and adjusts the preventive maintenance actions required per period to a level that would help dampen any upward trend. This is shown by the reduction in cumulative breakdowns over the lifetime of the system in the simulation runs as compared to the "only breakdown maintenance" (or zero preventive maintenance) policy. This model would be suitable for systems involving subsystems expected to undergo technological upgrade or replacement during the lifetime. Also it would be useful for systems involving complex subsystems which would require the maintenance crew to undergo training and get some "hands-on" experience before mastering the intricacies of the system.

The model provides enough flexibility, i.e., there is no constraint imposed on any of the parameter values. If the system consists of a large number of dependent subsystems (see Glossary), the interrelation between the various subsystems could necessitate a cross impact analysis to determine the inter-subsystem effects and to quantify these effects. This model may be applied to all the subsystems individually and the simulation may be carried out for the entire system by including the inter-subsystem influences or effects.

This model can be used for analysis anytime during the system's life-cycle. The model is also suitable when the breakdown rate and/or mission criticality vary with time. The varying preventive maintenance policy would be useful when the breakdown rate is not known accurately or only the breakdown rate of an equivalent system is known.

The feedback loop in the model (Figure 3.1) helps maintain the cumulative breakdown levels within a small range as seen from the simulation runs. This indicates that even if the breakdown rate is not known accurately the difference between the life-cycle cost incurred and the life-cycle cost does not differ significantly. This has been further explained in Section 4.7.

### 4.4 Incremental analysis for accounting life-cycle cost

The following procedure may be used to determine the maintenance policy for the first year. It may be noted that such a procedure would be useful if the life-cycle cost is the sum of all the expenses incurred throughout the life-cycle of the system and does not consider (quantify) the opportunity loss. If opportunity loss is included in the life-cycle calculations, then the procedure described below may not necessary. As mentioned earlier, the model requires the first year policy (at time t =0) to be set by the user. The policy for subsequent years is determined by the model feedback loop based on past performance.

A graph of the cumulative breakdowns versus life-cycle cost should be plotted. The *dominant* points should be selected for further analysis. The dominant policies are those points in the graph which give *good* or dominant combination of cumulative breakdowns and life cycle costs. A *good* or dominant combination of cumulative breakdown and life cycle cost is one that gives lower cumulative breakdowns compared to all other combinations for similar life cycle cost or a lower life cycle cost compared to all other combinations for the corresponding cumulative breakdowns.

For example, consider the runs obtained for an average initial breakdown rate of 5 (see Figure 4.1). Here the dominant alternatives are (59, 2238.82), (57, 2240.11) or planned preventive maintenance for year 1 values of 1,3. The minimum life cycle cost generated by cumulative breakdowns of 57 is less than that for cumulative breakdowns of 58. (57, 2240.11) *dominates* all the policies that give cumulative number of breakdowns of 58 since it gives a lower life-cycle cost for lower cumulative breakdowns.

In the example tabulated below, a policy of 1 preventive maintenance action in year 1 is expected to result in a life cycle cost of $2238.82, cumulative breakdowns resulting in an opportunity loss of $1278.07, and 107 preventive maintenance actions during the 15-year service life.

**Table 4.1:** Simulation Results for an Average Breakdown Rate in Year 1 = 5 (Exponential Distribution assumed for the Breakdowns occurring over the system's life-cycle)

| Planned Preventive Maintenance Actions in Year 1 | Cumulative Breakdown Maintenance | Cumulative Number of Preventive Maintenance Actions | Life-cycle Cost ($) | Opportunity Loss ($) | Good Alternatives |
|---|---|---|---|---|---|
| 0 | 58 | 107 | 2240.42 | 1269.54 | 1,3 |
| 1 | 59 | 107 | 2238.82 | 1278.07 | |
| 2 | 58 | 107 | 2240.9 | 1270 | |
| 3 | 57 | 107 | 2240.11 | 1247.56 | |
| 4 | 57 | 108 | 2257.15 | 1249.57 | |
| 5 | 57 | 109 | 2260 | 1234.28 | |

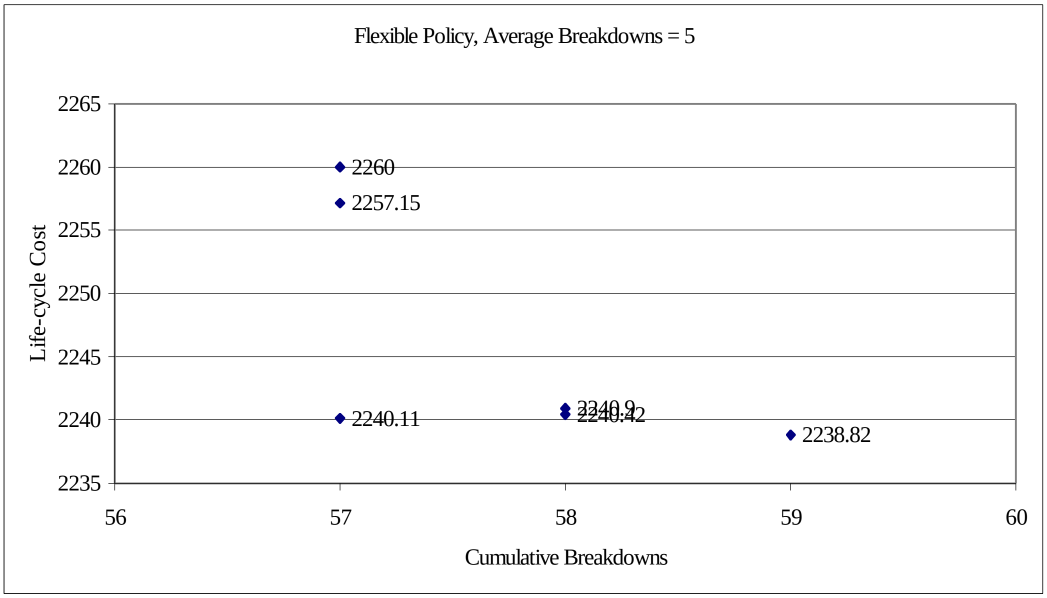



**Figure 4.1** Varying Policy, Average Breakdowns = 5.

Depending on the maintenance manager's (or management's) tolerance to increased breakdowns or life cycle costs, a particular maintenance policy may be selected for the first year. The trade-off between life cycle costs and cumulative breakdowns of the system is an important issue, which is subjective in nature. If the objective of the firm is to minimize breakdowns, then the policy that gives the least cumulative breakdown value should be selected.

In the above example, preventive maintenance policy 1 should be chosen if the objective is to minimize life-cycle cost. In the above example, preventive maintenance policy 3 should be chosen if the objective is to minimize cumulative breakdowns. A trade-off may be quantified by computing the ratio of life cycle cost due to changes in breakdowns, i.e., marginal cost. This would give an indication of the extra amount of money (marginal cost) required to reduce the number of cumulative breakdowns by 1. If this amount is less than the average loss per breakdown then the policy with lower cumulative breakdowns should be selected. In the above example, there is a reduction in the cumulative breakdowns by (59 *less* 57=) 2 for an increase in life cycle cost of ($2240.11 *less* $2238.82=) $1.29 or an increase of $0.65 for every reduction in cumulative breakdowns. Since this is below the assumed value of average loss per breakdown for this system it is recommended to choose a preventive maintenance policy with lower cumulative breakdowns, i.e., planned preventive maintenance of 3. It may be noted that in this example, the difference in the cumulative breakdowns of the different options is never huge due to the feedback loop. The feedback loop corrects any errors in setting the initial period maintenance policy. Even if the first year's maintenance policy is not set optimally and varies significantly from the optimal policy, the deviation from the optimal life cycle costs is not very significant. Sensitivity analyses have been performed in Section 4.8 that illustrate this point.

## 4.5 Comparison Between Fixed and Varying Maintenance Policies

A comparison between fixed and variable maintenance policies has been tabulated below for a few runs. The parameters used are as mentioned above. The simulation runs were carried for borrowing rate of 0 and 10%, 75% and 100% learning curves, aging factors of 0 and 0.5, i.e., no effect of aging on the breakdowns and a 50% increase in breakdowns due to breakdowns. These two values can represent extreme conditions in any system.

The results have been tabulated in Appendix [A]. The results indicate that the variable maintenance policy (as described in Chapter 3) gives a lower cumulative number of breakdowns when compared to the fixed policy. It can be seen that, in some cases, the life-cycle cost is lower for the fixed policy than for varying policy but with increased cumulative breakdowns. This leads us to another important issue, i.e., the use of life-cycle cost as a metric for evaluating maintenance policy. It may not be desirable to base the maintenance policy on the life-cycle cost. Even opportunity loss needs to be considered. Even if the opportunity loss is quantified and added in the life-cycle cost calculations, it may be noted that the discounting of the future cash flows may hide the excess opportunity losses to be incurred in future. This is discussed in the Section 4.6.

The differences between breakdowns and the life-cycle cost for the varying and fixed maintenance policies have been tabulated below for a factor by which time affects breakdowns of 0.5, i.e., 50% increase in breakdown rate every year. For example, consider the results of having 30 preventive maintenance actions in year 1 (refer figure 4.2). For a fixed policy of 30 preventive maintenance actions per year, the cumulative breakdowns is about 70% more than the corresponding cumulative breakdowns for a varying policy while the life-cycle cost is about 1% lower. This indicates that relying on the life-cycle cost alone may not be rational and justified. A trade-off analysis should be performed to determine the preventive maintenance policy since the estimation of the opportunity loss involves subjectivity. The results also do not indicate any significant changes in the breakdown pattern due to the reduction in the borrowing rate. The capital tied up in the inventory, if large, would affect the opportunity loss involved with breakdowns and thus would regulate the preventive maintenance policy. This analysis would be important when the borrowing rate is high or the inventory levels desired and the safety stocks levels are high. This will indicate the effect of the policy regarding the safety stock on the overall life-cycle cost.

**Table 4.2** Results for Fixed and Varying Policies for an Aging Factor = 0.5

| Preventive Maintenance Actions in Year 1 | Difference in Breakdowns | Difference in Life-cycle Cost |
|---|---|---|
| 0 | 0.68107 | -0.0374 |
| 10 | 0.71183 | -0.0184 |
| 20 | 0.64947 | -0.043 |
| 30 | 0.69907 | -0.0092 |
| 40 | 0.61569 | -0.0431 |
| 50 | 0.53142 | -0.0756 |
| 60 | 0.53017 | -0.0673 |
| 70 | 0.56419 | -0.0415 |
| 80 | 0.61786 | -0.0084 |
| 90 | 0.60399 | 0.00345 |
| 100 | 0.51076 | -0.0296 |

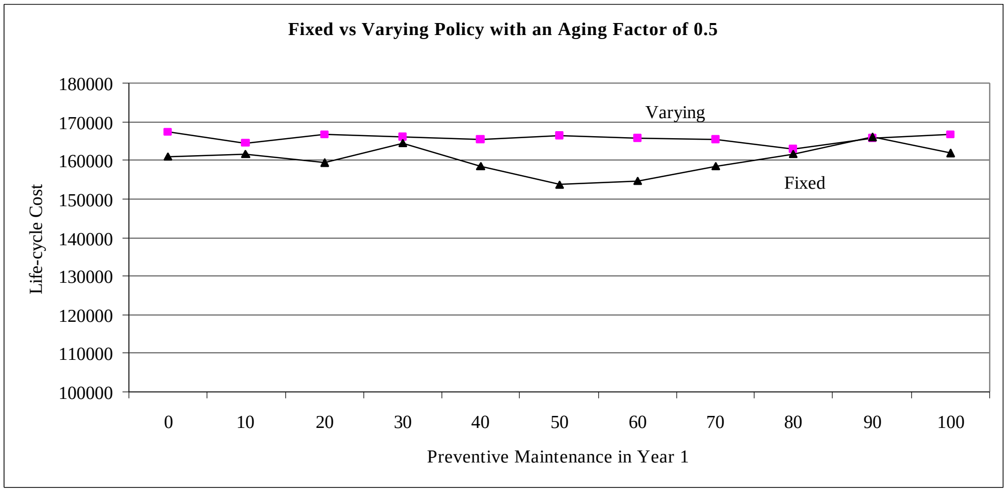
**Table 4.3** Results for Varying Maintenance Policy with an Aging Factor = 0.5

| Preventive Maintenance Actions in Year 1 | Cumulative breakdowns | Life-cycle Cost |
|---|---|---|
| 0 | 3819 | 167200 |
| 10 | 3727 | 164641 |
| 20 | 3800 | 166722 |
| 30 | 3775 | 165968 |

| | | |
|---|---|---|
| 40 | 3747 | 165578 |
| 50 | 3771 | 166303 |
| 60 | 3746 | 165785 |
| 70 | 3731 | 165319 |
| 80 | 3661 | 163059 |
| 90 | 3755 | 165630 |
| 100 | 3810 | 166759 |

**Table 4.4** Results for Fixed Policy for Aging Factor = 0.5

| Preventive Maintenance in Year 1 | Cumulative Breakdowns | Life-cycle Costs |
|---|---|---|
| 0 | 6420 | 160943 |
| 10 | 6380 | 161609 |
| 20 | 6268 | 159545 |
| 30 | 6414 | 164438 |
| 40 | 6054 | 158449 |
| 50 | 5775 | 153735 |
| 60 | 5732 | 154626 |
| 70 | 5836 | 158454 |
| 80 | 5923 | 161685 |
| 90 | 6023 | 166202 |
| 100 | 5756 | 161826 |



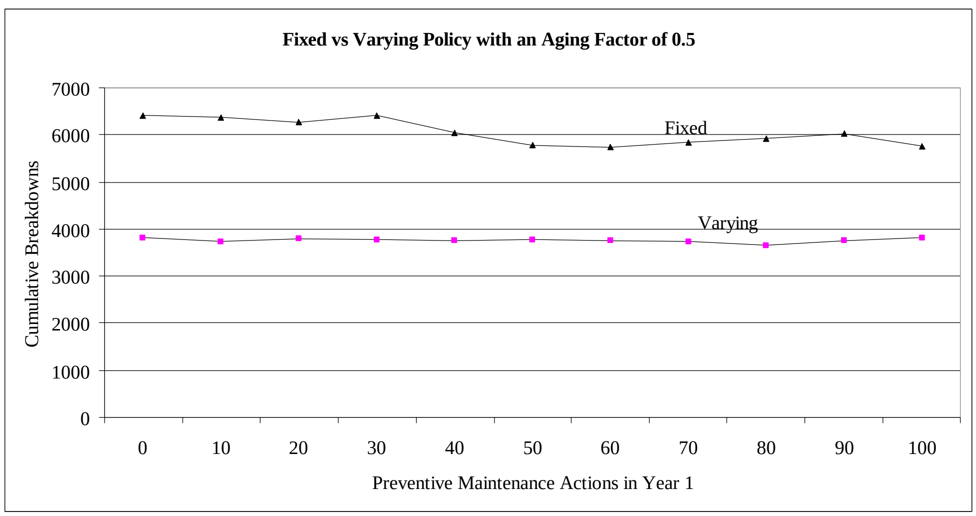




**Figure 4.2** Comparison of the Fixed and Varying Preventive Maintenance Policies with a Factor by which Time affects Breakdowns of 0.5

Similarly, for a factor by which time affects breakdowns of 0 (no aging), it can be seen that for lower to moderate initial maintenance requirements, the varying preventive maintenance policy gives a lower life-cycle cost and cumulative breakdowns than the fixed policy. If management decides to have conservative preventive maintenance policies, it would be a good option to adopt the varying preventive maintenance policy on the basis of a lower life-cycle cost and cumulative breakdowns. For higher maintenance requirements, it may be noted that both policies give very similar life-cycle cost (difference of about 5%). However, for very high maintenance actions (close to the upper limit on preventive maintenance actions per period), the fixed policy can give lower cumulative breakdowns.

From the results, it can be seen that as the factor by which time affects breakdowns increases, the varying policy helps achieve a reduction in cumulative breakdowns. Depending on the breakdown tolerance and budget limitations (target life-cycle cost) a policy may be chosen. For example, from figure 4.3, for the no aging case, the following rule may be used to determine a maintenance policy.

Assume that for the given system, the number of cumulative breakdowns is preferred over the life-cycle cost when determining the maintenance policy. Also, a difference in life-cycle cost of 5% (which is the case here) is not considered significant for the determination of maintenance policy, i.e., the life-cycle cost for different maintenance policies are estimated to be within a 5% range. Then the policy that is expected to give lower cumulative breakdowns is chosen. The breakeven point is the point where the expected cumulative breakdowns of the two policies are the same.

Therefore, the following rules apply:
If the tolerable or acceptable cumulative breakdowns (cbdm) < breakeven cumulative breakdowns, then prefer a fixed policy.

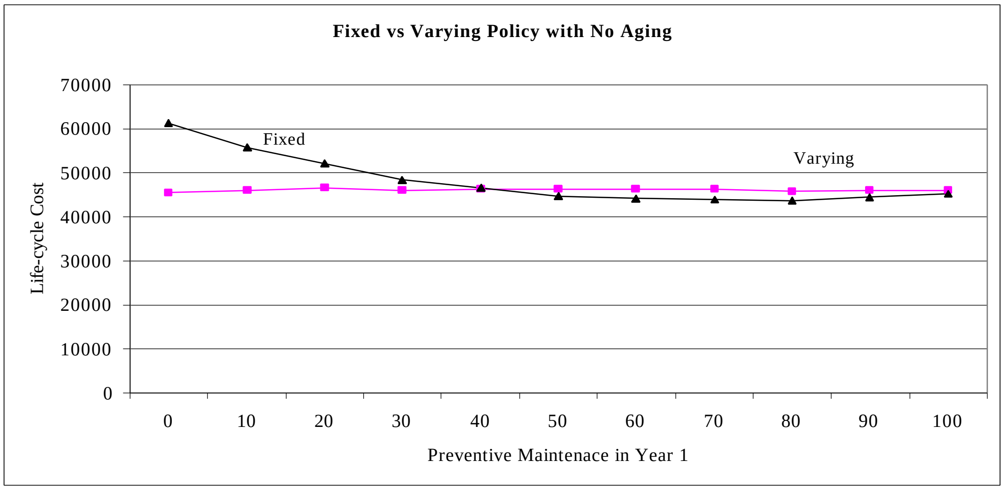
If the tolerable or acceptable cumulative breakdowns (cbdm) > breakeven cumulative breakdowns, then prefer a varying policy.

When the two are equal, then choose the one giving lower life-cycle cost.

**Table 4.5** Results for Varying Policy with No Aging

(Factor by which Time Affects Breakdowns is Zero)

| Preventive Maintenance Actions in Year 1 | Cumulative Breakdowns | Life-cycle Cost |
|---|---|---|
| 0 | 446 | 45653 |
| 10 | 453 | 45964 |
| 20 | 467 | 46590 |
| 30 | 449 | 46032 |
| 40 | 455 | 46305 |
| 50 | 451 | 46268 |
| 60 | 454 | 46338 |
| 70 | 452 | 46411 |
| 80 | 437 | 45899 |
| 90 | 440 | 46017 |
| 100 | 437 | 46075 |



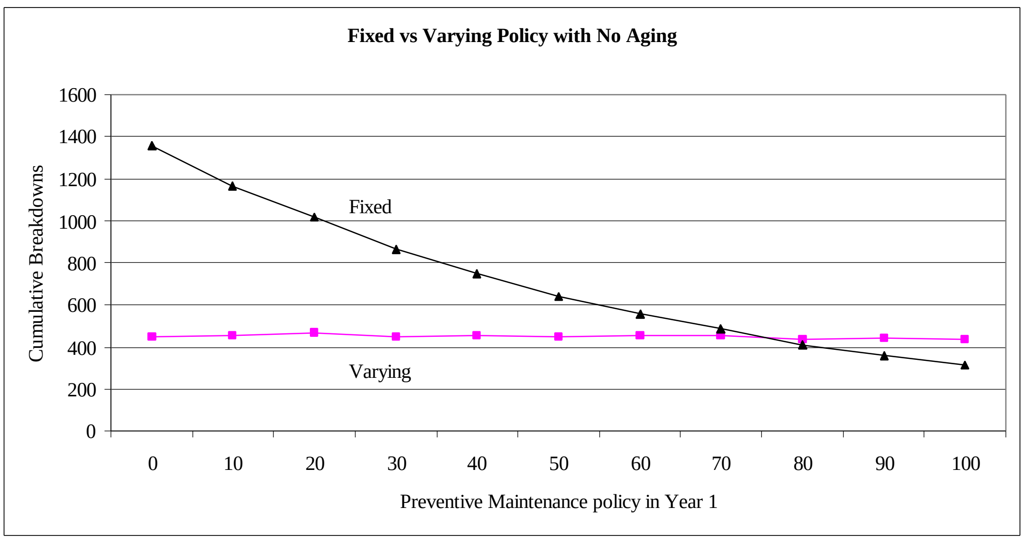




**Figure 4.3** Fixed vs Varying policies with no aging

(extreme case, factor by which time affects breakdowns = 0)

The varying policy worked better when aging occurs in a system at a faster rate. Such a phenomenon is likely to occur in mechanical system (due to wear and tear) than an electronic system. The varying policy would be more useful for a mechanical system with a long service life than for an electronic system.

### 4.6 Life-cycle Cost as a Metric for Evaluating Maintenance Policies

From the tables shown above, it can be seen that the life-cycle cost as a metric to determine an optimum maintenance policy for a system can be misleading if management does not set suitable policy parameters and objectives. For example, in many of the simulation runs, it was seen that policies involving a lower number of preventive maintenance actions give lower life-cycle costs but increase the number of cumulative number of breakdowns which results in increased opportunity loss (or unavailability). Since opportunity loss cannot be easily quantified, it may not be a good practice to take a decision based on the life-cycle cost estimate only. Some trade-off analysis may have to be used.

Often, life-cycle cost calculations do not consider the benefits of preventive maintenance actions and the opportunity loss (or unavailability) of the system. It considers the costs incurred and ignores the savings that result from the system. There may be systems that cost more to purchase and operate but the savings generated (compared to its challengers) may be sufficient to offset the increased costs. Such a system may get rejected on grounds of higher life-cycle costs though it may be viable on grounds of potential savings. It is not advisable to reduce life cycle cost at the expense of opportunity loss (or unavailability).

Also, due to the discounting factor used in the computation of the life-cycle cost, there is a possibility that systems with large number of breakdowns later in the life-cycle may have a lower life-cycle cost than those with less cumulative breakdowns. The interpretation of the life-cycle cost may be misleading if it is used to compare diverse systems with different breakdown patterns. A judicious use of the concept of life-cycle cost would be very useful in making long term decisions.

A suitable policy might be one that minimizes life cycle cost subject to a constraint on the opportunity loss or breakdowns (unavailability) of the system. The constraint could be in the form of an upper limit on the number of acceptable breakdowns or a dollar value representing opportunity loss (if measurable) or hours lost due to breakdowns. If the objective of management is to minimize the opportunity loss (or unavailability) of the system then a constraint on the life cycle cost may be introduced.

In all the simulation runs used to compare fixed and varying maintenance policies, it may be noted that, the (discounted) opportunity loss was included in the life-cycle cost calculations to include the opportunity cost involved with breakdowns.

### 4.7 Validation Tests

(a) Test for Extreme Condition - Zero Breakdowns.

To validate the logic of the model, the “extreme condition” test was performed as prescribed by [36]. The lower extreme condition was identified as zero breakdowns. The upper extreme condition cannot be considered since the upper limit would be very system-specific and for the hypothetical case considered, it has to be infinity. So only the lower limit was considered. The simulation runs for the zero breakdown case gave cumulative breakdowns of zero and cumulative preventive maintenance actions equal to the preventive maintenance actions in year as planned by the user. These results are as expected. Since the preventive maintenance policy of the subsequent period is decided by the model based on the past performance and the past performance always has zero breakdowns, the model should prescribe a preventive maintenance policy of zero every year beginning year 2 independent of the policy followed in year 1. The model follows the extreme condition test. The results have been tabulated below.

