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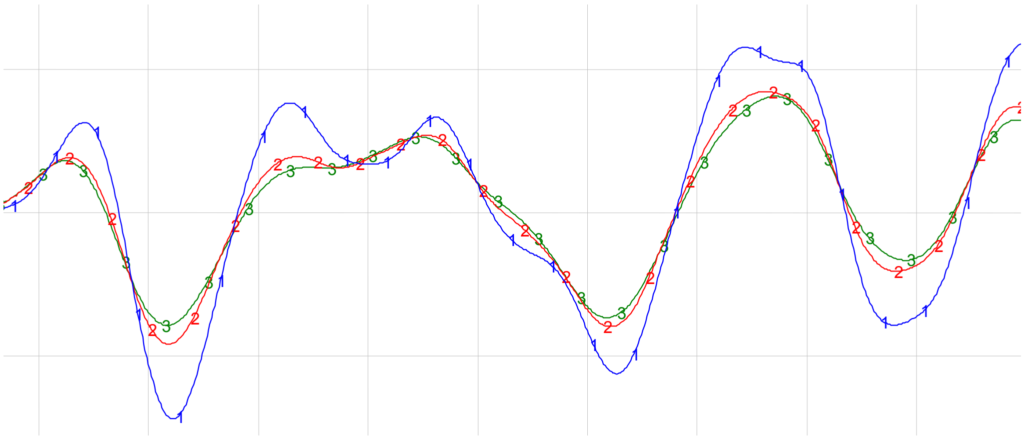

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Modelling Industrial Maintenance Systems and the Effects of Automatic Condition Monitoring

Tuomo Honkanen

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ABSTRACT

In this dissertation, industrial maintenance activities are researched from a systemic point of view. Maintenance is considered from the selected viewpoint as a control system for controlling the reliability of machines in a process environment. The control takes place through communication of information. Thus, maintenance can also be considered as an information processing system. Therefore, the viewpoint also supports development of future maintenance information systems. The specific interest of the research is in modelling the effects of automatic condition monitoring systems enabled by embedded electronics and software in industrial machines.

The research problem is to model maintenance systems and the effects of condition monitoring. Because the focus is on the maintenance systems, the research approach differs from the usual reliability engineering approaches, which focus on the reliability of mechanical systems. The applied methods are a literature study of the main reliability paradigms and the systems theory to derive a theory of maintenance systems. The theory is then applied by developing a UML knowledge model, an applied Gorry-Morton control activities model, a stochastic simulation model and a dynamic simulation model of the maintenance systems. Also, one additional simulation model is developed to study the effect of remote condition monitoring on the spare parts supply chain.

The main results indicate that the subjective nature of failures, the available information about the machines as well as the repeatability of the maintenance actions are the most important factors in the maintenance system control. Also, correct selection of the maintenance system cost functions is critical in determining the applied maintenance policies.

Condition monitoring increases observability of the states of the machines and therefore enables more effective maintenance systems with the help of condition-based maintenance. However, the effectiveness of condition-based maintenance depends on the accuracy of the monitoring and the coverage of the failure diagnosis. The failure patterns and the repeatability of the maintenance actions also contribute significantly to the effectiveness of condition-based maintenance. In spare parts supply chains, remote condition monitoring can be used to stabilise the supply chain variability and to reduce the supply chain sensitivity to random noise and sudden changes in the consumption.

Keywords: maintenance system, condition monitoring, condition-based maintenance, supply chain, information system

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Finally, my loving thanks to my wife Outi and my daughter Linda for giving me joy and support for the numerous days with this research.

Helsinki, October 13th, 2003
Tuomo Honkanen

Quidquid latine dictum sit, altum viditure.