**Table 4.6** Results: Test for Extreme Condition - Zero Breakdowns.

| Average Breakdowns in Year 1 | Planned Preventive Maintenance Actions | Cumulative Breakdowns | Cumulative Preventive Maintenance Actions |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 10 | 0 | 10 |
| 0 | 20 | 0 | 20 |
| 0 | 30 | 0 | 30 |
| 0 | 40 | 0 | 40 |
| 0 | 50 | 0 | 50 |
| 0 | 60 | 0 | 60 |
| 0 | 70 | 0 | 70 |
| 0 | 80 | 0 | 80 |
| 0 | 90 | 0 | 90 |
| 0 | 100 | 0 | 100 |

(b) Test for Non-Random Breakdowns, i.e., Deterministic Average Breakdowns Every Year.

This test is being performed to study the behavior when the average breakdown rate is deterministic (no randomness is involved). This will help us determine whether the logic of the model is working as required. When the factor by which time affects breakdowns is set to zero, i.e., the effect on aging of breakdowns is ignored, and the randomness is ignored, the number of breakdowns would reduce every year and preventive maintenance actions would adjust and stabilize at a level depending upon the mission criticality. For higher mission criticality the preventive maintenance stabilization level would be higher and the breakdown level would be lower.

As seen from Table 4.7 and Fig. 4.4 below, the breakdown rate is high (100) initially and decreases as preventive maintenance increases. As seen from the results, the two variables seem to reach equilibrium at about 50. This model is based on the principle of balancing the cost of preventive maintenance with the opportunity loss due to breakdowns. This test indicates that the model performs the balancing as required.

The values of the parameters used in the model were the same as mentioned above in section 4.2 except the following parameters:
preventive maintenance in year 1 = 0
average breakdowns in year 1 = 100
life-cycle =14 years.
mission criticality = 0.05. (This was changed to get a good graph of the stabilization of the preventive maintenance and breakdown levels.)

Higher the mission criticality, higher would be the level at which the number of preventive maintenance actions stabilizes and lower would be the level at which the number of breakdowns stabilizes. For a very high mission critical system, the preventive maintenance actions per year would be high while the breakdowns would be lower.

**Table 4.7** Results: Test for Non-Random Breakdowns.

| Period | Breakdowns | Preventive maintenance actions |
|---|---|---|
| 1 | 100 | 0 |
| 2 | 100 | 50 |
| 3 | 62 | 67 |
| 4 | 48 | 66 |
| 5 | 37 | 62 |
| 6 | 50 | 58 |
| 7 | 53 | 57 |
| 8 | 53 | 57 |
| 9 | 53 | 56 |
| 10 | 43 | 56 |
| 11 | 53 | 55 |
| 12 | 53 | 55 |
| 13 | 53 | 55 |
| 14 | 53 | 54 |

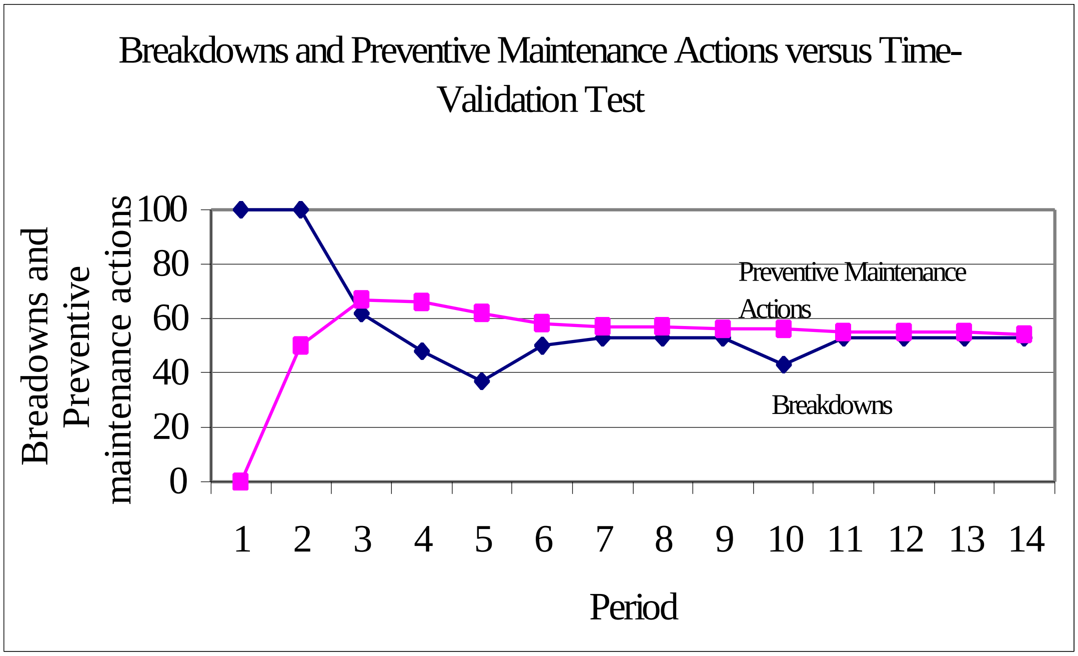



**Figure 4.4** Graph of Preventive Maintenance Actions and Breakdowns with Time for a Deterministic Average Breakdown Rate of 100 in Year 1

The other tests, described in section 2.2.5, are all subjective in nature. They are all based on experience, intuition and judgment of the user. Since a hypothetical system is being considered and the element of subjectivity cannot be easily handled, the other tests were not performed. The dimensional test was performed initially to check for possible errors in the dimensions or unit of measure of the parameters.

## 4.8 Sensitivity analyses

Sensitivity analyses have been performed to study the effect of variations in the estimation of parameters on the variation in the values on the cumulative breakdowns and life-cycle cost of the system. The sensitivity analyses helps us in determining the robustness of the model to variation in certain parameters with respect to maintenance policy-making. The results obtained from the sensitivity analysis are specific to the parameter values used in the model. The results obtained are discussed below. Tables 4.8 – 4.14 for the sensitivity analyses represent the percentage changes in the life-cycle cost and cumulative breakdowns for preventive maintenance policy in year 1 of 0, 25, 75, 100 for different variations in the parameter being tested.

In the sensitivity analyses, the trend curves were fitted to the data using EXCEL. The general rule followed in the sensitivity analyses for determining the trend equation was to have the value of the coefficient of determination greater than 0.75 and have the trend line follow the data points to give a reasonable fit based on visual inspection. This is as advocated by Forrester that the system dynamics model should not only be subjected to statistical tests but also should be subjected to user judgment.

A synopsis of the results obtained from the sensitivity analyses is presented here. The sensitivity analyses indicated that, for the life-cycle cost estimation, the learning effect is very important, i.e., the learning factor has comparatively more effect on the life-cycle cost estimate than the other parameters. Other parameters that were found to be important were the cost of capital (borrowing rate), factor by which preventive maintenance actions reduce breakdowns and factor by which time affects breakdowns.

Considering the cumulative breakdowns, the learning effect proved to be the most important parameter. The other important parameters were the factor by which preventive maintenance actions reduce breakdowns and the factor by which time affects breakdowns. The borrowing rate (or the cost of capital) did not have any significant effect on the varying maintenance policy.

Individually varying different parameters gave widely different results, i.e., different parameters gave widely different life-cycle costs and cumulative breakdowns. The sensitivity analysis for a 10% variation in all parameters gave a 10% variation in the estimates of the life-cycle cost and a 2% variation in the estimates of the cumulative breakdowns. This indicates that the variation in parameters cancel each other and reduce the variation in the estimates. The sensitivity analysis for various parameters helps in identifying the important parameters with respect to life-cycle cost and cumulative breakdowns.

It was also found that the varying preventive maintenance policy is useful when the system is subjected to higher aging rate (refer Fig. 4.2 and 4.3), i.e., factor by which time affects breakdowns. The preventive maintenance policy tends to catch up with the increasing breakdown rate, thus, arresting a runaway of the number of system breakdowns.

The sensitivity analyses have been performed for the following parameters:

(a) Factor by which time affects breakdown rate
(b) Factor by which preventive maintenance reduces breakdowns
(c) Learning factor
(d) Loss per breakdown
(e) Borrowing rate (cost of capital)
(f) Planned preventive maintenance in year 1
(g) Incremental and radical Technological upgrades
(h) 10% variation in all parameters.

### 4.8.1 Sensitivity to the Factor by Which Time Affects Breakdown Rate

From Table 4.8, it can be seen that a -25% variation in the factor by which time effects breakdowns gave an average fluctuation of -17.67% in the life-cycle cost of the system and -18.58% in cumulative breakdowns. This indicates that variations in the factor by which time affects breakdown rates vary the life-cycle cost and the cumulative breakdowns in a reduced proportion. In table 4.8(a), the simulation results for the runs with preventive maintenance actions in year 1 as 0, 25, 50, 75 and 100 have been tabulated. The simulation runs for all the runs have been attached in Appendix [B].

**Table 4.8** Sensitivity of Model with respect to the Factor by which Time Affects Breakdowns Using Varying Maintenance Policy On Life-cycle Cost Estimation and Cumulative Number of Breakdowns.

ppm = preventive maintenance in year 1.
cbdm = cumulative number of breakdowns.
lcc = life-cycle cost
ftebd = factor by which time affects breakdowns

(a) Simulation results for preventive maintenance actions in year 1 (ppm) = 0, 25, 50, 75, 100.

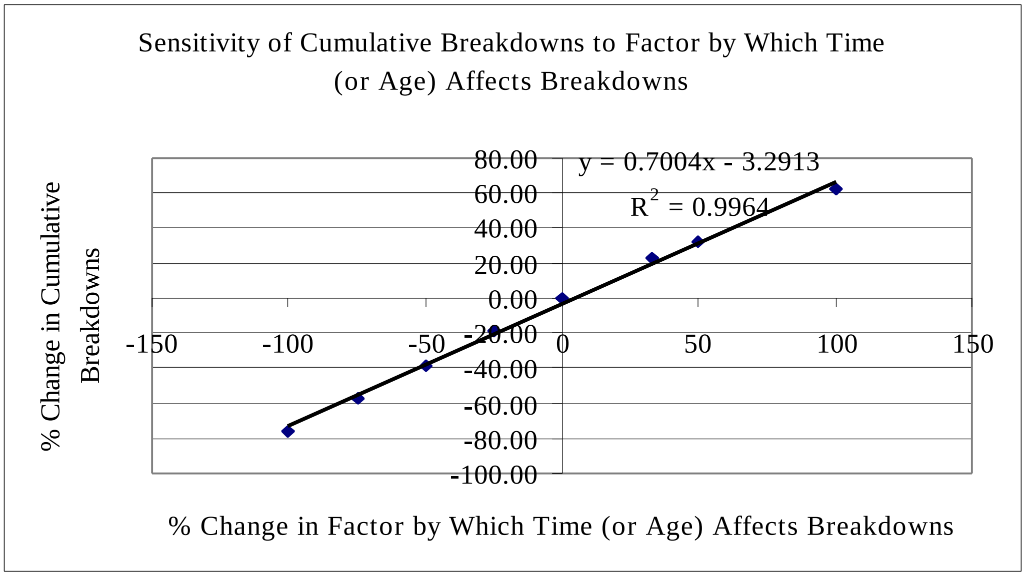
| | Ftebd =0 | | 0.1 | | 0.2 | | 0.3 | | 0.4 | |
|---|---|---|---|---|---|---|---|---|---|---|
| ppm | cbdm | lcc | cbdm | Lcc | cbdm | lcc | cbdm | lcc | cbdm | lcc |
| 0 | 805 | 35090.3 | 1431 | 57885.4 | 2078 | 80556.1 | 2733 | 103329 | 3328 | 124800 |
| 25 | 805 | 35103.8 | 1463 | 58640.5 | 2088 | 80668 | 2815 | 105374 | 3399 | 126788 |
| 50 | 814 | 35459.2 | 1423 | 57696.8 | 2081 | 80393 | 2743 | 103375 | 3403 | 126379 |
| 75 | 813 | 35568.4 | 1466 | 58800.1 | 2068 | 80110.7 | 2692 | 102510 | 3385 | 126241 |
| 100 | 802 | 35584.3 | 1436 | 58452.5 | 2114 | 81660.7 | 2790 | 104560 | 3401 | 126327 |

(b) Life-cycle cost

| % change in parameter → | -100% | -75% | -50% | -25% | 0% | 33% | 50% | 100% |
|---|---|---|---|---|---|---|---|---|
| Ppm = 0 | -71.88 | -53.62 | -35.45 | -17.20 | 0.00 | 20.78 | 28.27 | 54.92 |
| 25 | -72.31 | -53.75 | -36.38 | -16.89 | 0.00 | 20.32 | 30.63 | 57.17 |
| 50 | -71.94 | -54.35 | -36.39 | -18.20 | 0.00 | 22.25 | 28.59 | 57.20 |
| 75 | -71.83 | -53.42 | -36.54 | -18.80 | 0.00 | 23.15 | 27.96 | 57.58 |
| 100 | -71.83 | -53.73 | -35.36 | -17.23 | 0.00 | 20.82 | 28.04 | 54.70 |
| Average (% change in lcc) | -71.96 | -53.77 | -36.02 | -17.67 | 0.00 | 21.46 | 28.70 | 56.32 |

(c) Cumulative breakdowns

| % change in parameter → | -100% | -75% | -50% | -25% | 0% | 33% | 50% | 100% |
|---|---|---|---|---|---|---|---|---|
| ppm = 0 | -75.81 | -57.00 | -37.56 | -17.88 | 0.00 | 21.77 | 31.52 | 60.15 |
| 25 | -76.32 | -56.96 | -38.57 | -17.18 | 0.00 | 20.75 | 34.82 | 62.79 |
| 50 | -76.08 | -58.18 | -38.85 | -19.39 | 0.00 | 24.06 | 31.81 | 63.53 |
| 75 | -75.98 | -56.69 | -38.91 | -20.47 | 0.00 | 25.74 | 30.17 | 63.68 |
| 100 | -76.42 | -57.78 | -37.84 | -17.97 | 0.00 | 21.90 | 31.98 | 60.88 |
| Average (% Change in Cumulative Breakdowns) | -76.12 | -57.32 | -38.35 | -18.58 | 0.00 | 22.84 | 32.06 | 62.21 |



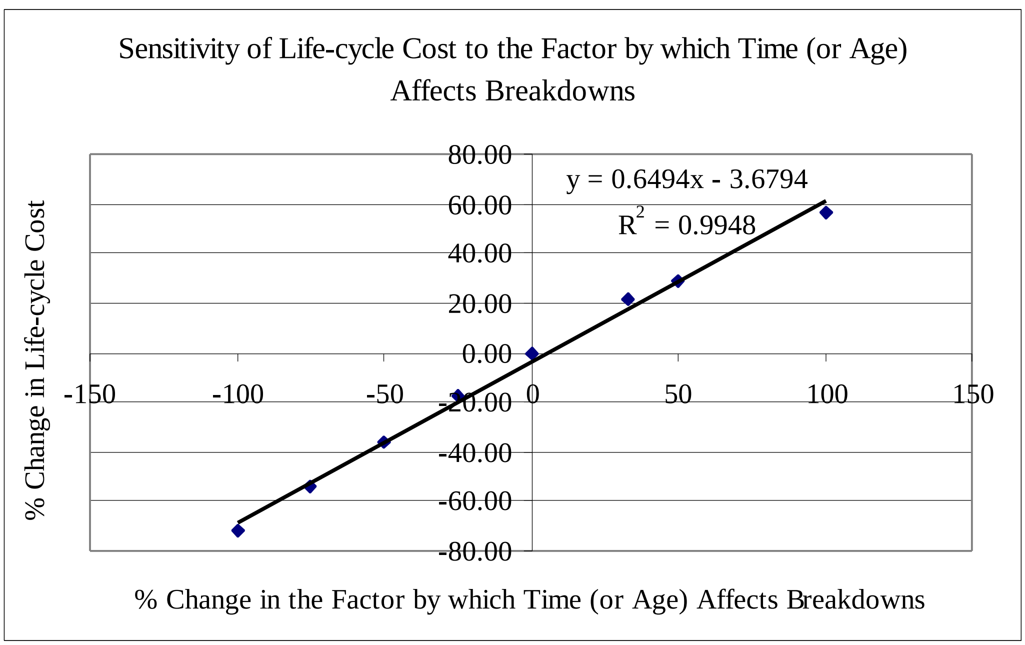




**Figure 4.5** Graphs Representing the Sensitivity of the Cumulative Breakdowns and Life-cycle Cost in Relation to the Variation of the Factor by which Time Affects Breakdowns

Table 4.8 (a) shows data regarding the estimates of life-cycle cost and cumulative breakdowns for various values of the preventive maintenance actions in year 1 and factor by which time affects breakdowns. Table 4.8 (b) shows data regarding the variation in life-cycle cost to variations in the factor by which time affects breakdowns. Table 4.8 (c) shows data regarding the variation in cumulative breakdowns to variations in the factor by which time affects breakdowns.

The variations of both the variables in relation to the variation of the factor by which time affects breakdowns are linear. The equations of the trend line for the variations are (from the figure 4.5):

Life-cycle cost [Table 4.8(b)]: $y = 0.6494x - 3.6794$, where x and y are percent changes in factor by which time affects breakdowns and changes in life-cycle costs.

Cumulative breakdowns [Table 4.8(c)]: $y = 0.7x-3.29$, where x and y are percent changes in factor by which time affects breakdowns and changes in cumulative breakdowns.

In the equations, the slope indicates the sensitivity of the output variable (life-cycle cost and cumulative breakdowns) with respect to the input parameters (factor by which time or age affects breakdowns) while the intercept value indicate the value of the output variable when the input parameter is zero. The intercept value can be regarded as an indicator of the error associated in the relationship between the input parameter and the output variable. Both the equations indicate that, for the hypothetical system, a variation of 1% in the estimation of the parameter would result in approximately 0.7% variation in the estimation of life-cycle cost and cumulative breakdowns.

This analysis can be used during the design stage of the system to study the effect of different aging factors on the life-cycle cost and cumulative breakdowns. In general, the "factor of safety" (see Glossary) used in the design process would be directly proportional to the aging factor, i.e., higher the aging factor, higher would the factor of safety required. If this relationship can be estimated, then the model can be used to simulate for different factors of safety. For example, in this case, a 33% increase in the factor by which time affects breakdowns is expected to cause an increase of about 21% in the life-cycle cost and the cumulative breakdowns. This can be modeled to incorporate the effect on the initial investment required (assuming that the designer is able to relate the factor of safety with the investment required). Thus, the parameter, factor by which time (age) affects breakdowns, can be used for design evaluations.

### 4.8.2 Sensitivity of the Model to the Factor by which Preventive Maintenance Actions Reduces Breakdowns

The results have been tabulated for the runs with planned preventive maintenance in year 1 of 0, 25, 50, 75 and 100. It may be noted that the variations of the factor and that of the life-cycle cost and cumulative breakdowns move in opposite directions. An increase in the factor by which preventive maintenance reduces breakdowns results in a decrease in the life-cycle cost and the cumulative breakdowns. This is logical since the more effective the maintenance process, the number of breakdowns and opportunity loss (and, hence, the life-cycle cost) will decrease. For example, a variation of -25% in the factor by which preventive maintenance reduces breakdowns gave an average change of 15.48% of the cumulative breakdowns and a change of 10.76% in the life cycle cost.

**Table 4.9** Sensitivity of the Model to the Factor by which Preventive Maintenance Actions Reduces Breakdowns for Varying Policy in terms of the Life-cycle Costs and Cumulative Breakdowns.

(a) Simulations results for preventive maintenance actions in year 1 (ppm) = 0, 25, 50, 75, 100.

ppm = preventive maintenance in year 1.
cbdm = cumulative number of breakdowns.
lcc = life-cycle cost.
fprbd = factor by which preventive maintenance reduces breakdowns.

| fprbd= 0.5 | | | 1 | | 1.5 | | 2 | |
|---|---|---|---|---|---|---|---|---|
| | cbdm | lcc | cbdm | lcc | cbdm | lcc | cbdm | lcc |
| ppm = 0 | 1983 | 75113 | 1496 | 62082.3 | 1209 | 53605.3 | 1039 | 48203.6 |
| 25 | 1997 | 75455.8 | 1525 | 62851.3 | 1221 | 53510.7 | 1078 | 48981.3 |
| 50 | 2013 | 76072.8 | 1484 | 61695.4 | 1215 | 53312.9 | 1056 | 48127.7 |
| 75 | 1989 | 75612 | 1479 | 61784.4 | 1221 | 53424 | 1035 | 47936 |
| 100 | 1995 | 76153.1 | 1498 | 62487.8 | 1236 | 54230.6 | 1077 | 48793.4 |

(b) Life-cycle Cost

% Change in the Factor by which Preventive Maintenance Reduces Breakdowns

| | -75% | -50% | -25% | 0% | 33% | 50% | 100% |
|---|---|---|---|---|---|---|---|
| ppm = 0 | 55.82 | 28.79 | 11.21 | 0.00 | -10.08 | -13.65 | -22.36 |
| 25 | 54.05 | 28.32 | 9.25 | 0.00 | -8.46 | -14.86 | -22.07 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 50 | 58.06 | 28.19 | 10.77 | 0.00 | -9.73 | -13.59 | -21.99 |
| 75 | 57.74 | 28.89 | 11.45 | 0.00 | -10.27 | -13.53 | -22.41 |
| 100 | 56.07 | 28.07 | 11.14 | 0.00 | -10.03 | -13.21 | -21.92 |
| Average (% change in lcc) | 56.35 | 28.45 | 10.76 | 0.00 | -9.71 | -13.77 | -22.15 |

(c) Cumulative breakdowns

% Change in Factor by which Preventive Maintenance Reduces Breakdowns

| | -75% | -50% | -25% | 0% | 33% | 50% | 100% |
|---|---|---|---|---|---|---|---|
| ppm = 0 | 90.86 | 43.98 | 16.36 | 0.00 | -14.06 | -19.18 | -30.55 |
| 25 | 85.25 | 41.47 | 13.27 | 0.00 | -11.71 | -19.93 | -29.31 |
| 50 | 90.63 | 40.53 | 15.06 | 0.00 | -13.09 | -18.13 | -28.84 |
| 75 | 92.17 | 42.90 | 17.97 | 0.00 | -15.23 | -17.44 | -30.02 |
| 100 | 85.24 | 39.09 | 14.76 | 0.00 | -12.86 | -17.49 | -28.10 |
| Average (% change in cbdm) | 88.83 | 41.59 | 15.48 | 0.00 | -13.39 | -18.44 | -29.36 |

The variations of both the variables in relation to the variations of the factor by which preventive maintenance reduces breakdowns are not linear. They fit a quadratic equation as shown in the figure 4.6. The equations of the trend line for the variations are (from the graphs):

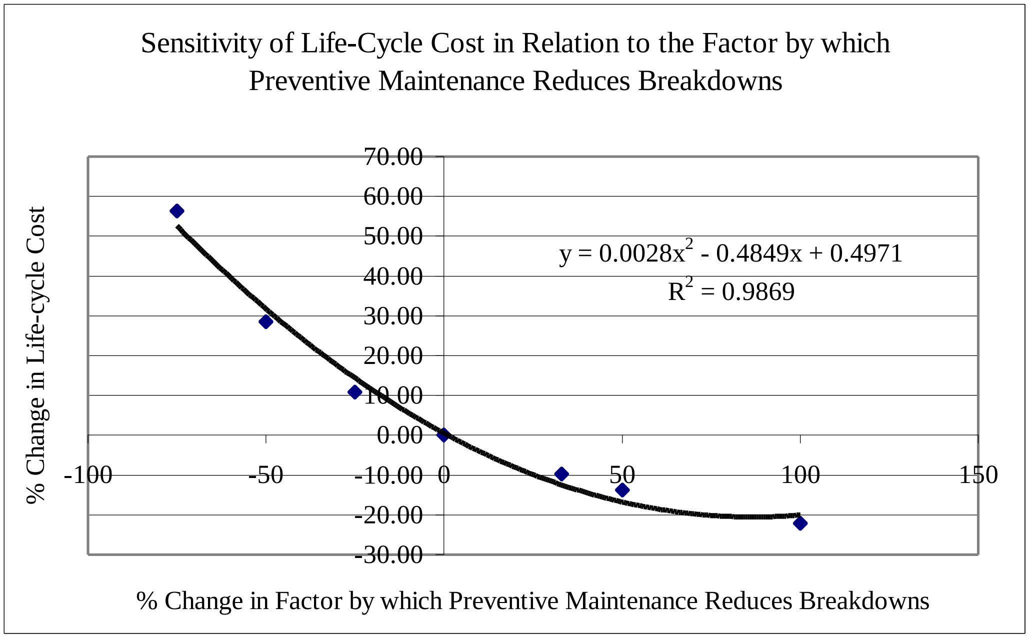
Life-cycle cost [Table 4.9(b)]: $y = 0.0047x^2 - 0.7271x + 0.6428$, where x and y are the percent changes in factor by which preventive maintenance reduces breakdowns and changes in life-cycle costs respectively.