CONTENTS

ABBREVIATIONS, SYMBOLS AND GLOSSARY

ABBREVIATIONS IN THE TEXT

AI	artificial intelligence
CBM	condition-based maintenance, a synonym for predictive maintenance
CE	control engineering
CM	condition monitoring
CMMS	computerised maintenance management system
EOQ	economic order quantity
FMEA	failure modes and effects analysis
FTA	fault tree analysis
MTBM	mean operating time between maintenance
MTTAM	mean operating time to arrange a maintenance break
MTTF	mean operating time to failure of a function or a machine
MTTFR	mean calendar time to reach first repaired failure
MTTM	mean calendar time to maintain
MTTR	mean calendar time to repair
OEE	overall equipment efficiency
PM	preventive maintenance
RE	reliability engineering
RCM / RCM II	reliability-centered maintenance
TPM	total productive maintenance
TTF	operating time to failure
UML	unified modelling language
UP	unified process

SYMBOLS AND VARIABLES IN EQUATIONS

α	Gamma distribution scale parameter
β	Weibull distribution shape parameter
η	Weibull distribution scale parameter
λ	average failure rate, failure rate
μ_{group}	average failure interval of a group of machines
A_o	operational availability
C	total number of components
c	number of working components
C_i	cost of one inspection
C_a	actual daily consumption
c_{co}	component price
c_{re}	repair work costs
c_{ma}	proactive maintenance costs
cd_{cap}	daily lost capacity expenses of proactive maintenance
cd_{op}	daily increased operating expenses caused by a failure
cd_{qu}	daily increased quality expenses caused by a failure
cd_{car}	daily lost capacity expenses caused by a failure
D_e	estimated daily demand
DC	diagnostics coverage
DT	failure detection time
E	reliability target error
EOQ	economic order quantity
fc	cost function of maintenance and failures
G_p	proportional error gain
G_i	integral error gain
K	safety factor
n	number of proactive maintenance actions in a year
n_{fd}	the number of components failed because of deterioration
n_{fi}	the number of components failed because of infant failures
n_r	the number of components being repaired
m	number of repairs in a year
mf	number of preventive maintenance actions per failure
MTBI	mean operating time between inspections
MTBM	mean operating time between maintenance, a synonym for *MTTF*
MTTAM	mean operating time to arrange a maintenance break
MTTF	mean operating time to failure
MTTFR	mean calendar time to reach first repaired failure
MTTM	mean calendar time to maintain
MTTR	mean calendar time to repair
OEE	overall equipment efficiency
OQ	order quantity
S	reliability target setpoint, system state
T	time to failure
T_m	time to failure of a maintained system or machine
T_d	transportation or production delay
TTF	operating time to failure
Ut	machine utilisation of calendar time
Y	controlled reliability variable

GLOSSARY

asset	in the context of industrial maintenance, an asset is physical property invested for production purposes
availability	the probability that at any given instant of time, including or excluding the proactive maintenance, a machine is not failed
controllability	the ability to control the reliability of the machine in order to achieve and maintain some specific maintenance system efficiency level[1]
diagnostics coverage	the probability that a failure state is detected correctly by a diagnostics system, see also *observability*
failure	a state of a machine in which the machine is not performing a required function at the required level
failure event	in this dissertation, an interchangeable term for failure mode
failure mode	any event which causes a functional failure
failure pattern	a failure rate pattern as a function of operation time
failure state	*see failure*
fault	an existence (state) or an occurrence (event) of a failure or a potential failure
maintenance	the combination of all technical and administrative actions, including supervision actions, intended to retain an entity in, or restore it to, a state in which it can perform a required function (IEC 60050-191, 1996)
maintenance policy	a decision to apply reactive, preventive or condition-based maintenance
maintenance program	a formal proactive maintenance plan for machines
maintenance strategy	a long-term company strategy to use some combination of various maintenance policies and reliability paradigms
observability	the probability that a system state is detected correctly
partial failure	partial loss of machine function
planned maintenance	maintenance action with planned procedures and resource needs
predictive maintenance	a proactive maintenance action triggered by condition monitoring
preventive maintenance	a proactive maintenance action executed in order to prevent a failure
proactive maintenance	maintenance action executed before occurrence of an individual failure
repeatability	the probability that any maintenance action of certain action type results always in the same target system state
reactive maintenance	maintenance action executed after occurrence of individual failure
reliability	the probability that a machine does not fail during a given time interval
reliability paradigm	a theoretical framework of a scientific school or discipline in maintenance or reliability
scheduled maintenance	time-scheduled proactive maintenance action
total failure	total loss of a machine function
unplanned maintenance	a proactive or reactive maintenance action with maintenance procedures and resource needs not planned before executing the maintenance task

[1] Note that the definition of controllability differs from the mathematical definition (Wolovich, 2000) in mathematical control theory.

1 INTRODUCTION AND OVERVIEW

1.1 MOTIVATION AND BACKGROUND

I have been working with automation and industrial information technology for eight years. During these years I have been involved in several development projects that aim for automatic machine condition monitoring (Honkanen, 1997) and machine data communications. Technically these projects have succeeded: the developed information systems have been technically modern and worked well. However, despite all the technical advantages these products have not been commercial successes.

Some years ago I noticed that a good business process consultant can achieve commercially much more successful results by just capturing the business requirements and doing a thorough analysis of the business processes before developing anything. I had forgotten that the word information in the information technology really refers to the substance of an information system.

An automatic condition monitoring system is essentially such an information system. The information in the system exists to be processed by humans and computers in order to serve a purpose. The other technologies that relate to automatic condition monitoring include applications in automatic machine failure diagnostics, failure prognostics, maintenance planning, and such future concepts as automatic spare parts orders from intelligent machines. All these activities interrelate to increase the efficiency of industrial production processes and maintenance.

The real problem was that I did not know the big picture, I could not find only one such, and no one could draw me one either, to analyse the effects of automatic condition monitoring on industrial maintenance activities.

1.2 PROBLEM SETTING AND GOALS OF THE STUDY

Some investment machine manufacturing companies have developed concepts (ABB, 2002; Metso, 2002) that aim at providing totally integrated information systems. According to their vision, in the future it will be possible to automate and integrate the maintenance activities in a system that consists of the machines, persons and information systems. New technologies, such as electronics, mechatronics, communication and software technologies make it possible to develop intelligent machines and condition monitoring systems. The problem is how to find the best application areas for such technologies.

This dissertation proposes that thinking industrial maintenance as an information processing system leads to a top-down view that helps in analysing the effects of automatic condition monitoring.

Therefore, *the research problem is to model maintenance systems and the effects of automatic condition monitoring.*

The main problem was divided in sub-problems to make the research problem easier to answer. The three research questions to address the problem can be derived from the systems theory approach of Saaty and Kearns (1985):

Q1: What is the purpose of maintenance?
Q2: What are the structures, behaviour and the information flows in the maintenance systems?
Q3: How does condition monitoring affect the systems?

The questions, Q1-Q3, form a logical top-down chain from the purpose of maintenance to the effects of the condition monitoring to maintenance systems.

1.3 RESEARCH APPROACH, METHODOLOGY AND DESIGN

The problem is to model maintenance systems and the effects of automatic condition monitoring on the functions of the maintenance systems. A model of maintenance systems means here some system model that is not bound to some single maintenance or reliability paradigm, but applicable to most common paradigms. The systems approach, which studies the *relations*, *organisation* and *interactions* of entities on an abstract level is proposed to formulate such a model. Contrasted to analytical approach, which focuses on the parts, the systems approach focuses on the whole (Schoderbek et al., 1990). This viewpoint emphasises that new scientific knowledge can be generated not only by researching a specific deep and strictly defined problem domain, but also by studying interrelations and integrating the problem domains.