Cumulative breakdowns [Table 4.9(c)]: $y = 0.0028x^2 - 0.4849x + 0.4971$, where x and y are the percent changes in factor by which preventive maintenance reduces breakdowns and changes in cumulative breakdowns respectively.

The regression graph indicates that as the value of x (% change in the factor by which preventive maintenance reduces breakdowns) changes in the positive direction, the effect on the life-cycle cost and the cumulative breakdowns flattens. In the negative direction, it can be seen that as x increases in the negative direction, the effect on the life-cycle cost and the cumulative breakdowns increases at a greater rate. It can be concluded that it is important to keep a frequent check on the maintenance process for effectiveness so that the system life-cycle cost and the breakdown rate do not go out of control. Also the graph indicates that the effectiveness of the maintenance process cannot be improved beyond a certain point irrespective of the improvements are made to the maintenance process. For example, here both the life-cycle cost and the cumulative breakdowns give only a 20-30% decrease for a 100% increase in the factor by which preventive maintenance reduces breakdowns.

This is because, in the regression equation, the $x^2$ term is always positive. When x is positive, due to the negative sign of the x term, the value works out lower than when x is negative. Hence the subdued graph on the positive side of the x-axis.

This analysis is useful in determining the maintenance crew skill level required for the system. A lower skill level would result in reduced effectiveness of preventive maintenance actions and vice-versa. For different values of the factors by which preventive maintenance affects breakdowns, we can determine the effect on the life-cycle cost and the cumulative breakdowns. This can be changed until the target life-cycle cost or the maximum tolerable cumulative breakdowns are reached. An iterative algorithm can be developed to perform the same as in [20]. This is a potential future research topic.



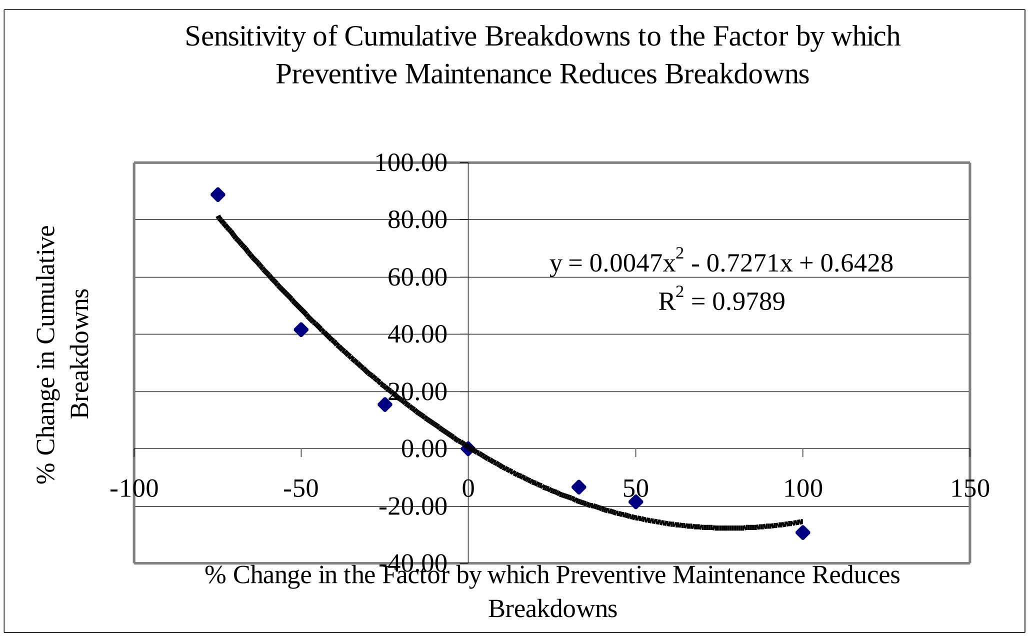




**Figure 4.6** Sensitivity of the Life-cycle Cost and Cumulative Breakdowns in Relation to the Factor by which Preventive Maintenance Reduces Breakdowns

### 4.8.3 Sensitivity of the model to the learning factor

The results have been tabulated for the runs with planned preventive maintenance in year 1 of 0, 25, 50, 75 and 100. It may be noted that the variations of the learning factor and that of the life-cycle cost and cumulative breakdowns move in opposite directions. An increase in the learning factor results in a decrease in life-cycle cost and cumulative breakdowns. This is logical since a faster learning process among the crew members results in a faster reduction in the number of breakdowns and opportunity loss (hence also the life-cycle cost). This indicates to management the effect on breakdowns by reducing the skill level of the work force.

**Table 4.10** Simulation Results of the Sensitivity of the Model in relation to Variations of the Learning Factor

ppm = preventive maintenance in year 1.
cbdm = cumulative number of breakdowns.
lcc = life-cycle cost.

(a) Simulations results for preventive maintenance actions in year 1 (ppm) = 0, 25, 50, 75, 100.

Learning curve

| | 50% | | 70% | | 90% | | 100% | |
|---|---|---|---|---|---|---|---|---|
| ppm | Cbdm | Lcc | Cbdm | lcc | cbdm | lcc | cbdm | lcc |
| 0 | 497 | 32192.9 | 971 | 47734 | 1502 | 62697.9 | 1745 | 68963.5 |
| 25 | 504 | 32473.1 | 974 | 47915.6 | 1510 | 62786.6 | 1758 | 69150.3 |
| 50 | 509 | 33064.7 | 958 | 47447.2 | 1503 | 62624.3 | 1774 | 69801.4 |
| 75 | 512 | 32975.1 | 957 | 47668.8 | 1500 | 62616.5 | 1757 | 69389.4 |
| 100 | 522 | 33941.5 | 963 | 48218 | 1528 | 63714.9 | 1757 | 69800.6 |

(b) Life-cycle Cost

% Change in Learning

| ppm | -50 | -44 | -30 | -28 | -22 | -10 | 0 | 40 | 80 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | -53.32 | -48.65 | -30.78 | -32.56 | -23.87 | -9.09 | 0.00 | 48.27 | 94.76 | 114.22 |
| 25 | -52.87 | -48.61 | -31.97 | -30.72 | -25.83 | -8.29 | 0.00 | 44.34 | 94.60 | 112.19 |
| 50 | -52.38 | -47.18 | -32.47 | -29.48 | -25.10 | -9.84 | 0.00 | 41.81 | 89.32 | 109.98 |
| 75 | -53.30 | -48.42 | -32.85 | -30.45 | -25.83 | -9.47 | 0.00 | 43.79 | 93.86 | 114.14 |
| 100 | -52.85 | -47.44 | -31.29 | -31.38 | -23.41 | -10.29 | 0.00 | 45.73 | 90.27 | 112.10 |
| Average | -52.94 | -48.06 | -31.87 | -30.92 | -24.81 | -9.40 | 0.00 | 44.79 | 92.56 | 112.53 |

(c) Cumulative Breakdowns

% Change in Learning

| ppm | -50 | -44 | -30 | -28 | -22 | -10 | 0 | 40 | 80 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | -71.52 | -66.91 | -44.36 | -48.82 | -35.35 | -13.93 | 0.00 | 95.37 | 202.21 | 251.11 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 25 | -71.33 | -66.62 | -44.60 | -48.25 | -35.50 | -14.11 | 0.00 | 93.25 | 199.60 | 248.81 |
| 50 | -71.31 | -66.13 | -46.00 | -46.87 | -36.26 | -15.28 | 0.00 | 88.21 | 195.28 | 248.53 |
| 75 | -70.86 | -65.87 | -45.53 | -46.50 | -36.20 | -14.63 | 0.00 | 86.91 | 189.66 | 243.16 |
| 100 | -70.29 | -65.84 | -45.19 | -45.79 | -36.98 | -13.03 | 0.00 | 84.48 | 192.72 | 236.59 |
| Average | -71.06 | -66.27 | -45.13 | -47.25 | -36.06 | -14.19 | 0.00 | 89.65 | 195.90 | 245.64 |

As shown by the figures, the equation describing the relationship between the variations of learning and that of the life-cycle cost and cumulative breakdowns is non-linear (or quadratic). The equations are as follows:

Life-cycle cost [Table 4.10(b)]:
$y = 0.0003x^2 + 1.1046x + 0.5194$, where x and y are the percent changes in the learning factor and the life-cycle costs respectively.

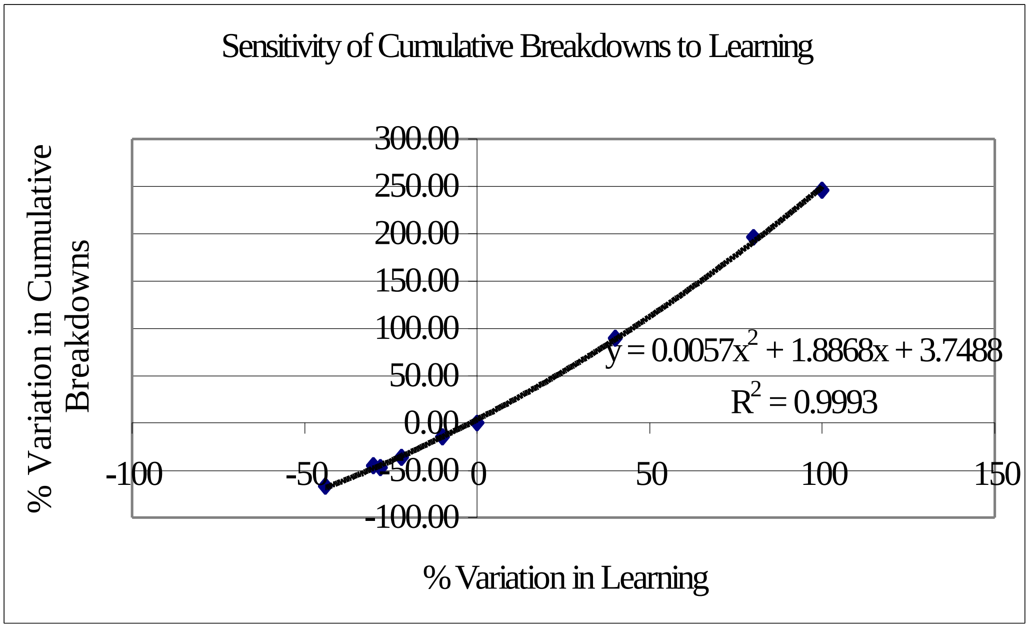
Cumulative breakdowns [Table 4.10(c)]:
$y = 0.0057x^2 + 1.8868x + 3.7488$, where x and y are the percent changes in the learning factor and cumulative breakdowns respectively.

In the regression equation, the coefficients of $x^2$ and x indicate the sensitivity of the variable to the parameter. In this case, since the coefficients of $x^2$ is smaller than the coefficients of x and they both have similar signs, the graph shows a tendency to go out of control as the skill level reduces, i.e., the crew requires more time to learn. It can also be seen that the curve flattens beyond a certain point as the crew's skill level increases and the learning process is faster which indicates that the life-cycle cost and the cumulative breakdowns can be controlled by increasing the skill of the crew. But it cannot be eliminated or reduced beyond a certain point.

It may be noted that the changes in the learning factor affect the cumulative number of breakdowns more than the life-cycle cost. This analysis helps to determine the effectiveness of training programs on system breakdowns. To incorporate the effect of future training programs in the model, the learning factor should be written as a function of time. The skill level of the labor force will have an influence on the operational cost of the system. This relationship may also be considered in the model in the form of operational cost = f {Skill level of the work force}.

The results indicate that learning affects breakdowns more than the life-cycle cost. This is because, learning helps reduce breakdowns in future and thus results in reduced expenses later in the life-cycle. But due to the discounting factor, the effect is reduced and hence the life-cycle cost is not affected as much as the cumulative breakdowns.

It is accepted here that training improves the learning process and thus helps improve the maintenance process. The manipulation of this parameter is useful in cases, such as high mission critical systems, where the cumulative breakdowns are considered more important than the life-cycle cost.



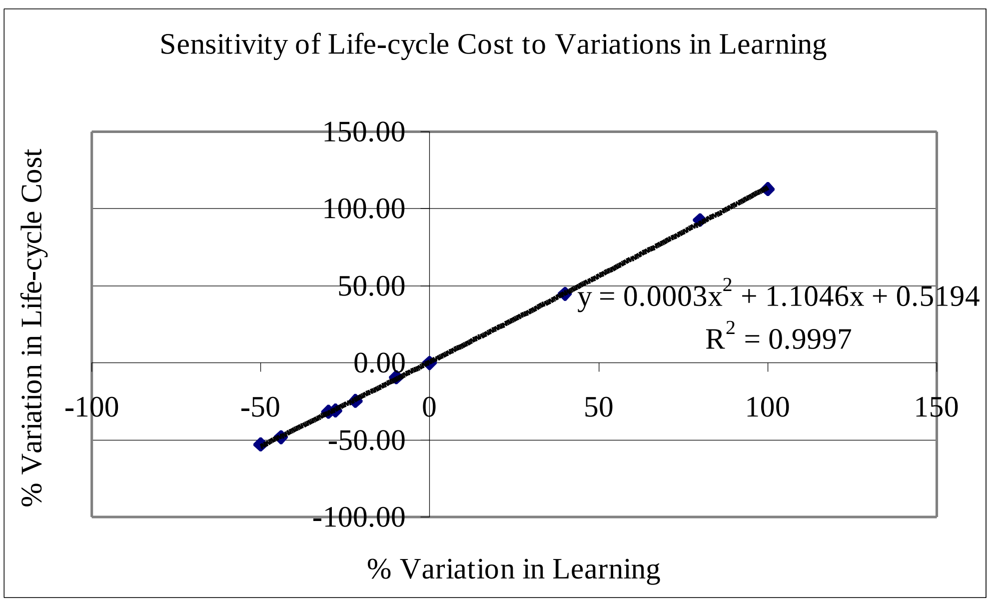




**Figure 4.7** Sensitivity of the Life-cycle Cost and Cumulative Breakdowns in Relation to the Factor by which Preventive Maintenance Reduces Breakdowns

### 4.8.4 Sensitivity of the Model to the Loss per Breakdown

The results have been tabulated for the runs with planned preventive maintenance in year one of 0, 25, 50, 75 and 100. It is observed that an increase in the average loss per breakdown results in a decrease in the cumulative breakdowns. This is as expected since the model prescribes a preventive maintenance policy depending upon the loss per breakdown for a given mission criticality. When the opportunity loss in a given period is greater than the average opportunity loss, the preventive maintenance actions in the next period for a given mission criticality would be increased. The loss per breakdown in conjunction with the mission criticality drives the preventive maintenance policy of the system.

**Table 4.11** Simulation Results of the Sensitivity of the Model in Relation to Changes in the Loss per Breakdown

ppm = preventive maintenance in year 1.
cbdm = cumulative number of breakdowns.
lcc = life-cycle cost.
lossbd = average loss per breakdown.

(a) Simulations results for preventive maintenance actions in year 1 (ppm) = 0, 25, 50, 75, 100.

| | lossbd = 5 | | lossbd = 20 | | lossbd = 35 | |
|---|---|---|---|---|---|---|
| ppm | cbdm | lcc | cbdm | lcc | cbdm | lcc |
| 0 | 2289 | 42499 | 1750 | 69149.8 | 1674 | 87977.5 |
| 25 | 2302 | 42775.4 | 1790 | 70151 | 1679 | 87953.8 |
| 50 | 2313 | 43178.1 | 1741 | 68950 | 1669 | 87651.9 |
| 75 | 2291 | 42920.2 | 1734 | 69003.4 | 1657 | 87346.6 |
| 100 | 2293 | 43378.7 | 1758 | 69800 | 1697 | 88942.9 |

| | lossbd = 50 | | lossbd = 65 | | lossbd = 80 | | lossbd = 95 | |
|---|---|---|---|---|---|---|---|---|
| ppm | cbdm | lcc | cbdm | lcc | cbdm | lcc | cbdm | lcc |
| 0 | 1657 | 106116 | 1616 | 122376 | 1621 | 140154 | 1638 | 159610 |
| 25 | 1704 | 107996 | 1662 | 124820 | 1675 | 143249 | 1631 | 158763 |
| 50 | 1655 | 105776 | 1651 | 123885 | 1637 | 141494 | 1656 | 160288 |
| 75 | 1630 | 105068 | 1630 | 122955 | 1634 | 140857 | 1606 | 156234 |
| 100 | 1676 | 106800 | 1640 | 123433 | 1621 | 139950 | 1641 | 159175 |

(b) Life-cycle cost

% Change in Loss per Breakdown

| Ppm | -95 | -75 | -43 | -30 | -18 |
|---|---|---|---|---|---|
| 0 | -73.37 | -38.54 | -21.40 | -17.09 | -12.68 |
| 25 | -73.06 | -39.02 | -20.24 | -18.56 | -12.87 |
| 50 | -73.06 | -37.38 | -21.34 | -17.13 | -12.45 |
| 75 | -72.53 | -37.80 | -21.00 | -16.87 | -12.71 |
| 100 | -72.75 | -37.85 | -21.52 | -16.72 | -11.80 |
| Average | -72.95 | -38.12 | -21.10 | -17.27 | -12.50 |

| Ppm | 0 | 18 | 30 | 43 | 75 | 90 |
|---|---|---|---|---|---|---|
| 0 | 0.00 | 13.88 | 15.32 | 20.62 | 27.23 | 50.41 |
| 25 | 0.00 | 10.83 | 15.58 | 22.79 | 25.38 | 47.01 |
| 50 | 0.00 | 13.28 | 17.12 | 20.68 | 27.12 | 51.54 |
| 75 | 0.00 | 10.92 | 17.02 | 20.29 | 26.58 | 48.70 |
| 100 | 0.00 | 13.74 | 15.57 | 20.08 | 27.43 | 49.04 |
| Average | 0.00 | 12.53 | 16.12 | 20.89 | 26.75 | 49.34 |

(c) Cumulative breakdowns

% Change in Loss per Breakdown

| Ppm | -95 | -75 | -43 | -30 | -18 |
|---|---|---|---|---|---|
| 0 | 39.74 | 30.80 | 4.54 | 1.03 | -0.31 |
| 25 | 41.14 | 28.60 | 6.61 | -1.47 | -0.78 |
| 50 | 39.67 | 32.85 | 4.31 | 0.85 | 0.86 |
| 75 | 42.65 | 32.12 | 4.65 | 1.66 | -0.24 |
| 100 | 39.73 | 30.43 | 3.59 | 1.25 | 1.17 |
| Average | 40.59 | 30.96 | 4.74 | 0.66 | 0.14 |

| Ppm | 0 | 18 | 30 | 43 | 75 | 90 |
|---|---|---|---|---|---|---|
| 0 | 0.00 | 1.05 | -2.47 | -1.02 | -4.34 | -1.15 |
| 25 | 0.00 | -2.63 | -2.46 | 1.49 | -6.20 | -4.28 |
| 50 | 0.00 | 1.16 | -0.24 | -0.84 | -4.14 | 0.06 |
| 75 | 0.00 | -1.71 | 0.00 | -1.63 | -4.44 | -1.47 |
| 100 | 0.00 | 1.23 | -2.15 | -1.24 | -3.47 | -2.09 |
| Average | 0.00 | -0.18 | -1.47 | -0.65 | -4.52 | -1.79 |

As shown by the graphs, the equation describing the relationship between the variations of loss per breakdown and that of life-cycle cost is linear (or quadratic). The relationship between the variation in loss per breakdown and that of cumulative breakdown is non-linear. The equations are as follows:

Life-cycle cost [Table 4.11(b)]:

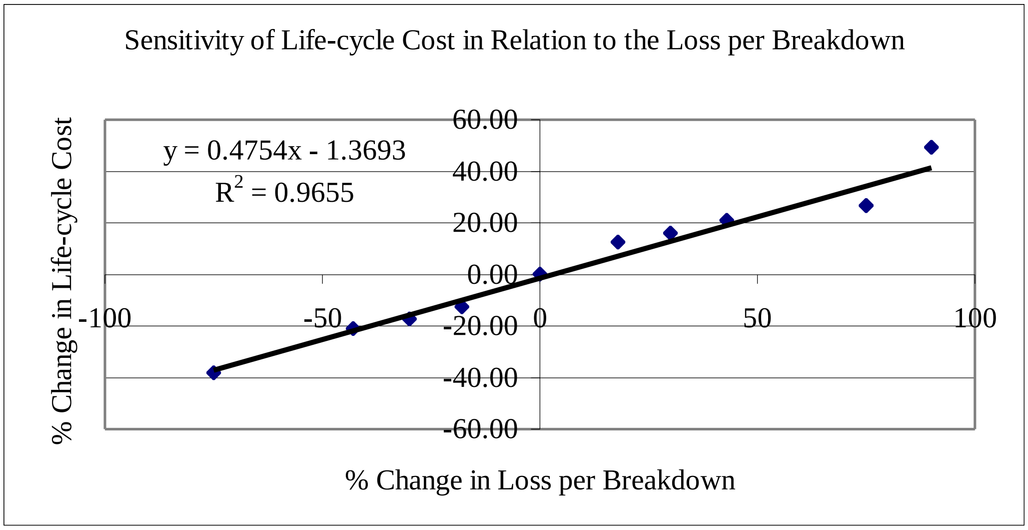
$y = 0.4754x - 1.3693$, where x and y are the percent changes of the loss per breakdown and life-cycle costs respectively.

Cumulative breakdowns [Table 4.11(c)]:

$y = -3*10^{-5}.x3 + 0.0029x^2 - 0.0329x - 2.1261$, where x and y are the percent changes in the loss per breakdown and in cumulative breakdowns respectively.

It may be noted that the variations in the average loss per breakdown affect the life-cycle cost less than the cumulative number of breakdowns. On an average, an increase (or decrease) of 1% of the loss per breakdown would result in approximately 0.5% increase (or decrease) of the life-cycle cost. It is observed from the simulation runs that the coefficients of the regression equation are all small. This indicates that for smaller variations of x (% change in the loss per breakdown), the variations of the life-cycle cost and cumulative breakdowns will also be smaller. This is also indicated by the graph. The graph also indicates that as negative variation in the value of the loss per breakdown is increased, then the loss per breakdown also increases rapidly. In general, the variations in the cumulative breakdowns in around 5% when the variation in the loss per breakdown is between –50% and +100%. It is important not to overestimate the loss per breakdown by more than 40% in order to get good estimates of cumulative breakdowns and the life-cycle cost. The purpose of this analysis is to give management a fair idea of the accuracy required to quantify the average loss per breakdown.