In general, the "what" problems of questions Q1 and Q2 aim at developing hypotheses and propositions for further study (Yin, 1994). That is, Q1 and Q2 aim at analysing maintenance systems. This dissertation is by nature constructive and the analysis was done by a conceptual literature study to induce the theory of maintenance systems from the existing reliability paradigms (Q1-Q2). Weinberg (1975, p. 143) calls this non-observing methodology academic science with the value of creating ideals not bound to a specific paradigm. Finding analogies between the paradigms makes it possible to generate a theory of maintenance systems that is derived from a family of paradigms. Operating with analogies is a form of inductive logic without the necessity of forming its conclusions logically from its premises. The strength of this methodology in this dissertation is that no specific regional or cultural maintenance paradigm dominates the theory. The main weakness is the possible generality of the theory, which may increase the probability of the existence of such a system, but reduce the informative value of the models based on the theory.

The literature study was aligned by data acquired from interviews and observations of representatives of industrial companies. The interviews were open and informal attempting to answer the question: how do/would you use information technology and automatic condition monitoring in maintenance processes. The weakness of open and unstructured interviews is the possibility that the interviewer manipulates the discussion unconsciously. Therefore, observations of discussions at a public discussion forum on the Internet were also used to verify that the interviews were focused on the right topics. The interviews and observations should not be considered as giving very high empirical evidence. The companies, subjects and interviewing times are presented in Appendix A: Interviews.

The theory of maintenance systems was then used for deriving the models to provide answers to questions Q2-Q3, and finally the conclusions of the research were derived. The methodological research approach is shown in Figure 1. It should be noted that the research was somewhat iterative from theory part to models and back to theory part.

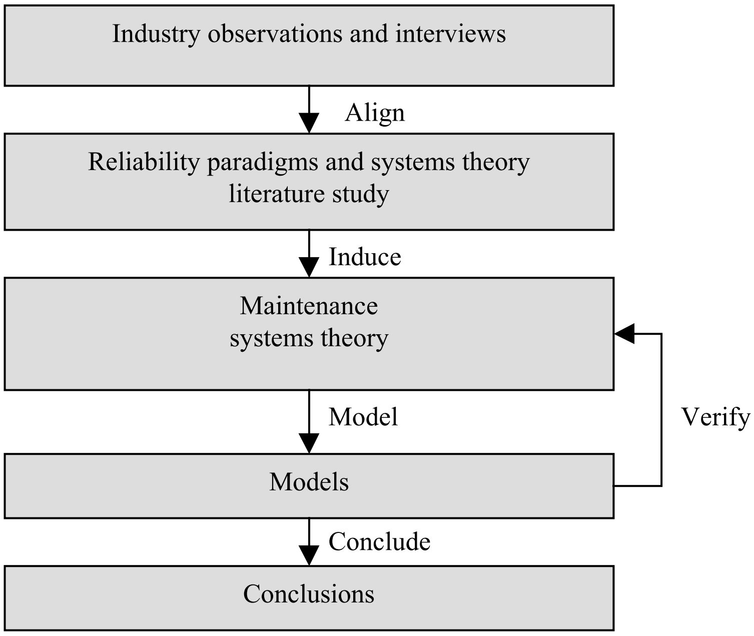

Figure 1 The methodological approach of the research.

1.4 MODELLING METHODOLOGIES

The focus of the developed theory of maintenance systems is to define and describe the maintenance systems and the boundary conditions for modelling such systems. Mathematical systems theory focuses on formal and rigorous quantitative models of systems, whereas applied systems theory, or systems technology, focuses on more qualitative, practical applications, such as software development for specific problems (Laszlo, 1972). The system models sought after in this dissertation are on the one hand knowledge models of the problem domain of interest, and on the other hand functional models that must be presented as mathematical models. Therefore, both applied systems thinking and quantitative systems modelling are used.

The synthesised maintenance information system theory is presented as figures, tables and written text. The knowledge constructs of the theory are presented in a more formalised knowledge representation format, namely unified modelling language (UML) domain models (Larman, 2002). The control aspects of maintenance systems are captured by mapping the information systems framework of Gorry and Morton (1989) to the maintenance activities. The cost model and stochastic behaviour are modelled with stochastic simulation, and the behavioural modelling is done with time-dependent dynamic models.

1.5 INCLUDED INDUSTRIES OF THE RESEARCH

Proactive maintenance and reliability are most important in industries where the cost of failures, the failure rates and the cost of maintenance are high (Komonen, 1998). Therefore, this dissertation applies best to highly integrated process industries, such as pulp and paper or chemical industries. The models and results may be applicable to other industries such as aeronautics and nuclear energy production but these specific application areas are not explicitly considered in the dissertation.

2 BACKGROUND INTERVIEWS AND OBSERVATIONS

As noted in Chapter 1, the observations and interviews should not be considered as empirical research with very high scientific evidence. However, they represent an important source of insight and alignment for the research. The interviews and observations are reviewed in this chapter.

2.1 INTERVIEWS

The interviews were unstructured open discussions and held between March 12, 2002 and January 7, 2003. The interviews consisted of 21 interview sessions including 29 different persons from 10 different companies. Fourteen interviewees came from Metso Corporation serving mainly the pulp and paper industry. The other interviewees came from the service and information technology providers, pulp and paper maintenance management and component manufacturers. Because a large proportion of the interviewees was from machine manufacturers and technology providers, the viewpoint is oriented towards machine-suppliers and information technology providers.

The purpose of the interviews was to ask how information technology and remote condition monitoring could be used to enhance industrial maintenance activities. A large proportion of the discussed topics fell either under computerised maintenance management system (CMMS) or remote condition monitoring and failure diagnostics (INTERVIEWS 2, 3, 4, 5.1, 5.2, 6, 8, 9, 10, 11, 12, 14, 15.1, 15.2, 16, 18.1, 18.2, 19, 20, 21.1, 21.2, 21.3, 21.4). The general sentiment among the interviewees was that the application of information technology was expected to bring dramatic results in machine reliability and maintenance process efficiency. At the same time, most interviewees were unable to show or calculate the benefits of the application of information technologies.

2.1.1 Business drivers

Some interviewees (INTERVIEWS 5.1, 5.2, 11) presented an idea that remote condition monitoring might help them bypass the other maintenance companies and help in offering maintenance services. The idea is that with condition monitoring the machine manufacturer could get so much information about the condition and operation of the machines, that the machine manufacturer is able to predict the failures and offer the optimal methods to operate the machines. This would change the service business so that the machine manufacturer would control the maintenance business with the help of remote condition monitoring. If using an in-house service organisation these technologies were seen as a means to enhance service efficiency and customer loyalty (INTERVIEWS 3, 4, 5.1, 5.2, 9, 10, 11, 12, 16, 20).

2.1.2 Computerised maintenance management

Interviews with CMMS providers (INTERVIEWS 8, 9, 12) indicated that the CMMS software packages are indeed very large and full of features, such as work-order management, reporting, inventory control, audit trails and much more. The actual problem seems not to be the CMMS technology but the implementation and usage of the CMMS systems. As an example, a CMMS implementation project was reported as successful, but only 15 % of the CMMS features were taken into use. Thus, the problem of implementing information systems to control a maintenance system is related to the structures and operation of the maintenance system rather than to being a technical problem.

2.1.3 Manufacturer and user-perceived failures and design criteria for machines

Some practical problems arise with the definition of failures. According to the interviewed representatives of an industrial valve manufacturing company (INTERVIEWS 4, 15.1) up to 30% of old plant control valves may be non-functional or oscillating and thus failed. Still, the plants produce good-quality products, which means that the valves have not necessarily failed from the user perspective.

An interviewed technology director (INTERVIEW 11) of an industrial valve manufacturer noted that equipment specifications are set at the plant design phase, but the specifications are often too tight or too loose, and seldom describe the real operating point or control limits of the process. This was confirmed by the interviewed consulting company representatives (INTERVIEW 18.1, INTERVIEW 18.2). According to them, the process equipment is usually oversized in order to be able to increase the plant capacity later. Therefore, the design-phase specifications cannot be used for defining whether the machine is failed or not.