In figure below for sensitivity of cumulative breakdowns, the polynomial equations of second and third power gave good statistical fits ($R^2 > 0.75$) but gave were unreasonable fit from the visual point of view. Hence the fourth degree polynomial equation has been used. The life-cycle cost sensitivity analysis gives a linear trend. It can be seen that for a varying policy the life-cycle cost increases linearly with the loss per breakdown at a rate of approximately 0.48 per unit.



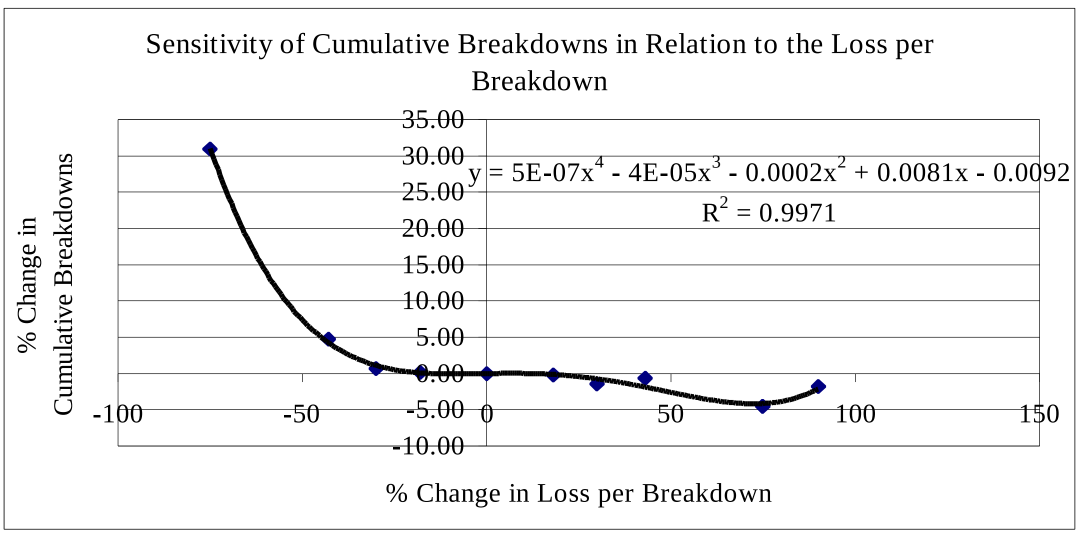




**Figure 4.8** Sensitivity of Life-cycle Cost and Cumulative Breakdowns in Relation to the Loss per Breakdown

### 4.8.5 Sensitivity of the Model to Changes in the Borrowing Rate

The analysis of the sensitivity to the borrowing rate has been performed to determine the effect of interest rate on the life-cycle cost and also on the number of breakdowns. The discounting of the future cash flows might change the optimum maintenance policy determination. For example, a system may have a low life-cycle cost but very large number of breakdowns (and, therefore, unavailability). This can also have an effect on the inventory holding cost. The results have been tabulated, as for all the above analyses, for runs with planned preventive maintenance in year 1 of 0, 25, 50, 75 and 100.
ppm = preventive maintenance in year 1.
cbdm = cumulative number of breakdowns.
lcc = life-cycle cost.

**Table 4.12** Simulation Results of the Sensitivity of the Model in Relation to Changes in the Borrowing Rate.

(a) Simulations results for preventive maintenance actions in year 1 (ppm) = 0, 25, 50, 75, 100.

Borrowing Rate

| | 0% | | 5% | | 10% | |
|---|---|---|---|---|---|---|
| ppm | cbdm | lcc | cbdm | lcc | cbdm | lcc |
| 0 | 1749 | 131370 | 1752 | 94495.1 | 1755 | 69222.4 |
| 25 | 1762 | 131969 | 1792 | 95945.5 | 1762 | 69265.9 |
| 50 | 1778 | 133125 | 1743 | 94139.3 | 1755 | 69037.9 |
| 75 | 1761 | 132404 | 1736 | 94220.7 | 1744 | 68905.1 |
| 100 | 1761 | 132735 | 1761 | 95197.1 | 1782 | 70139.3 |

Borrowing Rate

| 15% | | 20% | | 25% | |
|---|---|---|---|---|---|
| cbdm | lcc | cbdm | lcc | cbdm | lcc |
| 1758 | 51848.3 | 1727 | 39303.4 | 1731 | 30623.4 |
| 1805 | 52615.1 | 1764 | 39920.6 | 1784 | 30900.5 |
| 1757 | 51705.1 | 1758 | 39533.4 | 1745 | 31044.8 |
| 1731 | 51622.9 | 1740 | 39493.3 | 1748 | 30739.7 |
| 1783 | 52219 | 1754 | 39621.6 | 1740 | 30678.1 |

(b) Changes in the Life-cycle cost

% Change in Borrowing Rate →

| ppm | -100 | -50 | -33 | -25 | -20 |
|---|---|---|---|---|---|
| 0 | 39.02 | 36.51 | 33.51 | 31.92 | 28.34 |
| 25 | 37.55 | 38.52 | 31.65 | 31.80 | 29.19 |
| 50 | 41.41 | 36.36 | 33.52 | 30.79 | 27.34 |
| 75 | 40.53 | 36.74 | 33.48 | 30.71 | 28.48 |
| 100 | 39.43 | 35.73 | 34.32 | 31.79 | 29.15 |
| Average | 39.59 | 36.77 | 33.29 | 31.40 | 28.50 |

% Change in Borrowing Rate →

| ppm | 0 | 25 | 33 | 50 | 100 |
|---|---|---|---|---|---|
| 0 | 0.00 | -22.08 | -24.20 | -25.10 | -43.22 |
| 25 | 0.00 | -22.60 | -24.13 | -24.04 | -42.37 |
| 50 | 0.00 | -21.47 | -23.54 | -25.11 | -42.74 |
| 75 | 0.00 | -22.16 | -23.50 | -25.08 | -42.68 |
| 100 | 0.00 | -22.57 | -24.12 | -25.55 | -43.51 |
| Average | 0.00 | -22.18 | -23.90 | -24.97 | -42.90 |

(c) Changes in the Cumulative Breakdowns

% Change in Borrowing Rate →

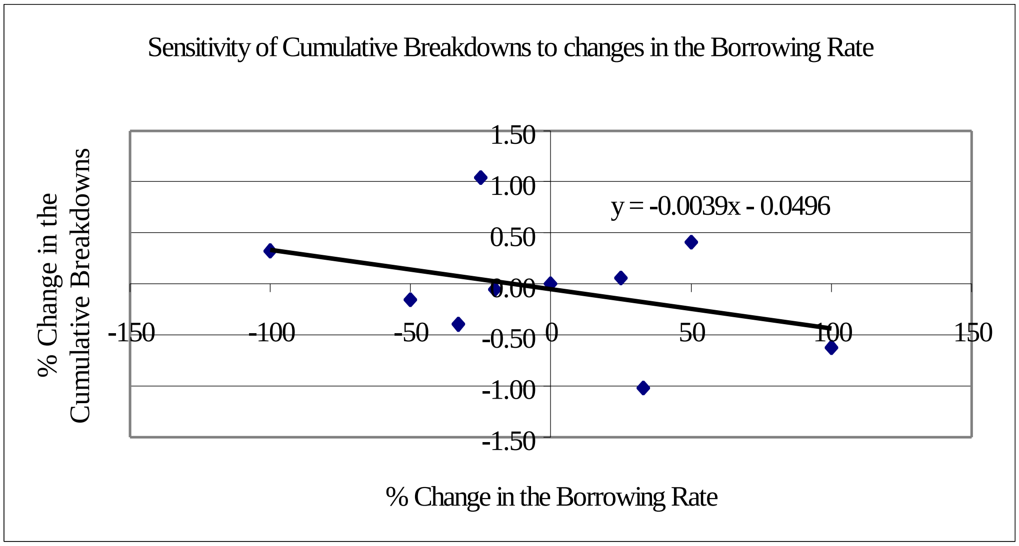
| ppm | -100 | -50 | -33 | -25 | -20 |
|---|---|---|---|---|---|
| 0 | -0.17 | -0.17 | -0.17 | 1.80 | -0.23 |
| 25 | -1.67 | 1.70 | -2.38 | 2.32 | -1.12 |
| 50 | 2.01 | -0.68 | -0.11 | -0.06 | 0.74 |
| 75 | 1.44 | -0.46 | 0.75 | -0.52 | -0.46 |
| 100 | 0.00 | -1.18 | -0.06 | 1.65 | 0.80 |
| Average | 0.32 | -0.16 | -0.39 | 1.04 | -0.05 |

% Change in Borrowing Rate →

| ppm | 0 | 25 | 33 | 50 | 100 |
|---|---|---|---|---|---|
| 0 | 0.00 | 0.23 | -1.76 | 0.17 | -1.60 |
| 25 | 0.00 | 1.13 | -2.27 | 2.44 | 0.11 |
| 50 | 0.00 | -0.74 | 0.06 | 0.11 | 0.17 |
| 75 | 0.00 | 0.46 | 0.52 | -0.75 | -0.23 |
| 100 | 0.00 | -0.80 | -1.63 | 0.06 | -1.57 |
| Average | 0.00 | 0.06 | -1.02 | 0.41 | -0.62 |

The regression equation for the sensitivity of life-cycle cost to the borrowing rate is:
$y = 5*10^{-5}x^3 - 0.0007x^2 - 0.8636x + 5.9246$.

The values of the coefficients of $x^3$, $x^2$ and x indicate that the life-cycle cost is more sensitive to lower variations of the borrowing rate than to higher variations of the borrowing rate. In other words, at lower changes in the borrowing rate, the life-cycle cost is very sensitive. The intercept of 5.9246 indicates the error involved in the regression equation when variation in the borrowing rate is zero. But as the borrowing rate increases, the trend flattens. Even a 100% increase or decrease results in only a 40% decrease or increase in the life-cycle cost. As expected, the life-cycle cost decreases with an increase (or positive change) in the borrowing rate due to higher discounting. The discounting rates and the life-cycle cost move in opposite directions. In general, at lower levels of changes in the borrowing rate, a 1% change in the borrowing rate results in about 0.9% in the life-cycle cost. For the cumulative breakdowns, the borrowing rate does not have a significant effect and also no trend. Also the changes in the borrowing rate do not indicate a significant change in terms of cumulative number of preventive maintenance actions required throughout the life-cycle of the system. This indicates that the borrowing rate affects the life-cycle cost but does not affect the maintenance policy significantly. The effect of the borrowing rate on the maintenance policies will be important only in cases where the inventory holding cost is high. A higher inventory holding cost would result in a higher opportunity loss and thus more preventive maintenance actions would be scheduled by the varying maintenance policy logic.



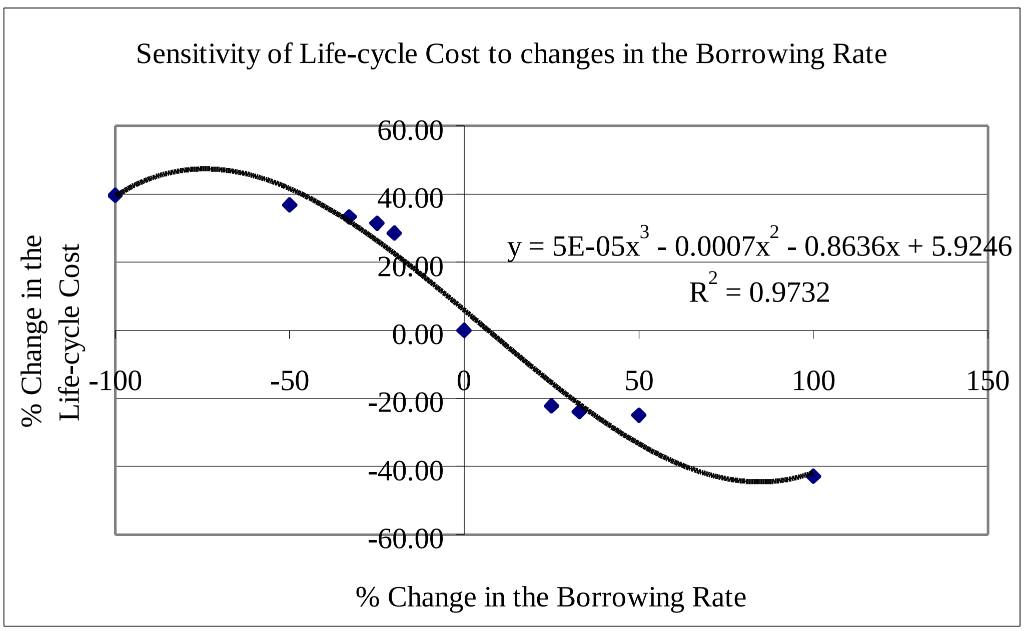




**Figure 4.9** Sensitivity of Life-cycle Cost and Cumulative Breakdowns to Changes in the Borrowing Rate

### 4.8.6 Sensitivity of the Model to the Planned Preventive Maintenance Actions in Year 1 (ppm)

As mentioned in Chapter 3, the preventive maintenance plan for the initial period has to be decided by the user depending upon the designer's recommendation. However, it may be noted that due to lack of accurate information about breakdowns of a new system, the initial preventive maintenance policy may be a challenging task. It depends upon whether the maintenance manager prefers to have a conservative maintenance policy initially or prefers a liberal one of more number of maintenance actions. The simulation runs indicate that the choice between a conservative and a liberal policy depends upon the various model parameters. For example, from the simulation runs, it can be seen that for a borrowing rate of 0% (no interest on capital) it is better to have a conservative initial preventive maintenance policy (start with lower preventive maintenance actions in year 1). This is due to the fact that as the number of initial preventive maintenance actions increases, the life-cycle cost also increases. However, there is a decreasing trend in the cumulative breakdowns as the initial preventive maintenance actions increase. The regression equations are:

(a) Life-cycle cost: y = 2.6523x + 132186

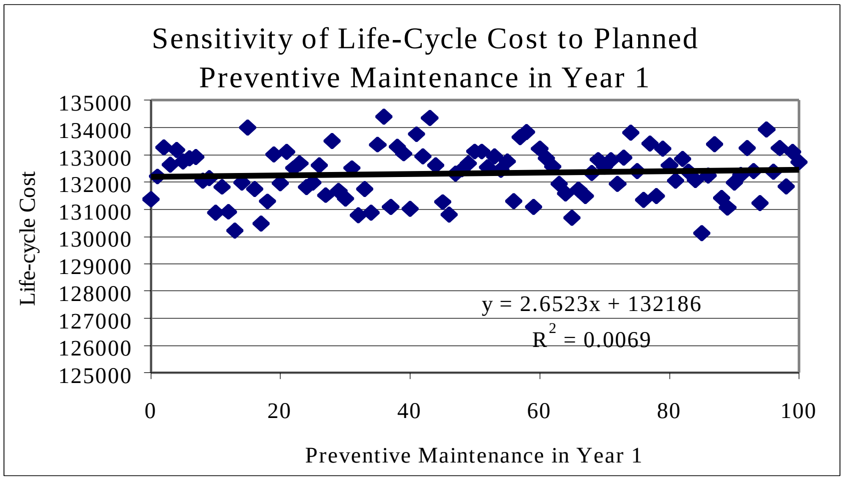
where x and y are the number of preventive maintenance actions in year 1 and the life-cycle cost respectively. The intercept indicates the estimate of the life-cycle cost when zero preventive maintenance actions are performed in the first year. A very low value of $R^2$ is due to the random number of breakdowns occurring throughout the life-cycle.

(b) Cumulative Breakdowns: y = -0.0417x + 1765.4

where x and y are the cumulative number of breakdowns in the life-cycle and the life-cycle cost respectively. The intercept is the estimate of the cumulative number of breakdowns when no preventive maintenance actions are performed in the first year.

From the slopes of the trend equations, it can be seen that cumulative breakdowns is less sensitive to the initial preventive maintenance plan than the life-cycle cost to the initial preventive maintenance plan. The decreasing trend in the number of breakdowns gives a very simple but important result that a system, which is maintained adequately from the initial period, performs better in the long run. This analysis is a good trade-off tool for management to choose among various maintenance philosophies depending upon the mission criticality of the system.

The simulation results have been attached in Appendix [B]. These simulation runs also indicate that any errors introduced into the maintenance model due to the errors in the initial preventive maintenance policy do not affect as much as in the case of fixed maintenance policy. Even though the simulation results seem to give very unclear results, it may be noted that the range (difference between the highest and the lowest values of the life-cycle cost) is not large. The inherent correction mechanism due to the feedback loop helps in correcting the errors depending upon the performance of the system. Hence, the plots are horizontal. Here, error refers to the excessive preventive maintenance actions performed in the first year.



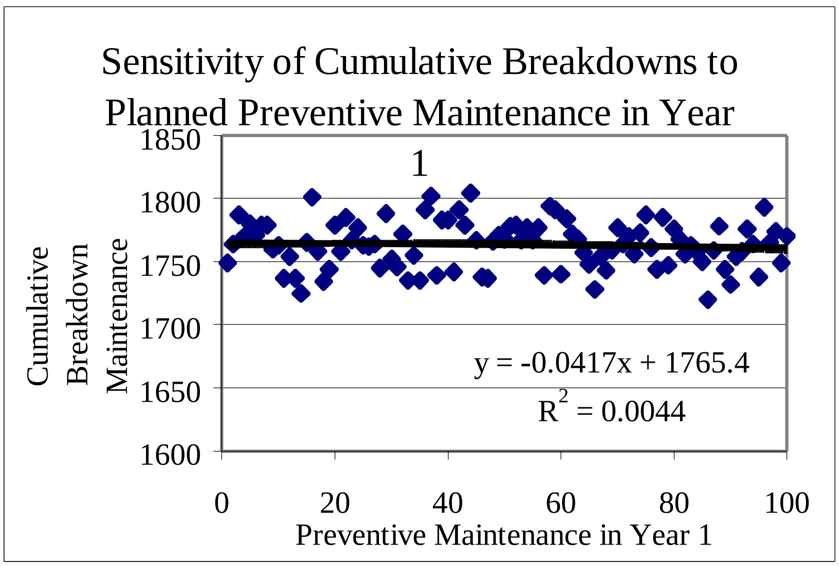




**Figure 4.10** Sensitivity of Cumulative Breakdowns and Life-cycle Cost to Planned Preventive Maintenance in Year 1

### 4.8.7 Sensitivity to Incremental and Radical Technological Upgrades

The impact of incremental and radical technological upgrades [see Glossary] was performed to study the importance of each type of upgrade. In the simulation for the case of incremental technological upgrades, it was considered that an incremental upgrade would be performed every period and that every upgrade would reduce average breakdowns by 10%. The other case was for a radical technological upgrade. For this case, it was considered that a radical technological upgrade would occur every 5 years and would reduce average breakdowns by 41% (when the average breakdown is reduced by 10% every period, the net reduction obtained in 5 years is 41%). The simulation runs for starting preventive maintenance policy of 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 have been attached in Appendix [C].

In practice, there would be both incremental and radical upgrades throughout the life-cycle. So the actual cost of technological upgrades would lie between the values of incremental and radical upgrade policies. The rigid policies for technological upgrades are defined by the extreme conditions.

It can be seen from the results that incremental technological upgrade policy was better than an equivalent radical upgrade policy. Incremental upgrades gave a lower life-cycle cost as well as a lower cumulative breakdowns. This indicates that *continuous improvement* of the system helps in reducing the breakdowns than equivalent discrete ones. The incremental upgrades help in reducing breakdowns every year and so the aging effect, which is a multiplier, has a reduced increasing effect on the breakdowns. It may be noted here that this analysis assumes that both, incremental and radical upgrades, reduce breakdowns every time at a constant rate.

### 4.8.8 Sensitivity to a 10% Change in all Parameters

This sensitivity analysis helps management decide the accuracy required when estimating the model parameters. Higher the accuracy of the estimations of the life-cycle cost and the cumulative breakdowns desired, higher would be the resources required. For example, to determine the probability distribution of the system breakdown for a dynamic simulation run, a large amount of data may be required from similar existing systems. If management decides to ignore the randomness and resort to a static simulation, relatively less data and hence less resources are required. It depends upon management's capacity to control ad hoc expenses such as the cost of repairs and preventive maintenance actions for the system during its operation. The model was tested for an increase and a decrease of all parameter values by 10%. The simulation runs for starting preventive maintenance policy of 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 have been attached in Appendix [D].

**Table 4.13** Sensitivity for a 10% Change in all Parameters

| | -10% | | +10% | |
|---|---|---|---|---|
| ppm | cbdm | lcc | cbdm | lcc |
| 0 | 2.00803 | -10.602 | -1.9277 | 10.7479 |
| 10 | 1.91235 | -10.636 | -1.9124 | 10.7415 |
| 20 | 1.8011 | -10.6 | -1.8794 | 10.6897 |
| 30 | 1.82395 | -10.582 | -1.9033 | 10.6819 |
| 40 | 1.89723 | -10.582 | -1.8972 | 10.6821 |
| 50 | 1.8283 | -10.596 | -1.9078 | 10.6905 |
| 60 | 1.89873 | -10.564 | -1.8196 | 10.6747 |
| 70 | 1.74742 | -10.604 | -1.8268 | 10.7023 |
| 80 | 1.85484 | -10.564 | -1.9355 | 10.6536 |
| 90 | 1.93392 | -10.516 | -1.9339 | 10.6138 |

| | | | | |
|---|---|---|---|---|
| 100 | 1.79445 | -10.581 | -1.876 | 10.7182 |
| **Average** | 1.86367 | -10.584 | -1.8927 | 10.6906 |
| **Max** | 2.00803 | -10.516 | -1.8196 | 10.7479 |
| **Min** | 1.74742 | -10.636 | -1.9355 | 10.6138 |

Ppm = Planned preventive maintenance in year 1

Cbdm = Cumulative breakdowns

Lcc = Life-cycle Cost.

It can be seen that a 10% change in all the parameters affects the life-cycle cost by approximately 10% and cumulative breakdowns by approximately 2%. The table below indicates the sensitivity of the model output to a 10% change in parameter values when the life-cycle cost does not include opportunity loss.

**Table 4.14** Sensitivity to 10% Change in all Parameters for Life-cycle Cost (without Opportunity Loss)

| | -10% | | +10% | |
|---|---|---|---|---|
| Ppm | cbdm | lcc | cbdm | lcc |
| 0 | 2.008032 | -11.844 | -1.92771 | 12.2399 |
| 10 | 1.912351 | -11.8626 | -1.91235 | 12.20632 |
| 20 | 1.801096 | -11.8017 | -1.8794 | 12.13608 |
| 30 | 1.823949 | -11.7874 | -1.90325 | 12.12712 |
| 40 | 1.897233 | -11.7857 | -1.89723 | 12.12356 |
| 50 | 1.828299 | -11.7788 | -1.90779 | 12.11152 |
| 60 | 1.898734 | -11.7438 | -1.81962 | 12.0937 |
| 70 | 1.747419 | -11.7722 | -1.82685 | 12.10213 |
| 80 | 1.854839 | -11.7296 | -1.93548 | 12.06076 |
| 90 | 1.933924 | -11.6835 | -1.93392 | 12.02112 |
| 100 | 1.794454 | -11.732 | -1.87602 | 12.11084 |
| **Average** | 1.863666 | -11.7747 | -1.89269 | 12.12119 |

| | | | | |
|---|---|---|---|---|
| **Max** | 2.008032 | -11.6835 | -1.81962 | 12.2399 |
| **Min** | 1.747419 | -11.8626 | -1.93548 | 12.02112 |

This analysis gives valuable information regarding the accuracy required in collecting data and estimating various parameters required for the model on the whole. As a part of this thesis, sensitivity for 10% variations (positive and negative) were tested. From the results above, it can be seen that the change in the life-cycle cost in both cases is approximately equal to the change in parameter values. A 10% variation in parameters has approximately a 10% change in life-cycle cost estimates.

### 4.8.9 Relationship Between Cumulative Breakdowns and Life-cycle Costs

Using the simulation results, the following relationships were determined for both fixed and varying policies with and without aging (increase in rate of breakdowns with time).