2.1.4 Preventive replacement policies and condition monitoring

An interviewed industrial valve maintenance manager (INTERVIEW 7) told that the paper and pulp industry customers are often willing to change the whole control valve, instead of changing just the valve, actuator or positioner even if the failure can be identified to one of these subsystems. The interviewee also told that in a petrochemical plant the whole plant is shut down every four years and every deteriorating and critical component is changed. Similarly, a paper industry representative (INTERVIEW 17) told that when changing a failed bearing in a paper machine roll, the other bearing is also changed regardless of its age. The reason for the change policy is that the additional cost of changing the other bearing as well is low when the whole roll is detached from the machine.

The reasoning of the interviewees seem to represent the ideology that the maintenance staff in these process industries always wants to make certain that the system under maintenance is totally restored. Restoring the system state at certain points of time may help in keeping track of the system state and in standardisation of the maintenance activities.

The same paper industry representative (INTERVIEW 17) told that under condition monitoring the bearing is changed only if the condition monitoring indicates failure or the age of the bearing is exceptionally high. This means that they do not fully trust to condition monitoring systems.

2.2 OBSERVATIONS OF DISCUSSION IN THE MAILING LIST OF RELIABILITYWEB.COM

The reliabilityweb.com e-mail discussion list is open for reliability and maintenance professionals. The discussion list is moderated so that commercial e-mails are filtered out quite well. The observed e-mails were sent between May 1, 2002 and January 25, 2003. During that time, a total of 497 e-mails were read through, archived and later categorised by reading them through one more time. There were 139 message senders from a large number of organisations around the world. The viewpoint the e-mail discussion list gives is user-oriented because of the large number of e-mails related to operative and maintenance management topics. The categories used in analysing the messages are shown in Table 1.

Category	Description of Discussion Topics
CM	Automatic and manual condition monitoring methods of machines
CMMS	Computerised maintenance management system, maintenance scheduling, planning and reporting software
MAINT MGMT.	Labour and cost management methods, job descriptions, cost estimates, maintenance and workforce planning
MATH MODELING	MTBM, MTTF, availability calculations, simulation and Markov models
OPERATIVE MAINT.	Specific machine functional problems, failures, technologies and opinions
PM	Preventive maintenance methods, such as lubrication, component change intervals
RCA	Root-cause analysis implementation and usage
RCM	Reliability-centered maintenance methodologies and implementation
TPM	Total productive maintenance related issues, such as autonomous maintenance by operators
UNRELATED	Author's messages (3) and replies to them (1), some commercials, accidental messages

Table 1 Reliabilityweb.com e-mail discussion list categories.

The number of messages and the fraction of total messages in each category are presented in Figure 2.

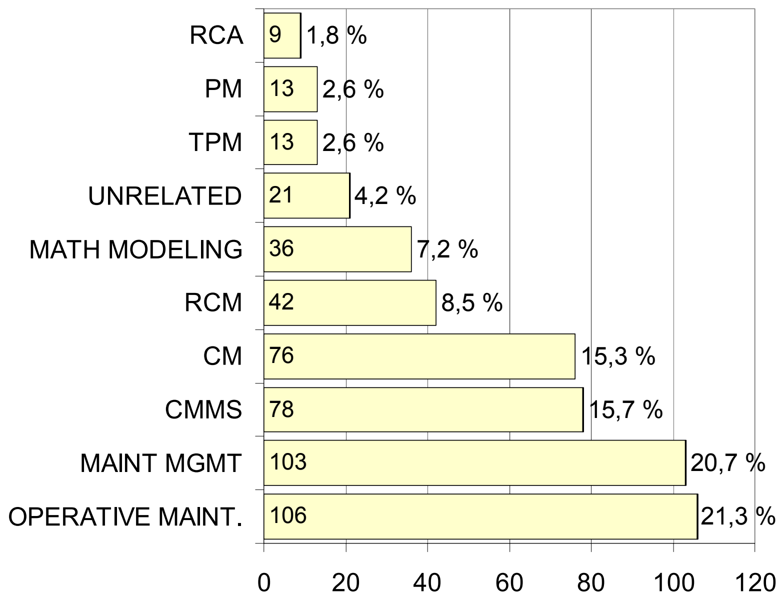

Figure 2 Number and percentage of Reliabilityweb.com e-mail discussion list messages by category.