(a) Fixed policy, No Aging

The trend equation is: $y = 0.0195x^2 - 15.819x + 47344$
Where y = Life-cycle cost, x = Cumulative breakdowns.

A good fit ($R^2 = 0.9922$) was obtained for a second degree polynomial trend. As cumulative breakdowns increase, the opportunity loss increases and, hence, the life-cycle cost increases. The value of the intercept indicates the expected value of the life-cycle cost when cumulative breakdowns equal zero, i.e., the system undergoes no breakdowns in its service life due to efficient maintenance process. The intercept represents the highest expected life-cycle cost.

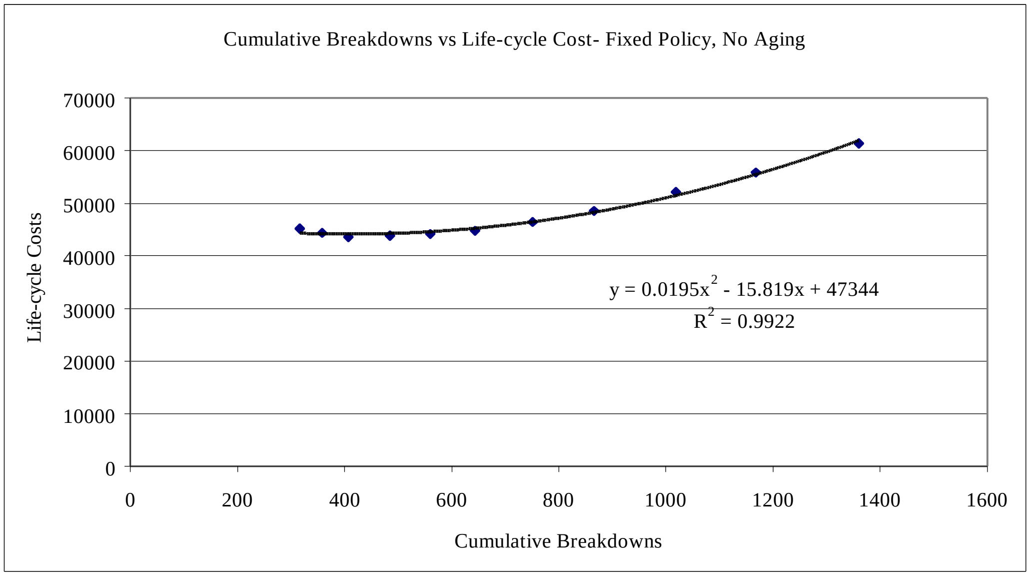



**Figure 4.11** Cumulative Breakdowns vs Life-cycle Cost - Fixed Policy, No Aging.

(b) Varying Policy, No Aging.

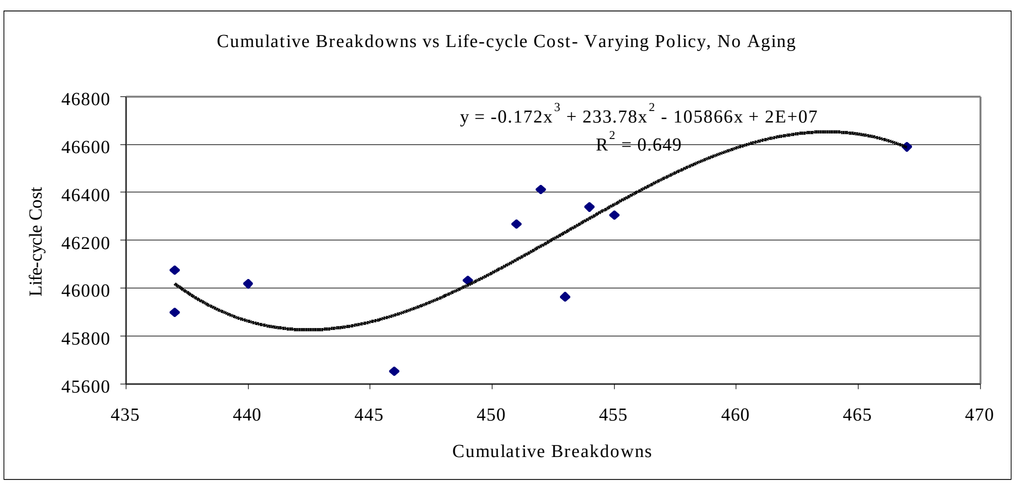



**Figure 4.12** Cumulative Breakdowns vs Life-cycle Cost - Varying Policy, No Aging

Here the best (statistical) fit was given by a second degree polynomial trend equation ($R^2$ = 0.65) but it can be seen that it does not have much significance in terms of relationship unlike the previous one. A few other trend equations were tried and the quadratic equation was found to be the best on statistical grounds and also visual inspection.

(c) Fixed Policy, Aging Factor = 0.5 (This is a large number and was chosen to check the model at the "upper limit" of the factor by which time affects breakdown rate)

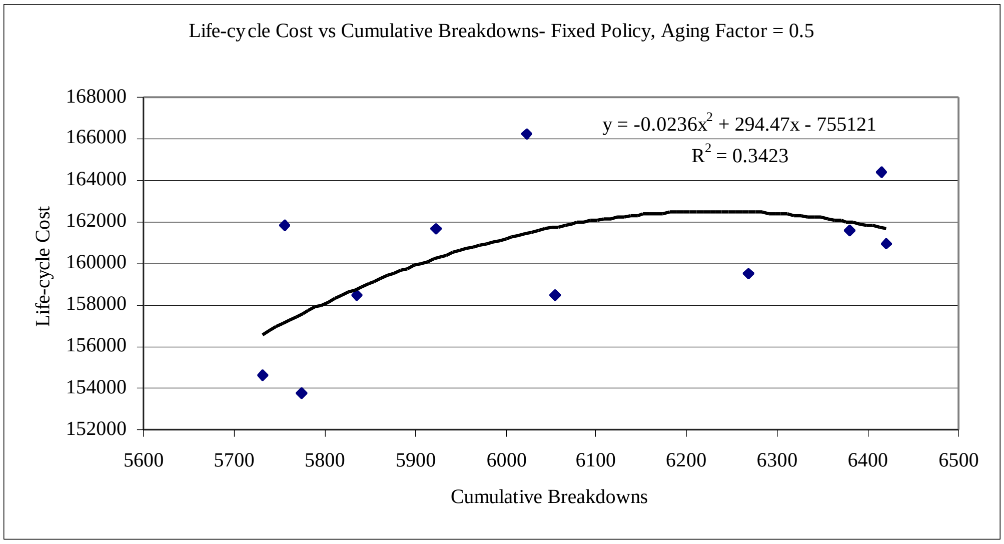



**Figure 4.13** Cumulative Breakdowns vs Life-cycle Cost- Fixed Policy, Aging Factor =0.5

The trend equation: $y = -0.0236x^2 + 294.47x – 755121$.

Where y = life-cycle cost and x = cumulative breakdowns.

As mentioned in the graph, the value of $R^2$ is low (0.34) indicating that the quadratic relationship mentioned in the graph above is statistically not very justified. Various other trend equations were tried using EXCEL but none gave any useful results. Here again no significant result could be derived from the graph of the relationship.

(d) Varying policy, aging factor = 0.5.

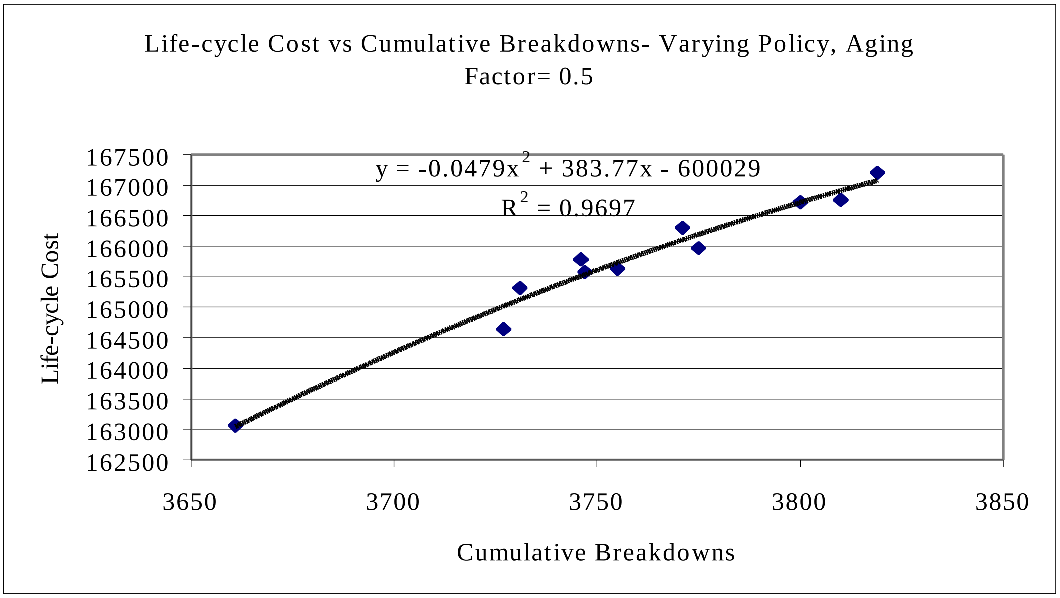



**Figure 4.14** Cumulative Breakdowns vs Life-cycle Cost- Varying Policy, Aging Factor = 0.5

The trend equation is as follows: $y = -0.0479x^2 + 383.77x – 600029$

Where y = Life-cycle cost and x = Cumulative breakdowns.

A good fit was obtained for a second degree polynomial trend equation ($R^2$ = 0.97). Though the data points appear to be almost linear, the quadratic equation was chosen since it gave higher $R^2$ and also a reasonable visual fit.

The value of the intercept is –600029 which represents the life-cycle cost when cumulative breakdowns equal zero through efficient maintenance process. Since life-cycle cost cannot be negative, it can be concluded that a system following varying maintenance policy can never have zero cumulative breakdowns. This is because the varying policy used in this thesis tends to allow some amount of breakdowns depending upon the mission criticality. As mission criticality increases, the cumulative breakdowns would reduce. When mission criticality would be large or infinity, the cumulative breakdowns would be a very small number (ideally zero).

It may be noted that fixed policy with no aging and varying policy with aging gave a good fit while the other two scenarios did not yield any useful results.

### 4.9 Application of the Model Using Historical Data

The system dynamics model was presented to seven people involved with the maintenance department of the concerned organization. The logic was approved by all of them. In one of the meetings, the organization claimed that they follow a fixed maintenance schedule for all systems. But the data obtained from their system reflects that the maintenance actions are not fixed but varies every year since the number of preventive maintenance actions is not constant every year. It is possible that the maintenance manager prefers to deviate from the fixed policy and regularly maintain the systems that had relatively more breakdowns in the recent past. This is a very logical approach as it helps the maintenance crew study these systems closely and monitor the operations of such systems. This would help in locating any defects in the design of these systems. The framework model provides a basis to formulate a procedure to determine the varying maintenance policy. This would help the manager get better estimates of the resources (personnel, materials and money) required for the system. The fixed maintenance practice requires the maintenance manager to be indifferent to increased breakdowns of the system. This may not be possible in actual practice.

The model was applied to an electronic and a mechanical (pneumatic) system. Using historical data, the subjective factors like the factors by which time affects breakdowns, preventive maintenance actions reduce breakdowns and technological upgrades reduces breakdowns were determined by using regression technique. The approaches used for the determination of the parameters were analytical and then cross-checking by experimenting with other values than those obtained by analytical method. The factors were used in running the model and they were adjusted until the model output matched the actual data. The matching was performed by visual inspection.

### 4.9.1 Application to an Electronic System

#### 4.9.1.1 Data Set

The organization identified certain systems as high maintenance cost systems. The electronic system considered in this application is one of them. The data obtained for the analysis included the following:

(a) Fiscal year
(b) Number of failures per year
(c) Number of preventive maintenance actions per year
(d) Total man-hours for maintenance per year
(e) Total logistics time for maintenance actions per year
(f) Total repair costs per year
(g) Ownership cost.

The definitions of all these terms have been listed in Glossary.

**Table 4.15** Breakdowns- Electronic System

| Year | Breakdowns |
|---|---|
| 1990 | 215 |
| 1991 | 295 |
| 1992 | 300 |
| 1993 | 355 |
| 1994 | 178 |
| 1995 | 236 |
| 1996 | 200 |
| 1997 | 220 |

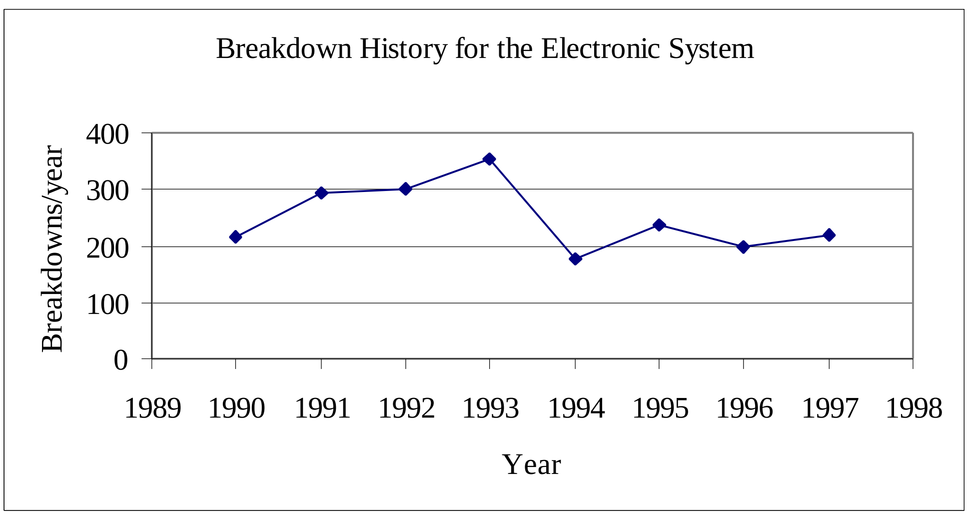



**Figure 4.15** Breakdowns for the Electronic System

The data indicates that, in general, the number of failures increased with time. Also it may be noted that in the year 1994 the number of breakdowns has a different trend. It is *assumed* that such a decrease occurred due to a technological upgrade and not due to errors in data or change in the recording procedure of the data. A general procedure for determining each of these factors is discussed below.

#### 4.9.1.2 Determination of factors required for the model

(a) Determination of the Factor by which Time (Age) Affects Breakdown Rate

A linear trend equation was determined for the data using EXCEL. A linear trend was assumed to obtain a constant slope of the trend in data points. If a non-linear trend is assumed then the trend curve would have variable slopes (at different data points). For simplicity, a constant factor is assumed for the model to forecast future breakdown trends. The slope represents the increase in breakdown rate every year, was divided by the number of breakdowns in the first year (1990) to determine the factor by which time (age) affects breakdown rate.

$$\text{Factor by which time (age) affects breakdown rate} = \frac{\text{Slope}}{\text{Breakdowns in the first year}}$$

The rationale behind this equation is that the slope gives the rate of increase in breakdowns every year. This rate when divided by the breakdowns in year 1 would give the fractional increase in breakdowns every year. If the breakdowns in year 1 were more than that in subsequent years, then the average breakdowns over the given period would be useful to determine this factor.

The trend equations are:

1990-1993: $y = 42.5x - 3597.5$, $R^2 = 0.906$

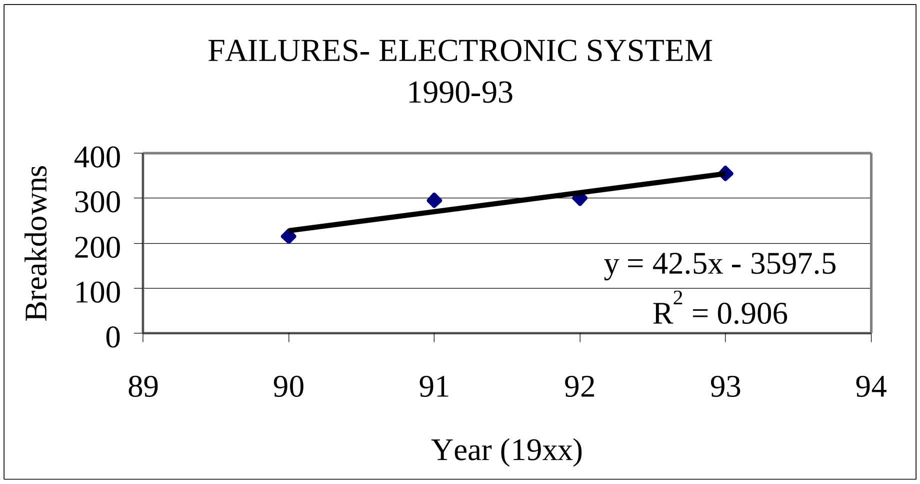
1994-1997: $y = 9x – 651$,     $R^2 = 0.2142$

where y = Breakdowns and x = Year.

For the period 1990-93, the trend equation gives a good statistical fit as shown. However, for the period 1994-97, the statistical fit obtained does not seem to be on statistical grounds (low value of $R^2$). This is due to the increased number of failures in the year 1995 (outlier). For the application of the model, a constant is required for the model parameter and hence a linear trend was selected

For the period between year 1990-93, this factor = 9/215 = 0.0418

For the period between year 1994-97, this factor =42.5/178 = 0.2388



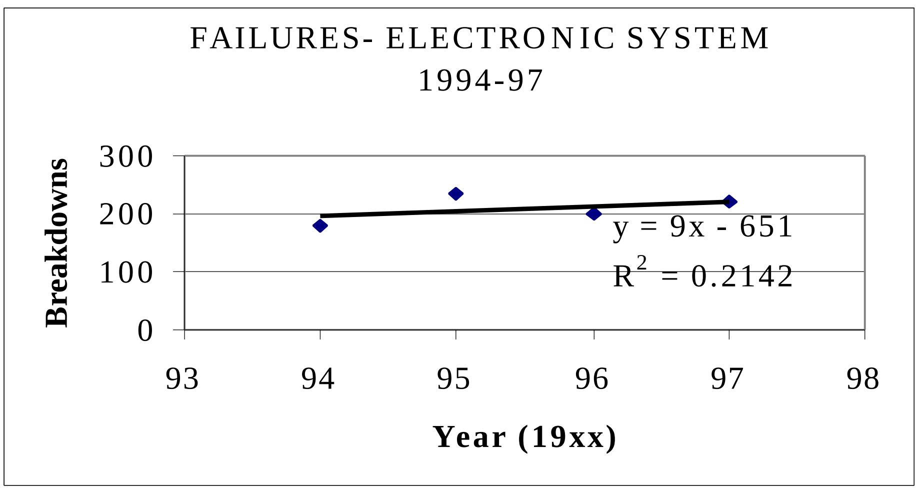



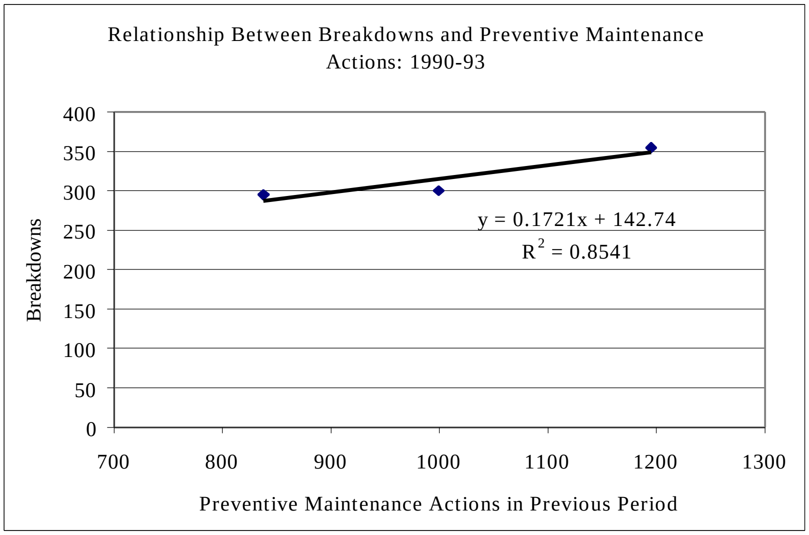

**Figure 4.16** Maintenance Data for the Electronic System

This shows that during 1994-97 the breakdowns increased at a faster rate than during 1990-93. A value between 0.04 and 0.23 (average) was chosen for the application of the model. A trial run was taken for the parameter values of 0.04, 0.1 and 0.23. It was found that the value of 0.1 gave a trend similar to the actual data. So the parameter was assumed to be 0.1 in the application.

(b) Factor by which preventive maintenance reduces the average breakdown rate

**Table 4.16** Data on Preventive Maintenance Actions for the Electronic System

| Preventive Maintenance actions | Breakdowns |
|---|---|
| 669 | 220 |
| 760 | 200 |
| 634 | 236 |
| 1154 | 178 |
| 1195 | 355 |
| 999 | 300 |
| 838 | 295 |



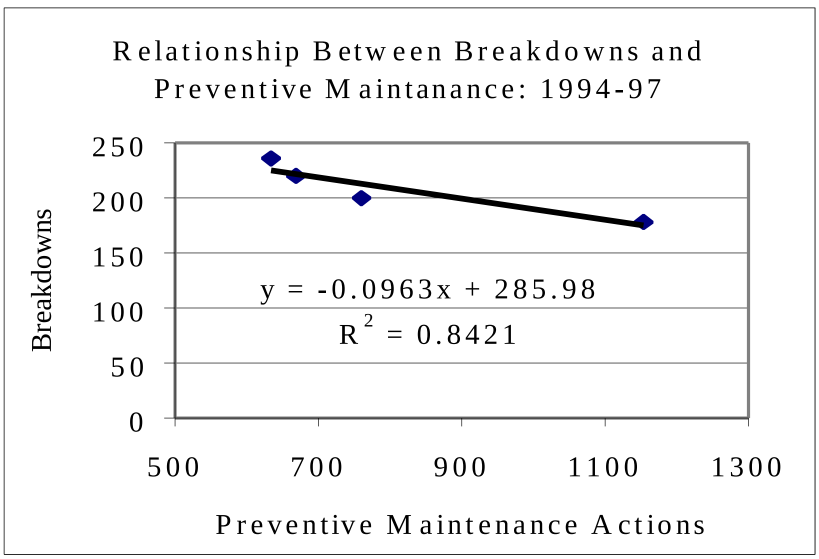




**Figure 4.17** Relationship Between Preventive Maintenance Actions and Breakdowns

Figure 4.17 indicates that preventive maintenance actions reduce breakdowns. Only the data for the periods 1994-97 was used to avoid problems associated with decrease in breakdowns between 1993 and 1994. It can be seen from the graph for the period 1990-93, the trend was contrary to the assumption of preventive maintenance reducing breakdowns of a system. The reasons for the anomalous behavior of data (increase in breakdowns in the next period with an increase in preventive maintenance in a period) during these periods have not been researched in this thesis. Hence, these data points have been discarded in the analysis. A linear equation was determined, as before, using EXCEL for the period 1994-97. The equation is as follows:

$y = -0.0963x + 285.98$

where, $y$ = Number of breakdowns

$x$ = Number of preventive maintenance actions.

$R^2 = 0.8421$.

The value of the intercept is equal to the number of breakdowns when no preventive maintenance actions are made. If corrective maintenance policy is used, then the expected breakdowns would be 285.98 or 286.

The factor by which preventive maintenance reduces breakdowns can be calculated by dividing the absolute value slope of the equation by the average preventive maintenance actions. For the electronic system, this value worked out to 0.096/208 = 0.00046. This value generated breakdown values during the simulation very similar to the actual values.

This indicates that the preventive maintenance actions would reduce breakdowns by a very small value. The maintenance process needs to be looked into since if preventive maintenance actions do not have significant effect on future breakdowns then the purpose of preventive maintenance is not served. The results indicate that either the accounting procedure or the maintenance process or both may be responsible for such a low value of this factor. It may be noted that for the value of 0.00046 the graphs for fixed maintenance policy of 850 and 900 follow very closely the actual data indicating that the values are not erroneous. The fixed policy of 850 and 900 were chosen since the average number of preventive maintenance actions for the actual data is in that range (893).

(c) Factor by which Technological Upgrade Affects Breakdowns

As mentioned above, for the application of the model to the electronic system, it has been assumed that a *technological upgrade* occurred in the year 1993 to account for the reduction in breakdowns in the year 1994. This assumption has been made because the sudden decrease in breakdowns in 1994 and the linear increasing trend maintained even after 1994 indicating increase in breakdowns with time. The data regarding the cause of decrease in breakdowns could not be obtained from the concerned organization.

The factor has been calculated as the fraction by which the average breakdowns were reduced after the technological upgrade occurred. This is the ratio of the reduction in average breakdowns in the periods before and after the upgrade to the average breakdown level before the upgrade.

**Table 4.17** Breakdowns- Electronic System

| Year | Breakdowns | 4-year average |
|---|---|---|
| 1997 | 220 | |
| 1996 | 200 | |
| 1995 | 236 | |
| 1994 | 178 | 208 |
| 1993 | 355 | |
| 1992 | 300 | |
| 1991 | 295 | |
| 1990 | 215 | 291 |

The (integer) average number of breakdowns in 1990-93 is 291 and that in 1994-97 is 208.

The factor by which technological upgrades affect breakdowns = (291-208)/291 = 0.28.

This indicates that the (assumed) technological upgrade reduced the average breakdown level by about 28%.

(d) Determination of other parameters

Other parameters required to run the model like cost per preventive maintenance, cost per breakdown maintenance, loss per breakdown were calculated using historical data. As mentioned earlier, costs of preventive and breakdown maintenance were assumed to be equal due to lack of data. Also the cost of technological upgrade in 1994 was ignored due to lack of data.

Cost per maintenance was calculated by dividing the total cost of maintenance by the number of preventive maintenance actions. Loss per breakdown was calculated by dividing the total man-hours lost due to breakdowns by the number of breakdowns to obtain the average loss per breakdown in hours. This was multiplied by the hourly wage (assumed $20/hour) to obtain the loss per breakdown in terms of dollars. Also, it was assumed that the cost of capital for the organization is 10%.

(e) Comparison of Model Estimate and Actual Recorded Life-cycle Cost

(i) Fixed maintenance policy

The average number of preventive maintenance actions performed per year worked out to be 892.7. So the model was run for fixed preventive maintenance actions of 850 and 900. The actual life-cycle cost amounted to $ 4.2E7 considering a discounting rate of 10%. The simulated life-cycle cost worked out to:

For fixed preventive maintenance of 850: $ 3.23E+07. The ratio of simulated to actual life-cycle cost works out to 0.77.

For fixed preventive maintenance of 900: $3.38E+07. The ratio of simulated to actual life-cycle cost works out to 0.80.

**Table 4.18** Results for Fixed Maintenance Policy for the Electronic System.

| Actual Breakdowns | Simulated Breakdowns | Actual and Simulated | Fixed Preventive Maintenance | Discounted Annual Cost (Simulated) | Life-cycle Cost (Simulated) |
|---|---|---|---|---|---|
| 215 | 215 | 0 | 850 | 4.89E+06 | 4.89E+06 |
| 295 | 236 | 59 | 850 | 4.69E+06 | 9.57E+06 |
| 300 | 257 | 43 | 850 | 4.48E+06 | 1.41E+07 |
| 355 | 279 | 76 | 850 | 4.29E+06 | 1.83E+07 |
| 178 | 216 | -38 | 850 | 3.78E+06 | 2.21E+07 |
| 236 | 231 | 5 | 850 | 3.59E+06 | 2.57E+07 |
| 200 | 247 | -47 | 850 | 3.40E+06 | 2.91E+07 |
| 220 | 262 | -42 | 850 | 3.22E+06 | **3.23E+07** |

**Table 4.19** Results for fixed maintenance policy for the electronic system.

| Actual Breakdowns | Simulated Breakdowns | Actual – Simulated | Fixed Preventive Maintenance | Discounted Annual Cost (Simulated) | Life-cycle Cost (Simulated) |
|---|---|---|---|---|---|
| 215 | 215 | 0 | 900 | 5.11E+06 | 5.11E+06 |
| 295 | 236 | 59 | 900 | 4.90E+06 | 1.00E+07 |
| 300 | 257 | 43 | 900 | 4.68E+06 | 1.47E+07 |
| 355 | 279 | 76 | 900 | 4.48E+06 | 1.92E+07 |
| 178 | 216 | -38 | 900 | 3.96E+06 | 2.31E+07 |
| 236 | 231 | 5 | 900 | 3.75E+06 | 2.69E+07 |
| 200 | 247 | -47 | 900 | 3.56E+06 | 3.04E+07 |
| 220 | 262 | -42 | 900 | 3.36E+06 | **3.38E+07** |

(ii) Varying Maintenance Policy

The model was run for the varying policy and the following results were obtained. The model was run for two different mission criticality values of 0.02 and 0.03. The values of mission criticality were so chosen since the value of actual life-cycle cost lied in between the values of the life-cycle costs for mission criticality values of 0.02 and 0.03. From the model point of view, the value of mission criticality of the system under consideration lies between 0.02 and 0.03. It was found that both the runs gave similar results in terms of the number of preventive maintenance actions as indicated by the F-test values and the coefficient of correlation.

**Table 4.20** Results for varying maintenance policy for the electronic system.

Mission criticality = 0.03

| Actual Breakdowns | Simulated Breakdowns | Actual – Simulated | Preventive Maintenance Actions (Simulated) | Annual Total Cost (Simulated) | Life-cycle Cost (Simulated) |
|---|---|---|---|---|---|
| 215 | 215 | 0 | 850 | 4.89E+06 | 4.89E+06 |
| 295 | 236 | 59 | 1428 | 7.15E+06 | 1.20E+07 |
| 300 | 257 | 43 | 1498 | 7.08E+06 | 1.91E+07 |
| 355 | 278 | 76 | 1568 | 6.98E+06 | 2.61E+07 |
| 178 | 216 | -38 | 1638 | 6.55E+06 | 3.27E+07 |
| 236 | 231 | 5 | 1597 | 6.04E+06 | 3.87E+07 |
| 200 | 247 | -47 | 1587 | 5.67E+06 | 4.44E+07 |
| 220 | 262 | -42 | 1594 | 5.35E+06 | **4.97E+07** |

Mission criticality = 0.02

| Actual Breakdowns | Simulated Breakdowns | Actual – Simulated | Preventive Maintenance Actions (Simulated) | Annual Total Cost (Simulated) | Life-cycle Cost (Simulated) |
|---|---|---|---|---|---|
| 215 | 215 | 0 | 850 | 4.89E+06 | 4.89E+06 |
| 295 | 236 | 59 | 952 | 5.12E+06 | 1.00E+07 |
| 300 | 257 | 43 | 998 | 5.08E+06 | 1.51E+07 |
| 355 | 279 | 76 | 1045 | 5.02E+06 | 2.01E+07 |
| 178 | 216 | -38 | 1093 | 4.64E+06 | 2.47E+07 |
| 236 | 231 | 5 | 1065 | 4.30E+06 | 2.90E+07 |
| 200 | 247 | -47 | 1058 | 4.04E+06 | 3.31E+07 |
| 220 | 262 | -42 | 1063 | 3.83E+06 | **3.69E+07** |

The life-cycle cost obtained by simulating were:

Mission criticality = 0.02: Life-cycle cost = $ 3.69E+07.

Mission criticality = 0.03: Life-cycle cost = $ 4.97E+07.

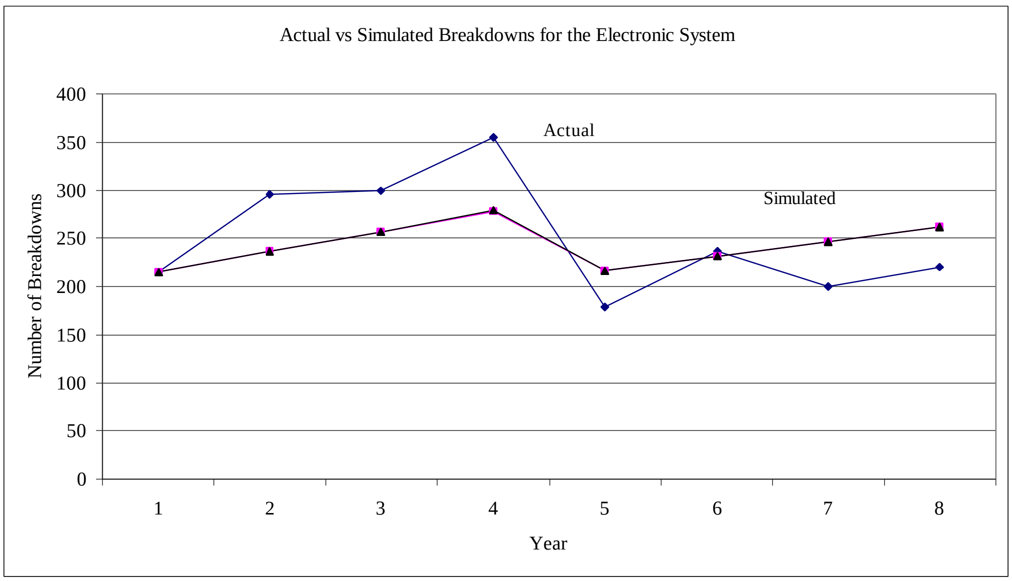



**Figure 4.18** Actual versus Simulated Breakdowns for the Electronic System

**Table 4.21** Statistical tests for Simulation Runs for the Varying Maintenance Policy for the Electronic System.

| Mission criticality | 0.03 | 0.02 |
|---|---|---|
| F test | 0.018 | 0.019 |
| Coefficient of correlation | 0.675 | 0.679 |

Figure 4.18 and the statistical tests indicate that the simulation runs for both the mission criticality yielded similar results even though the runs for a mission criticality of 0.02 was

marginally better and the simulation results for this value may be used for further analysis.

It can be seen from the table that the statistical tests do not support the claim that the simulation gave results very close to actual. This is because the simulation carried out for the application was a static simulation. Dynamic simulation requires large amount of data to fit a statistical distribution. Due to non availability of large amount of data (only 7 data points were available as compared to the statistical requirement of 30), it was not possible to perform dynamic simulation. It is accepted that dynamic simulation performs better when randomness is involved as in the present case of random breakdowns. The entire exercise was carried out to suggest to the reader a general procedure evaluate the varying maintenance policy.

The difference between the simulated and the actual values of breakdowns were the same in all the above cases irrespective of the number of preventive maintenance actions carried out in the previous period. This is due to the low values of the factor by which preventive maintenance actions reduce breakdowns. This indicates that the organization needs to check their maintenance process.

A bivariate and multivariate regression analysis was performed for additional insights and results. The multivariate regression analysis did not give any useful results since we do not have sufficient data to make reasonable conclusions, this analysis is not used any further. The results obtained for bivariate analysis were as follows:

(i) Bivariate Regression

(a) Breakdowns and Time.

1990-1993

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 185 | 26.5165 | 6.976787 | 0.019932 |
| Preventive maintenance | 42.5 | 9.682458 | 4.389381 | 0.048183 |

1994-1997

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 150 | 80.39963 | 1.86568 | 0.203076 |
| Preventive maintenance | 9 | 12.19016 | 0.7383 | 0.537212 |

The slopes of the trend lines obtained earlier were similar to the values obtained for the coefficients using regression analysis.

(b) Breakdowns and Preventive Maintenance Actions in Previous Period.

1990-1993

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 399.0228 | 142.8408 | 2.79348 | 0.107816 |
| Preventive maintenance | -0.10826 | 0.140072 | -0.77289 | 0.520431 |

1994-1997

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 283.3359 | 198.8634 | 1.424776 | 0.389596 |
| Preventive maintenance | -0.11771 | 0.295689 | -0.39809 | 0.758814 |

It may be noted that the coefficient for the preventive maintenance in 1994 - 1997 in the bivariate regression analysis yielded similar results to that of the procedure followed previously. But the results for the period 1990- 1993 yielded different results.

The multivariate regression analysis did not yield any useful results due to the small amount of data available and certain trends in breakdowns not considered for the analysis. It may be argued that the model runs using parameters determined by a procedure that closely matches the coefficients of bivariate regression analysis. Though no other explanation is available for counter argument except that the factors determined earlier gave similar trends in breakdowns as the actual data. The factor by which preventive maintenance reduces breakdowns was subjected to sensitivity analysis and it was found that the factor used gave a reasonable trend.

The regression analysis indicates that the model factors can be determined using the bivariate regression method. The bivariate analysis reinforces the confidence in the logic of the model in terms of its parameters. It, along with the simulation output, shows that the parameters are not unrealistic.

### 4.9.2 Application to a Mechanical (Pneumatic) System

The mechanical system to which the model has been applied has also been identified as a high maintenance cost system by the organization. The data obtained were similar to that for the electronic system.

Again, the parameters required for the model was determined using historical data. The parameters were checked for accuracy by substituting them in the model and comparing them with the actual data.

**Table 4.22** Maintenance Data for the Mechanical System.

| Sr. No. | Year | Breakdowns | Preventive Maintenance Actions |
|---|---|---|---|
| 1 | 1990 | 3720 | 10578 |
| 2 | 1991 | 3838 | 11873 |
| 3 | 1992 | 3581 | 10281 |
| 4 | 1993 | 3796 | 9988 |
| 5 | 1994 | 3741 | 10124 |
| 6 | 1995 | 4149 | 11700 |
| 7 | 1996 | 3762 | 10193 |

The trend equation is: $y = 32.429x + 3668.4$, $R^2 = 0.1613$.

Where y = Number of breakdowns and x = Time.

The slope is the factor by which time affects breakdowns and the intercept value is the expected number of breakdowns in year 1.

The value of $R^2$ is very low since there are outliers. The trend equation has to be linear so that the constant value of the slope can be used in the model.

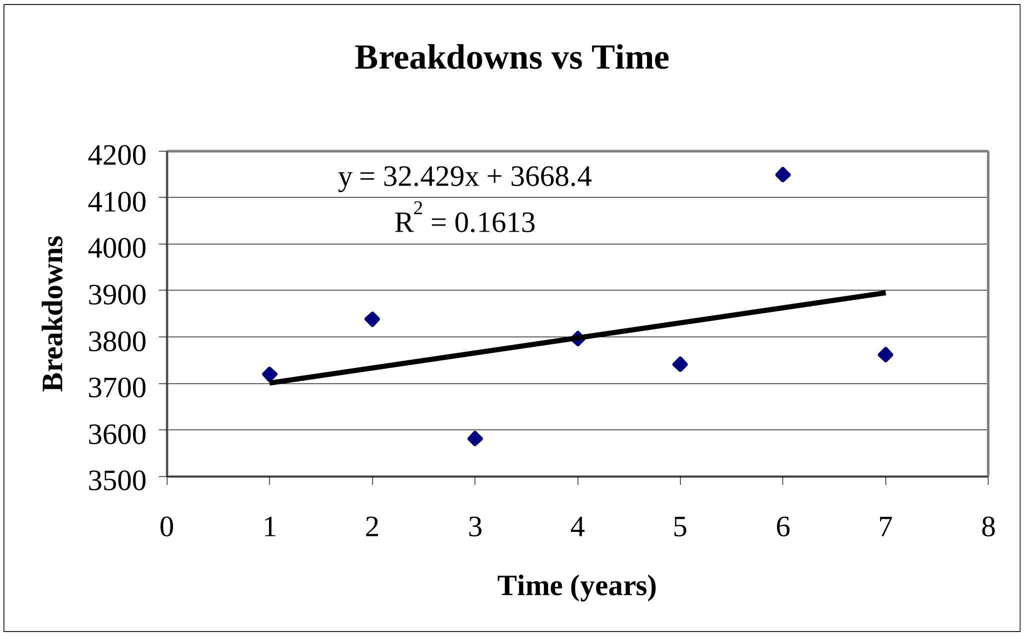



**Figure 4.19** Maintenance Data for the Mechanical System

The data for the mechanical system has some abnormalities involved like the reduction in breakdowns in year 3, 5 and 7. This is due to randomness involved in breakdowns of the system. In this case, we again determine the linear trend in the data. It may be noted that the data has a linear upward trend indicating that with age the breakdowns also increase. Since this is in agreement with the basic premise of the model, no technological upgrade was assumed.

#### 4.9.2.1 Determination of Factors

(a) Factor by which Time (Age) Affects Breakdowns

**Table 4.23** Simulated Results for the Mechanical System.

| Actual | Simulated |
|---|---|
| 3720 | 3720 |
| 3838 | 3753 |
| 3581 | 3786 |
| 3796 | 3820 |
| 3741 | 3854 |
| 4149 | 3888 |
| 3762 | 3922 |
| F-test (95% confidence level) | 0.049477 |
| Coefficient of correlation | 0.404474 |

From the table above and graph below it can be seen that, like the electronic system application, both the F-test and the coefficient of correlation have a very low value. Again in this application, the statistical tests do not yield good results since the randomness was ignored. Since only 8 data points were available, it was not possible to fit a statistical distribution to the breakdown data. So again a static simulation had to be performed. This is a general procedure presented for the user.

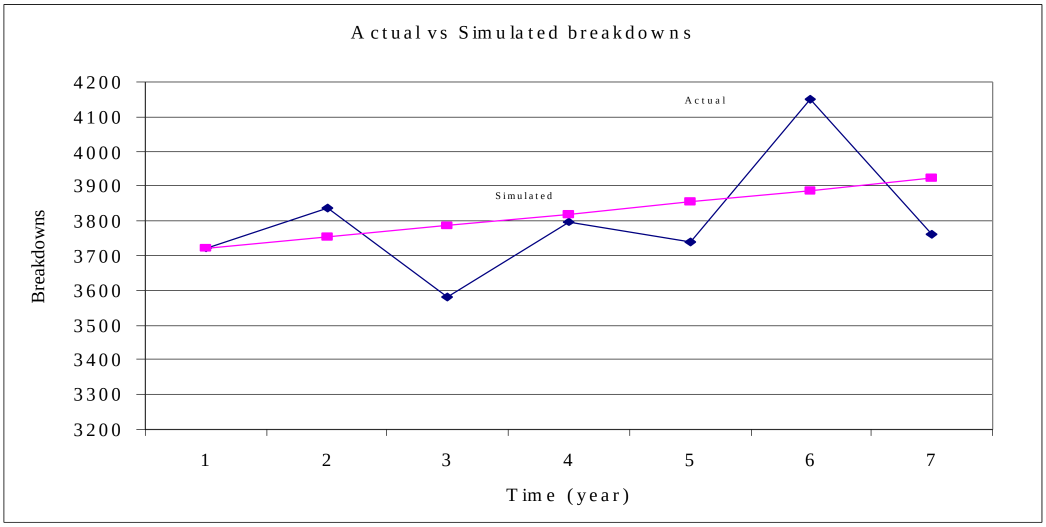



**Figure 4.20** Comparison of actual and simulated runs

The graph indicates that the simulated breakdowns follow the trend of the actual data. The actual cumulative breakdowns and the simulated cumulative breakdowns are 26587 and 26743, a difference of 0.6%. This indicates that the aging factor determined is within the acceptable range.

(b) Factor by which Preventive Maintenance Reduces Breakdowns

**Table 4.24** Data on Breakdowns and Preventive Maintenance Actions

| Breakdowns | Preventive Maintenance Actions in Previous Year |
|---|---|
| 3838 | 10578 |
| 3581 | 11873 |
| 3796 | 10281 |
| 3741 | 9988 |
| 4149 | 10124 |
| 3762 | 11700 |
| Average | 10757 |

The data in the above table represents the breakdowns in a period and the preventive maintenance actions performed in the previous period.

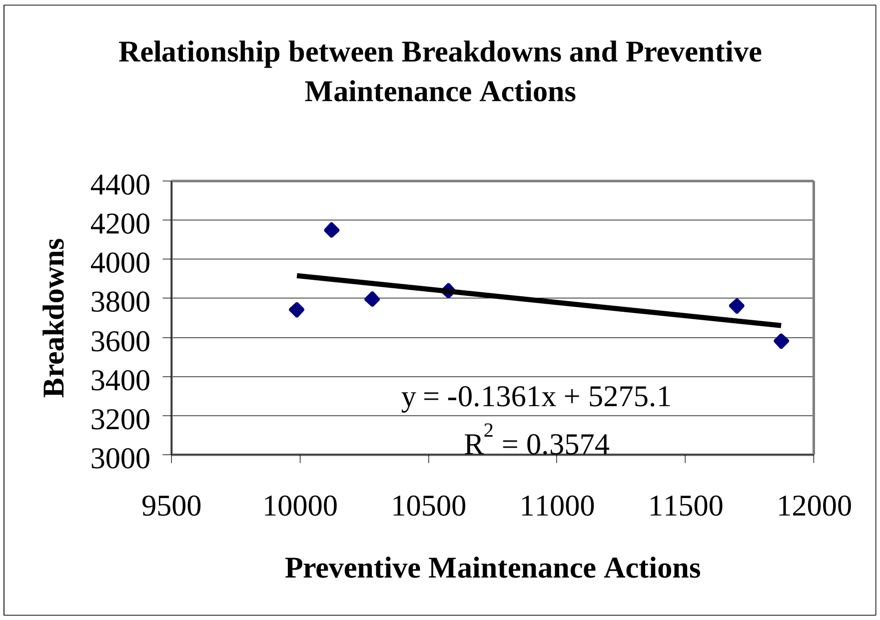



**Figure 4.21** Breakdowns versus Preventive Maintenance in the Previous Period

As calculated for the electronic system, the factor was calculated for the mechanical system. The factor by which preventive maintenance actions reduce breakdowns = 0.136/3798 = 0.000034.

The small value of this factor indicates that the maintenance process needs to be checked for possible flaws. This value indicates that a preventive maintenance action reduces breakdowns by 0.000034. This effect is insignificant as seen from the analysis using this data.

(c) Factor by which Technological Upgrade Affects Breakdowns

Since the data in case of the mechanical system does not have any steps, unlike the electronic system, this factor has been assumed to be zero, i.e., no technological upgrade was carried out during the given period.

(d) Comparison of Life-cycle Cost Estimate and Actual Recorded Life-cycle cost

**Table 4.25** Results for Breakdowns and Preventive Maintenance Actions for the Mechanical System

| Policy | Cumulative Breakdowns | Cumulative Preventive Maintenance Actions | Life-cycle Cost |
|---|---|---|---|
| Actual | 26587 | 74737 | 1.26E+08 |
| Fixed | 26739 | 74739 | 1.07E+08 |
| Varying | 26739 | 73966 | 1.06E+08 |

The model was run for the values of the parameters calculated above and other parameter values, a procedure similar to that for the electronic system. It can be seen that the model values and the actual values do not differ widely for the breakdowns. The difference between the simulated and the actual values for the cumulative breakdowns and the life-cycle cost are 0.6% and 16% respectively. The parameters such as preventive maintenance in year 1, the financial parameters, learning factor may be changed to assess the effect of the maintenance policies on the life-cycle cost and the opportunity loss.

It is interesting to note that both fixed and varying maintenance policies gave the same number of breakdowns every year. This is due to the low value of the factor quantifying the effect of preventive maintenance actions on breakdowns. The effect of varying the maintenance has a negligible effect on the breakdowns. This is not very desirable from the point of view of the maintenance manager. If preventive maintenance does not reduce breakdowns then it may be better to resort to only corrective maintenance.

As for the electronic system, bivariate and multivariate regression analyses were performed. As for the electronic system the multivariate regression did not yield useful results for similar reasons mentioned above. It may be noted that the coefficient for time is approximately equal to the slope of the trend line (value = 32) obtained earlier.

(a) Bivariate analysis.

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 4353.348 | 1162.091 | 3.746133 | 0.020014 |
| Preventive maintenance | -0.05136 | 0.108388 | -0.47383 | 0.660322 |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 3668.429 | 147.8792 | 24.80693 | 1.99E-06 |
| Time | 32.42857 | 33.06678 | 0.980699 | 0.371779 |

In this case, the coefficient for time matches closely with the slope of the relationship determined earlier. The coefficient for the preventive maintenance does not closely resemble the previous value.

As mentioned earlier, this exercise helped develop a procedure to apply the model to a system.

### 4.9.3 Some Observations from the Applications

A few important observations were made from the application of the model to the system. The data revealed that the maintenance process probably was not very efficient. The effect of preventive maintenance on future system breakdowns for both the systems was found to be very low. It indicates that the process of maintenance needs to be improved or that the maintenance crew needs training. Here, it was assumed that the data had no errors.

For the hypothetical system, it was found that the learning effect was a very important aspect with respect to the maintenance process. This indicates that management needs to pay attention to the training of the maintenance workers.

As mentioned in Chapter 2, system dynamics helps to determine the existing flaws in the system that were overlooked previously. Here the determination of the model parameters brought to light the fact that the maintenance process needed. The low values of factor by which preventive maintenance actions reduces breakdowns for both the systems shows that it preventive maintenance do not seem to have substantial effect to reduce breakdowns.

As mentioned previously, the preventive maintenance actions performed do not follow a fixed policy and that it deviates from the fixed policy. The number of preventive maintenance varies every year and this framework model is a good tool to formalize the varying preventive maintenance policy.

The determination of the factors by which time and preventive maintenance affect breakdowns becomes subjective if large amounts of data are not available. Large amount of data for similar systems is necessary to fit a distribution and run the model (dynamic simulation). For both the applications it was found that the factor by which preventive maintenance reduces breakdowns was negligible while the factor by which time affects breakdowns was significant.

This chapter was devoted to the validation and application of the model. In Chapter 5, some of the results, future research issues and certain lessons learned from the entire exercise have been documented.

# Chapter 5 Conclusion

This chapter contains conclusions that may be gathered from the model developed in this thesis. Recommendations for future research are also provided.

## 5.1 Insights from the model

This model would be particularly useful when the breakdown rate of a system is not accurately known or if a system is expected to undergo significant changes in its breakdown rate. It is particularly useful when the system is likely to be operational for a long time that could bring about changes in failure rates due to deterioration with time, learning and technological upgrades or even replacement of certain parts. The model gives a good picture of the tradeoffs and the important parameters associated with preventive maintenance actions. For example, for the hypothetical system it was seen that the learning effect would be important in relation to the system life-cycle cost.

This model can be applied to all subsystems and at any stage of the life-cycle. This thesis attempts to estimate the life-cycle cost for any system accurately by considering the dynamic nature of the technology involved, the learning effect of the maintenance crew and possible changes in the breakdown patterns throughout the system's life-cycle. Also, many other factors can be incorporated in the model to improve the estimate of the life-cycle cost depending upon the system. Apart from this, it introduces the varying maintenance policy philosophy by applying it to a system involving random breakdowns.

This model can form the basis for a decision-support tool that could be used by management to check the economic and operational impact of their maintenance policies. It is, primarily, a tradeoff tool for managers to overcome their dilemma regarding the maintenance policy-making and to get a better understanding of the tradeoffs associated with different policies. It can help them discover various ways of reducing life-cycle cost without increasing the opportunity losses. The penalty function to quantify loss due to breakdowns may also be checked for different values (or expressions). The model can provide invaluable help for policy setting. For example, the effect of defining mission criticality on breakdowns or opportunity losses may be checked for different values. Also the policy regarding the technological changes may be checked for various values of the future investment required to incorporate certain technological changes. If detailed statistics are gathered, the timings of the technological upgrades or part replacements due to failures resulting from the deterioration of the system could be obtained. The annual budget for the preventive maintenance actions may be tested for various scenarios to set a rational budget. In this model, the upper limit on the number of preventive maintenance actions in any period has been set to be equal to the expected breakdown rate in that period. The maintenance manager can convince himself, using this model, that his policies do not hinder the effectiveness of operations by comparing it with other upper limits. The model would correct any error introduced by the initial preventive maintenance policy setting due to the feedback loop. The basis of this varying preventive maintenance modeling process is that the preventive maintenance required for a system is directly proportional to its past record or the breakdowns (or opportunity loss) expected in the next period.

The financial terms could be written in the form of econometric equations as it is not very practical to assume constant financial conditions for long periods (periods more than five years). This could have significant effect on the estimation of the life-cycle cost.

This framework model can be adapted to electronic, mechanical and chemical engineering applications. In case of electronic components, where the components fail instantaneously, the effect of preventive maintenance on future breakdowns may not be easy to quantify. Also the effect may be very low. In case of mechanical and chemical engineering, this effect may be more easily visualized and quantified also it may be very pronounced. Similarly, the factor by which time affects breakdowns can be modified to any type of system.

To study the maintenance policies of various subsystems constituting a system and to include the inter-subsystem effects, a Pareto analysis may be performed to identify the systems that are major cost drivers. The model may also be individually applied to each subsystem, neglecting the inter-subsystem effects to reduce complexity.

## 5.2 Conclusions

The research was directed toward the hypotheses listed in Section 1.2. The main objective of this thesis was to introduce and assess a varying maintenance policy. The general idea used was to forecast the breakdowns using simple average forecasting technique and set the preventive maintenance policy accordingly for the next period.

The null hypothesis being considered was that "there is a difference between fixed and varying maintenance policy". In Section 4.5, the simulation results and the interpretation of these results have been presented. The results presented in the previous chapter demonstrate that fixed and varying preventive maintenance policies are different in terms of the expected cumulative breakdowns and the life-cycle cost. The two policies are useful under different scenarios. For example, the varying policy is better when the aging factor and learning factor are both important.

This exercise brought out an important issue of trade-off between life-cycle cost and cumulative breakdowns. It also brought out the need to define certain requirements for the system before determining the preventive maintenance policy in terms of the life-cycle budget and the maximum tolerable breakdowns. Also, it points out to the fact that the maintenance manager must be clear of his objectives. The objectives may be either to minimize life-cycle cost or to minimize cumulative breakdowns or a combination of the two with certain constraints on the maximum allowable value for each variable and so on.

The results do not explicitly support the hypothesis that a varying preventive maintenance policy (of the type considered in the model- simple average method) is better than a fixed preventive maintenance policy by achieving both lower life-cycle costs and lower cumulative breakdowns. The simulation results indicate that both could not be achieved consistently for various scenarios. When the aging factor was high (0.5) along with learning (0.75), the simulation showed that a varying policy gave better results in terms of lower cumulative breakdowns (50-70%) for a small increase in the life-cycle cost (about 1%). This indicates that a minor error in judging the opportunity loss may tilt the analysis in favor of the fixed policy since the opportunity loss has been already adjusted in the life-cycle cost calculations. In such cases, it is better to perform the incremental analysis described earlier or use other techniques.

Though it could not be quantitatively proved that a particular policy is better over the other, the varying policy has been shown to be better than the fixed policy when the objective is to minimize the expected cumulative breakdowns for systems with a higher aging factor, i.e., the factor by which time affects breakdowns.

Some of the conclusions from the sensitivity analyses are as follows:

(a) The sensitivity of the factor by which time (age) affects breakdowns can be used in the design stage as explained in Section 4.8.1. This would require the manager to estimate the effect of the factor of safety on the factor by which time affects breakdowns (or the aging factor).

(b) The sensitivity of the factor by which preventive maintenance reduces breakdowns and the learning factor can be used to determine the skill level required for the maintenance crew. The analysis would require the subjective judgement of the manager to estimate the learning curve before and after training

(c) The sensitivity of the loss per breakdown can be used to determine the effect of errors introduced due to the underestimation of the loss per breakdown. This may play an important role during the trade-off analysis.

(d) The other parameters did not yield any specific results. It was shown using a specific case of equivalent incremental and radical technological upgrades that it is better to have continuous improvements in the process and technology.

The relationship between the life-cycle cost and the cumulative breakdowns has been discussed in Section 4.8.9

A framework has been developed in Section 3.5 to relate the maintenance policy for each individual subsystem with that of the overall system.

## 5.3 Recommendations for Future Research

The model developed in this thesis is a framework to be used for the assessment of a varying system maintenance policy and its effect on the life-cycle cost and the cumulative breakdowns of the system. In this section, many modifications that may be incorporated in the model to get more or better information to aid decision-making.

Due to the complex nature of the problem given in Section 1.2, an analytic solution could not be developed to compute the expected life-cycle cost or cumulative breakdowns. By making certain simplifications, e.g., considering non-random breakdowns, it may be possible to derive some analytical expression for life-cycle cost, cumulative breakdowns and opportunity loss. This thesis developed a model that could be used to test the maintenance policies of different systems.

A database may be developed for some of the model parameters, similar to many cost estimating parameter databases available [3]. It may be possible to estimate the effect of preventive maintenance actions on the future breakdowns of the system by experienced personnel or from historical data for certain groups of systems. It may be possible to estimate these parameters for a category of systems like machine tools, pneumatic equipment, forging equipment, computer hardware, communication systems etc. It may also be possible to estimate these parameters depending upon the (mechanical) dynamics or load on the system. Equipment like forging hammers and compressors require more frequent maintenance than the conventional machine tools such as lathes and milling machines. Also preventive maintenance actions may have more effect on breakdowns in case of more dynamic systems like forging hammers as compared to the less dynamic ones.

In the basic feedback loop, the manpower requirement could have been included to address the issue of resource allocation every year. As the average breakdown rate increases, the manpower requirement also increases and that would increase the total cost. Also an effective policy regarding the “hire and fire” policy may have to be devised to implement the varying policy. It may not be pragmatic to hire and fire maintenance workers every year as the costs of hiring and retraining may be too high. The organization needs to have a policy regarding the minimum number of workers required in the maintenance crew as a buffer for breakdown maintenance, even if zero preventive maintenance actions are to be performed in the next period.

The preventive maintenance in the previous period has only been assumed to effect the breakdowns in the next period. The model also assumes that preventive maintenance is adjusted based on the cumulative opportunity loss throughout the life cycle. Here, the model forecasts future breakdowns using a simple average method. More sophisticated forecasting techniques like a moving average and exponential smoothing may be adopted to predict the future preventive maintenance actions. The model may be modified to use the exponential smoothing forecasting technique that would consider a weighted average of the breakdowns in the previous period and the average of the cumulative breakdowns from the first year to the period before the previous period. Also a minimum number of maintenance actions may be fixed per year along with an upper limit as used in this model, i.e., a combination of fixed and varying maintenance policies may be tried.

This model only deals with the macro aspects of maintenance policy-making and does not deal with the details of the maintenance process. It also does not specify the timing of the preventive maintenance shutdowns within a period. So the effect of preventive maintenance on the breakdowns of the same period has not been considered. The operational details like preventive maintenance actions within a year are not provided by this model; unlike other Operations Research models described in Chapter 2. An attempt should be made to integrate the system dynamics framework with some of the traditional Operations Research maintenance models to determine the timing of each preventive maintenance action within a period. It may be noted that system dynamics modeling and the traditional Operations Research modeling are complimentary approaches and can be very useful when used together. The Operations Research models deal with the details whereas the system dynamics deals with the high level (or tactical) decision making process.

The average loss per breakdown has been considered to be constant (an estimate of average breakdown losses). This may be defined as a random variable. The extent to which the parameters used in the model can be quantified has not been addressed in great detail. They may be explained by probability distributions or by membership functions.

The issue of inventory control of spares has not been considered explicitly. This may be incorporated in the model to determine the inventory levels desired at various stages of the life-cycle.

The output of the model may be subjected to some more analysis using other techniques to aid better decision-making. Since the model gives the life-cycle cost (pay-off) and cumulative breakdowns (risk), game theory can be used. As mentioned earlier, often, the opportunity loss due to breakdown of a system may be underestimated due to certain "hidden" or intangible issues like combat readiness. So reliance on the life-cycle cost, which even includes opportunity loss, may not be very desirable in certain cases. For example, the simulation runs yielded the following results for different policies where the difference between life-cycle costs was about 1% but the difference in the cumulative breakdowns was about 30%. A small error in estimating the opportunity loss due to breakdowns may be tilt the decision in favor of fixed policy when the varying policy would give a lower number of breakdowns. To make better decisions in such cases, further analysis is required.

In the application of the model to the electronic and the mechanical systems, insufficient data was available to fit a statistical distribution. As explained in Chapter 4, a large data set (30 or more data points) is considered essential to fit a statistical distribution. In the applications in Chapter 4, only 7 data points were available for both the systems. Hence static simulation had to be used. Dynamic simulations are considered to be more powerful than static simulations in cases where randomness in involved. So dynamic simulation should be preferred whenever sufficient data is available. This would help estimate the life-cycle cost and the cumulative breakdowns better.

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# Glossary

### Chapter 1

*Complex system:* A system comprising many interrelated subsystems working as one unit. The interrelationships among various subsystems may be implicit or explicit.

*Effectiveness:* refers to achievement of organizational objectives.

*Efficiency:* refers to achievement of organizational objectives by employing the optimum amount of resources.

*Holistic view:* refers to consideration of the problem (or system) in its entirety rather than just a part of it.

*Large system:* A system comprising many subsystems.

*Mission Criticality:* It is an indicator of the tolerance to breakdowns of a system. It is the factor by which preventive maintenance policy in the next period would depend upon the average cumulative opportunity loss incurred.

*Modeling framework:* It is a recommended general procedure to be followed for the issue the framework has been developed. It needs to be adapted for every application in terms of setting the parameters.

*Rational decisions:* Decisions that would help achieve organizational objectives.

*Spares requirements:* Inventory of spare parts required for repair work.

**Chapter 2**

*Closed boundary systems:* Systems involving feedback loops.

*Cost estimating relationships (CER):* These are relationships used to estimate the cost of a system or a process using certain parameters of the system or the process. These relationships are established using historical data.

*Decision matrices:* These are useful at the planning stage for forecasting in order to structure the thinking and the explicit demand for a forecast of end-uses.

*Deterministic systems:* Systems that do not involve randomness.

*Dimensional consistency:* This refers to the equivalency of the dimensions (units of measure) on both sides of the equation.
For example, for the equation area = length * breadth, both length and breadth must be in meters to get the value of area in square meters.

*Dynamic systems:* Systems in which the variables are functions of other variables or time.

*Mission flow diagrams:* are used to analyze any sequential process. In this approach, all possible alternatives by which some task can be accomplished are mapped. The problems and costs associated with each alternative are determined. The performance requirements for the technologies are derived using numerical weights placed on the all the alternatives. The results from this analysis are used as normative forecast.

*Morphological analysis:* It is a system for breaking a problem down into parallel parts as distinguished from the hierarchical breakdown of the relevance tree. All possible combinations of the last level of the hierarchy are considered for further analysis.

*Network techniques:* These are based on flow charts that show all the branches of technological development. These charts help in identifying the critical paths in terms of disciplinary areas, functional subsystems etc.

*Non-linear system:* Systems in which the relationships among various variables and parameters are not linear in nature.

Consider a general function: $ax^n + c$, where a,c are constants.

If $n > 1$, then the function is non-linear.

If $n = 1$, then it is linear.

If $n = 0$, then it is a constant.

*Opportunity cost:* Loss due to breakdowns resulting from lost sales, repairs, loss of direct expenses during breakdown time (wages are paid even during the breakdown period), loss of readiness and other losses perceived by the management.

*Relevance Trees:* are tracing method which emphasizes structural relationships, i.e., a chain of causes and effects. In general, the relevance tree consists of the main objective at the top, followed by tasks that are followed by potential approaches. The lower levels of the hierarchy of the tree involve finer distinctions or subdivisions. Relevance trees graphically indicate the effect between various levels of variables via relationships.

*System analysis:* It refers to the systematic breakdown of a problem and dealing with one level of the problem at a time.

*System structure:* The relationships among the various variables and parameters in the system is referred to as its structure.

**Chapter 3**

*Dependent subsystems:* A system wherein the subsystems are all dependent on each other, i.e., impact each other's operations, are referred to as "dependent subsystems".

*Imperfect maintenance actions:* Maintenance crew actions that are not free of errors.

*Independent subsystems:* If in a system the subsystems are independent of each other, i.e., they do not impact each other's operations, then the subsystems are referred to as "independent subsystems".

*Inventory costs:* include all expenses related to inventory such as loss of interest on capital tied up, storage costs and labor involved in inventory handling.

*Proactive policy:* is one that calls for action before the occurrence of the problem (or accident).

*Reactive policy:* is one that calls for action after the occurrence of the problem (or accident).

*Variable as a function of time:* When a variable changes its value with time 't' (or is time variant), it is said to be a function of time.
For example, displacement, $x = 3t$, implies that displacement increases by 3 units every unit of time.

*Factor of safety:* This is the factor by which certain parameters and variables in mechanical designs are multiplied to account for inherent defects in material, manufacturing processes, certain unforeseen working conditions and to allow for flexibility in the usage of the structure (or system).

**Chapter 4**

*Failures:* A count of maintenance actions for work on equipment not operational or equipment with reduced capability.

*Number of preventive maintenance actions per year:* This is the total number of preventive maintenance actions performed per year by the maintenance department.

*Ownership cost:* This is the total amount spent in repairs and replacements per year.

*Pulse function:* A function of the form:

$$f(x) = u.x, \ x = a$$
$$= 0, \text{ otherwise.}$$

*Total logistics time for maintenance actions per year:* The total average delay time to fault isolate a failure and to obtain the necessary parts to complete a maintenance action.

*Total man-hours for maintenance per year:* This is total man-hours spent on maintenance per year and is an indicator of the total labor that was used for maintenance.

*Total repair cost per year:* This is the total amount spent in repair works (excluding replacements) per year.

# Appendix A - Fixed vs Varying Policy

Flexible policy, no aging

| Learning | Preventive Maintenance Actions year 1 | Cumulative Breakdowns | Life-cycle Cost |
|---|---|---|---|
| 0.75 | 0 | 446 | 45653 |
| 0.75 | 10 | 453 | 45964 |
| 0.75 | 20 | 467 | 46590 |
| 0.75 | 30 | 449 | 46032 |
| 0.75 | 40 | 455 | 46305 |
| 0.75 | 50 | 451 | 46268 |
| 0.75 | 60 | 454 | 46338 |
| 0.75 | 70 | 452 | 46411 |
| 0.75 | 80 | 437 | 45899 |
| 0.75 | 90 | 440 | 46017 |
| 0.75 | 100 | 437 | 46075 |

Fixed policy  no aging

| Learning | Preventive maintenance actions year 1 | Cumulative breakdowns | Life-cycle cost |
|---|---|---|---|
| 0.75 | 0 | 1360 | 61395 |
| 0.75 | 10 | 1168 | 55888 |
| 0.75 | 20 | 1019 | 52180 |
| 0.75 | 30 | 866 | 48547 |
| 0.75 | 40 | 751 | 46467 |
| 0.75 | 50 | 643 | 44774 |
| 0.75 | 60 | 560 | 44170 |

| | | | |
|---|---|---|---|
| 0.75 | 70 | 484 | 43867 |
| 0.75 | 80 | 407 | 43584 |
| 0.75 | 90 | 358 | 44394 |
| 0.75 | 100 | 316 | 45183 |

Flexible policy, aging factor = 0.5

| Learning | Preventive maintenance actions year 1 | Cumulative breakdowns | Life-cycle cost |
|---|---|---|---|
| 1 | 0 | 3819 | 167200 |
| 1 | 10 | 3727 | 164641 |
| 1 | 20 | 3800 | 166722 |
| 1 | 30 | 3775 | 165968 |
| 1 | 40 | 3747 | 165578 |
| 1 | 50 | 3771 | 166303 |
| 1 | 60 | 3746 | 165785 |
| 1 | 70 | 3731 | 165319 |
| 1 | 80 | 3661 | 163059 |
| 1 | 90 | 3755 | 165630 |
| 1 | 100 | 3810 | 166759 |

Fixed policy, aging factor = 0.5

| Learning | Preventive maintenance actions year 1 | Cumulative breakdowns | Life-cycle cost |
|---|---|---|---|
| 1 | 0 | 6420 | 160943 |
| 1 | 10 | 6380 | 161609 |
| 1 | 20 | 6268 | 159545 |
| 1 | 30 | 6414 | 164438 |

| | | | |
|---|---|---|---|
| 1 | 40 | 6054 | 158449 |
| 1 | 50 | 5775 | 153735 |
| 1 | 60 | 5732 | 154626 |
| 1 | 70 | 5836 | 158454 |
| 1 | 80 | 5923 | 161685 |
| 1 | 90 | 6023 | 166202 |
| 1 | 100 | 5756 | 161826 |

# Appendix B- Simulation Runs for Varying Policy

| Mission criticality | Learning rate | Factor by which time affects breakdowns | Preventive maintenance in year 1 | Cumulative breakdowns | Life-cycle cost |
|---|---|---|---|---|---|
| 0.15 | 1 | 0.15 | 0 | 1755 | 69222.4 |
| 0.15 | 1 | 0.15 | 1 | 1787 | 70162.8 |
| 0.15 | 1 | 0.15 | 2 | 1783 | 69820.8 |
| 0.15 | 1 | 0.15 | 3 | 1764 | 69596.2 |
| 0.15 | 1 | 0.15 | 4 | 1753 | 69339.1 |
| 0.15 | 1 | 0.15 | 5 | 1755 | 69276.7 |
| 0.15 | 1 | 0.15 | 6 | 1762 | 69552.7 |
| 0.15 | 1 | 0.15 | 7 | 1749 | 68871.8 |
| 0.15 | 1 | 0.15 | 8 | 1777 | 69866 |
| 0.15 | 1 | 0.15 | 9 | 1785 | 70141.4 |
| 0.15 | 1 | 0.15 | 10 | 1785 | 69938.5 |
| 0.15 | 1 | 0.15 | 11 | 1718 | 68092 |
| 0.15 | 1 | 0.15 | 12 | 1773 | 69633.1 |
| 0.15 | 1 | 0.15 | 13 | 1761 | 69551.7 |
| 0.15 | 1 | 0.15 | 14 | 1763 | 69496.6 |
| 0.15 | 1 | 0.15 | 15 | 1754 | 69444.3 |
| 0.15 | 1 | 0.15 | 16 | 1777 | 69947.3 |
| 0.15 | 1 | 0.15 | 17 | 1768 | 69642.8 |
| 0.15 | 1 | 0.15 | 18 | 1747 | 69117.8 |
| 0.15 | 1 | 0.15 | 19 | 1770 | 69812.2 |
| 0.15 | 1 | 0.15 | 20 | 1739 | 68974.8 |
| 0.15 | 1 | 0.15 | 21 | 1765 | 69425 |
| 0.15 | 1 | 0.15 | 22 | 1772 | 69907.1 |

| | | | | | |
|---|---|---|---|---|---|
| 0.15 | 1 | 0.15 | 23 | 1736 | 68866.8 |
| 0.15 | 1 | 0.15 | 24 | 1782 | 69770.6 |
| 0.15 | 1 | 0.15 | 25 | 1762 | 69265.9 |
| 0.15 | 1 | 0.15 | 26 | 1767 | 69661.7 |
| 0.15 | 1 | 0.15 | 27 | 1763 | 69199.1 |
| 0.15 | 1 | 0.15 | 28 | 1769 | 69616.8 |
| 0.15 | 1 | 0.15 | 29 | 1733 | 68544.6 |
| 0.15 | 1 | 0.15 | 30 | 1761 | 69671.8 |
| 0.15 | 1 | 0.15 | 31 | 1757 | 69061.8 |
| 0.15 | 1 | 0.15 | 32 | 1764 | 69553.1 |
| 0.15 | 1 | 0.15 | 33 | 1744 | 68811.5 |
| 0.15 | 1 | 0.15 | 34 | 1764 | 69645.6 |
| 0.15 | 1 | 0.15 | 35 | 1784 | 70196 |
| 0.15 | 1 | 0.15 | 36 | 1751 | 69092.9 |
| 0.15 | 1 | 0.15 | 37 | 1740 | 69027.3 |
| 0.15 | 1 | 0.15 | 38 | 1772 | 69507 |
| 0.15 | 1 | 0.15 | 39 | 1740 | 69007.1 |
| 0.15 | 1 | 0.15 | 40 | 1761 | 69334.6 |
| 0.15 | 1 | 0.15 | 41 | 1744 | 69108.6 |
| 0.15 | 1 | 0.15 | 42 | 1742 | 68855.5 |
| 0.15 | 1 | 0.15 | 43 | 1766 | 69688.5 |
| 0.15 | 1 | 0.15 | 44 | 1771 | 69581.3 |
| 0.15 | 1 | 0.15 | 45 | 1727 | 68494.3 |
| 0.15 | 1 | 0.15 | 46 | 1758 | 69363.7 |
| 0.15 | 1 | 0.15 | 47 | 1744 | 69196.8 |
| 0.15 | 1 | 0.15 | 48 | 1762 | 69431.1 |
| 0.15 | 1 | 0.15 | 49 | 1757 | 69457 |
| 0.15 | 1 | 0.15 | 50 | 1755 | 69037.9 |
| 0.15 | 1 | 0.15 | 51 | 1731 | 68760.8 |
| 0.15 | 1 | 0.15 | 52 | 1769 | 69478.3 |

| | | | | | |
|---|---|---|---|---|---|
| 0.15 | 1 | 0.15 | 53 | 1730 | 68825.6 |
| 0.15 | 1 | 0.15 | 54 | 1762 | 69320.7 |
| 0.15 | 1 | 0.15 | 55 | 1752 | 69068.5 |
| 0.15 | 1 | 0.15 | 56 | 1732 | 69063.9 |
| 0.15 | 1 | 0.15 | 57 | 1742 | 69118.8 |
| 0.15 | 1 | 0.15 | 58 | 1736 | 69114.1 |
| 0.15 | 1 | 0.15 | 59 | 1770 | 69724.5 |
| 0.15 | 1 | 0.15 | 60 | 1748 | 69302.6 |
| 0.15 | 1 | 0.15 | 61 | 1736 | 68962.3 |
| 0.15 | 1 | 0.15 | 62 | 1748 | 69099.8 |
| 0.15 | 1 | 0.15 | 63 | 1763 | 69632.4 |
| 0.15 | 1 | 0.15 | 64 | 1769 | 69710.7 |
| 0.15 | 1 | 0.15 | 65 | 1767 | 69452.9 |
| 0.15 | 1 | 0.15 | 66 | 1730 | 68886 |
| 0.15 | 1 | 0.15 | 67 | 1746 | 69234.1 |
| 0.15 | 1 | 0.15 | 68 | 1739 | 68976.2 |
| 0.15 | 1 | 0.15 | 69 | 1764 | 69640.5 |
| 0.15 | 1 | 0.15 | 70 | 1749 | 69199.1 |
| 0.15 | 1 | 0.15 | 71 | 1750 | 69282.9 |
| 0.15 | 1 | 0.15 | 72 | 1762 | 69077.8 |
| 0.15 | 1 | 0.15 | 73 | 1739 | 69083.4 |
| 0.15 | 1 | 0.15 | 74 | 1742 | 68785 |
| 0.15 | 1 | 0.15 | 75 | 1744 | 68905.1 |
| 0.15 | 1 | 0.15 | 76 | 1751 | 69215.2 |
| 0.15 | 1 | 0.15 | 77 | 1805 | 70553.4 |
| 0.15 | 1 | 0.15 | 78 | 1765 | 69714.6 |
| 0.15 | 1 | 0.15 | 79 | 1768 | 69673.2 |
| 0.15 | 1 | 0.15 | 80 | 1764 | 69416.1 |
| 0.15 | 1 | 0.15 | 81 | 1766 | 69724.8 |
| 0.15 | 1 | 0.15 | 82 | 1739 | 69232.2 |

| | | | | | |
|---|---|---|---|---|---|
| 0.15 | 1 | 0.15 | 83 | 1744 | 68945.7 |
| 0.15 | 1 | 0.15 | 84 | 1795 | 70465.2 |
| 0.15 | 1 | 0.15 | 85 | 1774 | 69866.5 |
| 0.15 | 1 | 0.15 | 86 | 1782 | 70046.6 |
| 0.15 | 1 | 0.15 | 87 | 1780 | 70315.5 |
| 0.15 | 1 | 0.15 | 88 | 1776 | 70081.4 |
| 0.15 | 1 | 0.15 | 89 | 1718 | 68595.1 |
| 0.15 | 1 | 0.15 | 90 | 1725 | 68579.8 |
| 0.15 | 1 | 0.15 | 91 | 1748 | 69186.3 |
| 0.15 | 1 | 0.15 | 92 | 1725 | 68797.1 |
| 0.15 | 1 | 0.15 | 93 | 1730 | 69119.8 |
| 0.15 | 1 | 0.15 | 94 | 1737 | 69090 |
| 0.15 | 1 | 0.15 | 95 | 1739 | 69048.1 |
| 0.15 | 1 | 0.15 | 96 | 1783 | 70159.1 |
| 0.15 | 1 | 0.15 | 97 | 1771 | 70067.2 |
| 0.15 | 1 | 0.15 | 98 | 1753 | 69250 |
| 0.15 | 1 | 0.15 | 99 | 1749 | 69389.3 |
| 0.15 | 1 | 0.15 | 100 | 1782 | 70139.3 |

# Appendix C - Simulation Runs for Incremental and Radical Technological Upgrades

Incremental technological upgrade

| mc | borrow | learning | lossbd | fprbd | ftebd | avgbd 1 | ppm | cbdm | lcc |
|---|---|---|---|---|---|---|---|---|---|
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 0 | 741 | 32549.1 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 10 | 727 | 32197.7 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 20 | 744 | 32754.7 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 30 | 724 | 32186.3 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 40 | 712 | 31895.7 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 50 | 732 | 32419 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 60 | 735 | 32493.1 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 70 | 740 | 32720.5 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 80 | 721 | 32415.5 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 90 | 727 | 32557.5 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 100 | 722 | 32514.9 |
| | | | | | | | | | |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 0 | 3096 | 116004 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 10 | 3073 | 115485 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 20 | 3091 | 115539 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 30 | 3103 | 116216 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 40 | 3101 | 115555 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 50 | 3144 | 116936 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 60 | 3089 | 115501 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 70 | 3078 | 115483 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 80 | 3101 | 115803 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 90 | 3100 | 116208 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 100 | 3065 | 114570 |

Radical technological upgrades

| mc | borrow | learning | lossbd | fprbd | ftebd | avgbd1 | ppm | cbdm | lcc |
|---|---|---|---|---|---|---|---|---|---|
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 0 | 788 | 33894 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 10 | 771 | 33519.6 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 20 | 792 | 34162.5 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 30 | 771 | 33572.4 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 40 | 758 | 33245.1 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 50 | 778 | 33747.8 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 60 | 783 | 33874.6 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 70 | 785 | 34030.2 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 80 | 765 | 33717.8 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 90 | 770 | 33779 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0 | 100 | 100 | 768 | 33857.2 |
| | | | | | | | | | |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 0 | 3278 | 120189 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 10 | 3268 | 120042 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 20 | 3282 | 119940 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 30 | 3287 | 120412 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 40 | 3298 | 120172 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 50 | 3326 | 121013 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 60 | 3263 | 119445 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 70 | 3268 | 119789 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 80 | 3301 | 120376 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 90 | 3290 | 120548 |
| 0.15 | 10 | 1 | 20 | 0.7 | 0.4 | 100 | 100 | 3253 | 118746 |

# Appendix D- Sensitivity Analysis for 10% Change in All Parameters

Cbdm = Cumulative number of breakdowns.

Lcc = Life-cycle cost.

| -10% | | 0 | | 10 | |
|---|---|---|---|---|---|
| cbdm | lcc | Cbdm | Lcc | Cbdm | Lcc |
| 1270 | 53903.4 | 1245 | 60295.7 | 1221 | 66776.2 |
| 1279 | 54144.1 | 1255 | 60588.3 | 1231 | 67096.4 |
| 1300 | 54784.5 | 1277 | 61280.2 | 1253 | 67830.9 |
| 1284 | 54409.1 | 1261 | 60847.8 | 1237 | 67347.5 |
| 1289 | 54592.8 | 1265 | 61053.3 | 1241 | 67575.1 |
| 1281 | 54428.2 | 1258 | 60878.6 | 1234 | 67386.8 |
| 1288 | 54528.9 | 1264 | 60969.6 | 1241 | 67477.9 |
| 1281 | 54441.8 | 1259 | 60899.9 | 1236 | 67417.6 |
| 1263 | 54092.6 | 1240 | 60482 | 1216 | 66925.5 |
| 1265 | 54245.1 | 1241 | 60620.2 | 1217 | 67054.3 |
| 1248 | 53954.9 | 1226 | 60339.6 | 1203 | 66806.9 |

# Appendix E - Example of Auxiliary Variable

In general, the following convention has been used for the variables.

a.k = Value of variable at time t.

a.j = Value of variable at time t-1.

r.kl = Rate variable in the time interval t and t+1.

c = Constant

Consider the following set of equations written using auxiliary variables:

s.k = s.j + (dt) (sh.jk)

sh.kl = (ds.k – s.k) / st

ds.k = b.k / d

b.k = r * f.k

f.k = s.k * g

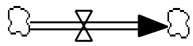
The auxiliary variables used in the above set of equations are ds, b, f. If the same set of equations is written without using auxiliary variables then the equivalent equations are:

s.k = s.j + (dt) (sh.jk)

sh.kl = (((r * g * s.k) / d) – s.k) / st

When a complex system is being described using system dynamics equations, the auxiliary variables help in reducing complexity of the level and rate variable equations. Auxiliary equations make the understanding of the system easy. The above example consists of a few variables and parameters. The auxiliary variables are useful as the number of parameters and variables and therefore the complexity increases.

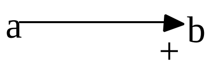
# Appendix F – Symbols used in the Model Sketch



– Symbol for Rate Variables


– Symbol for Level Variables

Auxiliary Variable/Constant – Auxiliary Variables and constants have no symbols.




– The arrows represent the effect between two variables/ parameters

The polarity of the relationship between the two variables/parameters being linked by an arrow is represented a symbol (+ or -) below the arrow-head

# Appendix G - The C++ Program

The C++ program is a substitute for VENSIM (version 1.62) to incorporate the seed changing facility for random number generation. It can be used for any preventive maintenance policy (fixed, flexible or a combination) by changing the assignment statement for npm[t+1]. The program code is as follows:

```
/********* C++ program for determining the effect of maintenance policy on system performance and life-cycle cost *********/


/******* HEADER FILES **************/

# include <iostream.h>
# include <stdlib.h>
# include <math.h>
# include <fstream.h>

/* Maximum value of the random number to be generated */
# define RAND_MAX 32767;

void main()
{
/* VARIABLE AND PARAMETER DECLARATION */

float coc, debt, equity, interest, oppor_loss,  inv, tu[100], ftubd, learning;
float borrow, it, beta, premium, rf, infl, lossbd, repl, ss, disp, avgbd, avgbd1, stdev_bd, mc, invest, zz;
```

```
float l, lcc, tc[100], fprbd, ftebd, flccetc, oper_cost, bdm, pm, tbdm[100], tpm[100],
normal;
float lcc1, oppor_loss1, lccavg, oppor_lossavg;
float w1, w2;

int cbdm, cnpm, npm[100], max_pm, ppm, nbdm[100], life, t, iter, maxtol, cbdm1,
cnpm1, cnpmavg, cbdmavg;

double b;

/* SUBROUTINE DECLARATION */
float distrib_normal (float avgbd, float stdev_bd);    /* Normal distribution */
float distrib_expo (float avgbd1);                     /* Exponential distribution */


/* SYSTEM PARAMETERS - to be manually input by the user */
life =15;              /* Study period */
avgbd1 = 100;          /* Average breakdown rate in year 1 */

pm = 15;               /* Cost per preventive maintenance */
bdm = 12;              /* Cost per breakdown */
oper_cost =100;        /* Direct cost of operations per period (year) */
lossbd =20;            /* Average loss per breakdown in $ or hours */

learning =0.95;        /* Learning rate */
invest =1000;          /* Initial investment */
ppm = 0;               /* Preventive Maintenance in year 1 */



/* FACTORS */
```

```
fprbd = 0.7;     /* Quantifying the effect of preventive maintenance on breakdowns */
ftebd = 0.5;     /* Quantifying the aging effect */
flccetc = 0;     /* Factor used in the dummy loop for life-cycle cost */
mc = 0.3;        /* Mission criticality - Number of preventive maintenance actions per
                 dollar average loss */


/* FINANCIAL PARAMETERS */
borrow =10;              /* % borrow rate */
it = 40;                 /* Income tax rate */
beta = 1;                /* Volatility of the company stocks */
premium = 6;             /* % market premium  */
rf = 5;                  /* % risk free bonds */
infl = 4;                /* % inflation */

w1= 0;                   /* Proportion of equity in capital structure */
w2= 1 - w1;              /* Proportion of debt in capital structure */

/* Note: Sum of proportions of debt and equity = 1 */


/* INVENTORY PARAMETERS */
ss =15;          /* Safety stock */
repl=5;          /* Replenishment */

srand (rand());          /* Seed generated randomly */


/******** CALCULATING PARAMETERS *****************/
equity = (rf + premium * beta)/100;   /* Capital Asset Pricing Model equation for cost of
equity */
```

```
debt = borrow/100 * (1- it/100);        /*Cost of debt */
coc = w1*equity + w2*debt;              /*Cost of capital */
b = log10(learning)/log10(2);           /*Learning exponent */


/*****  INITIALIZING  INTERMEDIATE  (PROGRAM)  VARIABLES
***************/

          cbdmavg = 0;
          cnpmavg = 0;
          lccavg = 0;
          oppor_lossavg = 0;


/*****  SIMULATING  FOR  DIFFERENT  STARTING  PREVENTIVE
MAINTENANCE POLICIES *************/

          for (ppm=0; ppm<=avgbd1; ppm+=10)
          {

          cbdm1 =0;
          cnpm1 =0;
          lcc1 =0;
          oppor_loss1 =0;


               for (iter=1; iter<=100; iter++)
                    {

                                        /* INITIALIZATION */
```

```
{
                    oppor_loss= 0;
                    cbdm = 0;
                    cnpm = 0;
                    lcc = invest;


        /* INITIALIZATION OF ARRAYS*/

        for (t=1; t<=life; t++)
        {
                nbdm[t] = 0;
                npm[t] = 0;
                npm[1] = ppm;
        }


/** SIMULATING FOR EVERY PERIOD THROUGHOUT THE LIFE CYCLE ***/

    for (t=1; t<=life; t++)
    {

/* Max tolerable breakdown rate = 2 x initial average breakdown rate */
    maxtol = avgbd1*2;
    zz = float (t)/5;



        if (zz==t/5 && t!=0 | cbdm/t > maxtol)
/* Technological upgrade every 5 years or when breakdowns more than the maximum
tolerable rate. This loop represents the pulse function. */

        {
```

```
                    tu[t] =10;
                    ftubd = 0.1;
                }
                else
                {
                    tu[t] = 0;
                    ftubd = 0;
                }

            l =pow(t,b); /* Calculating the learning factor every period */



/* Average breakdown rate affected by age and technological upgrade */
        avgbd = avgbd1 * (1+ftebd*t)*(1-ftubd);

/* Generate random breakdowns using distribution */
        normal = distrib_expo(avgbd);

/* Breakdowns in period t +1 are affected by the number of preventive maintenance
actions in the period 't' */
        nbdm[t+1]= normal- npm[t]*fprbd/l;

/* Note: npm[t] is the policy set at the beginning of any time period t, nbdm[t] occurs
during (t-1,t) */

        /* Avoiding negative breakdowns */
        if(nbdm[t+1] <0)
            {
                nbdm[t+1] = 0;
            }
```

```
                    /* INVENTORY CALCULATIONS */
            inv = nbdm[t] * repl + ss;
            oppor_loss= oppor_loss + (nbdm[t]*lossbd + inv*coc);


/* DETERMINATION OF MAINTENANCE POLICY */

/* Number of preventive maintenance = f(oppor loss) for FLEXIBLE*/
npm[t+1]= oppor_loss/t*mc;

/* Number of preventive maintenance = preventive maintenance in year 1 for FIXED */
/* npm[t+1] = ppm; */

/* Preventive maintenance budget (upper limit) based on the average number of
breakdown of the system during that period */

max_pm = avgbd;

/* Limiting the number of preventive maintenance actions within budget */
    if (npm[t+1]>max_pm)

    {
        npm[t+1]= max_pm;
    }

                /* Calculating cumulative variables */
                cbdm = cbdm+ nbdm[t];
                cnpm = cnpm+ npm[t];


/* Costs incurred in time 't' */
```

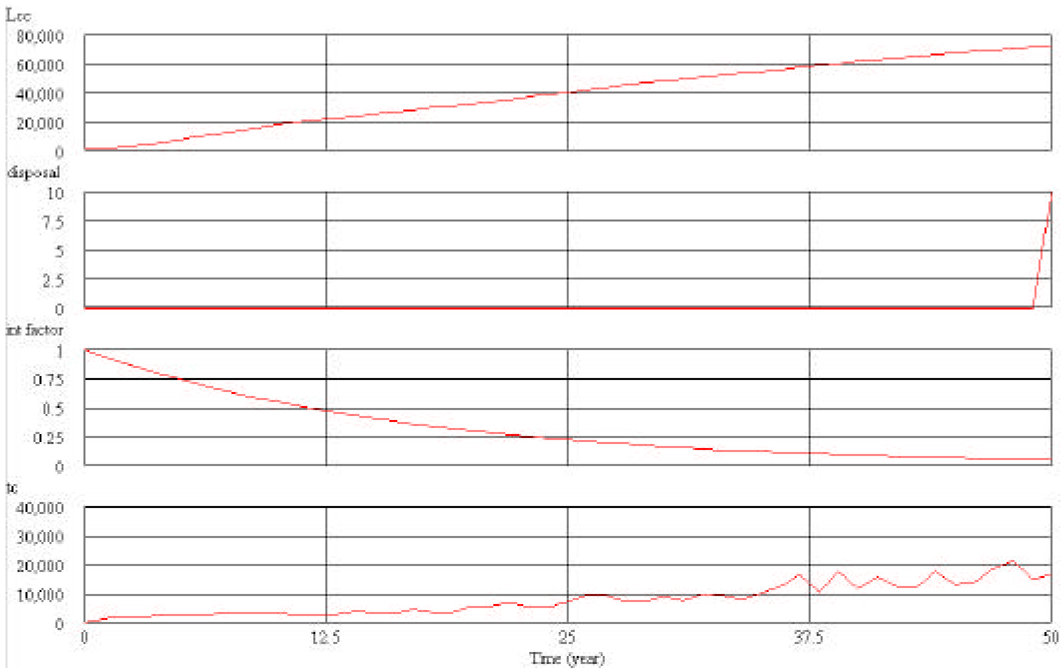
```
	tbdm[t] = nbdm[t]*bdm;
	tpm[t] = npm[t]*pm;

				/* Continuous compounding */
				interest = exp(-coc*t);

/* Computing total annual cost including opportunity loss */
tc[t] = (oper_cost + tbdm[t] + tpm[t] + tu[t] + (nbdm[t]*lossbd + inv*coc))* (1+
infl/100*t) * interest;


/* Disposal cost only at the end of service life */
	if (t!=life)
	{
		disp = 0;
	}

	else
	{
		disp = 20;
	}


/* Computing life cycle cost */
	lcc = lcc + tc[t] + disp*interest;

				}		/* "life" loop ends */


/* Accumulating for each iteration to calculate the average */
```

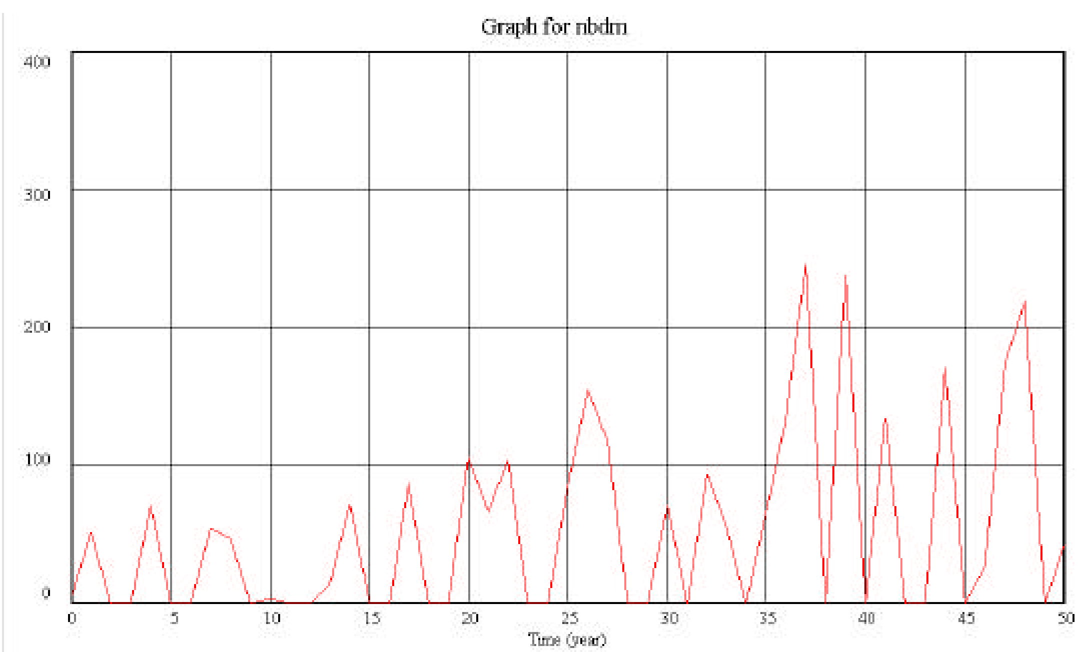
```
        cbdm1 = cbdm1 + cbdm;
        cnpm1 = cnpm1 + cnpm;
        lcc1 = lcc1 + lcc;
        oppor_loss1 = oppor_loss1 + oppor_loss;


                        }               /* iterations end */

                        /* Calculating the average for each iteration */

                                        cbdmavg = cbdm1/100;
                                        cnpmavg = cnpm1/100;
                                        lccavg = lcc1/100;
                                        oppor_lossavg = oppor_loss1/100;


/* Directing output to a file, append mode */
ofstream tfile ("xyz.xls", ios::app);

tfile << mc << "\t" << borrow << "\t" << learning << "\t" << lossbd << "\t" << fprbd <<
"\t" << ftebd << "\t" << avgbd1 << "\t" << ppm <<  "\t" << cbdmavg <<"\t" << cnpm <<
"\t" << lccavg << "\n";

} /* ppm loop ends */
} /* main ends */

/*************** SUBROUTINES ***************************/
/* Subroutine for exponentially distributed breakdowns */

float distrib_expo (float avg)
```

```
{

        int u, n;
        float uu;

        u = rand();
        uu= float(u+1)/32768;
/* Note: Adding 1 and dividing by 32768 to avoid 0 since log (0) is not defined and to
generate random numbers between 0 and 1*/

        n = -avg* log(uu);

        return n;
}
```

## Appendix H – Graphs for a Simulation Run (using VENSIM)

The following are graphs for a few important variables and parameters for a simulation run of 15 years.



# VITA

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