During the observation period, the e-mail discussion list was heavily used by maintenance managers and also by some reliability consultants. A large number (42.0 %) of the messages were directly related to maintenance management and practical maintenance and reliability problems, such as selecting the correct maintenance method or tool. The CMMS and condition monitoring were also (31.0 %) lively topics.

These messages support the interviews: efficiency and reliability gains are sought from condition monitoring and CMMS technologies. Some interest was seen in using hand-held devices in reporting the maintenance actions, but the main CMMS discussion was about how and which CMMS system to implement and how to use a CMMS system. The condition monitoring discussion focused much on vibration analysis of bearings and electrical motors.

Compared to total productive maintenance (TPM) (2.6 %) reliability-centered maintenance (RCM) (8.5 %) was also a popular topic. Perhaps the reason was that there were quite many discussion participants from the USA, Europe, Australia and South-America where RCM is the dominating paradigm.

Quite surprisingly, several participants were interested in mathematical modelling (7.2 %): reliability, availability and cost calculation methods were raised quite frequently. The motivation for the calculations was quite obviously to prove the effectiveness of the selected maintenance policies and technologies.

Preventive maintenance (2.6 %) was not a popular topic by itself. Probably this does not indicate that preventive maintenance is not interesting or being applied, but the interest was expressed under other topics, such as mathematical modelling and discussion related to operative maintenance. Root-cause analysis (1.8 %) was a topic that could have been categorised under maintenance management. However, as a specific reliability method it deserves its own category.

2.3 SUMMARY OF INTERVIEWS AND RELIABILITYWEB.COM OBSERVATIONS

Both the interviews and e-mail discussion list indicate that there are two equally interesting areas among machine manufacturers and users to apply information technology in industrial maintenance: CMMS and condition monitoring. However, the interviews and observations give conflicting signals that while the technology providers are trying to develop more and more advanced tools, the maintenance departments seem to struggle with daily problems of implementing and operating such systems. The technology providers or the users do generally not know the feasibility of applying these technologies, but apparently they seem to improve the efficiency of the maintenance activities. The users combine their experience and heuristics in defining maintenance policies and in usage of condition monitoring systems. Some help is sought from maintenance paradigms such as RCM or TPM. The resulting maintenance systems seem to be a heterogeneous combination of methods and systems in which the integrating factor of the information and business processes is the maintenance personnel. The information in the maintenance systems goes through these human minds forming an organisational information system and creating a high reliance on the expertise of the maintenance staff.

3 SCOPING OF THE RESEARCH

Some basic simplifications and assumptions of the research are defined in this chapter to scope the rest of the dissertation. The first simplification is that the production operations and raw material supplies are assumed reliable and stable, and initially no maintenance is being executed. In a homogeneous environment and with stable operation nothing else than the failures of machines can disturb the production process. *It is therefore is assumed that machine failures are the only source of production disturbances.*

The assumption about a constant production environment is fair considering the scope of this dissertation: studying entire production systems would extend the research way too far from the original research problem. If no maintenance is done, then the only source of disturbances must be the machines, since they are the only deteriorating and variability-generating elements in the production system. For practical purposes this assumption about the lack of maintenance is not realistic. A production system without maintenance or would eventually cease operating regardless of how durable the system initially was. Therefore reliability, the probability that a machine does not fail during a given time interval, decreases. In mathematical terms this means that the reliability function $R(t)=P(T>t)$, $t>0$, where T is operating time to failure (TTF), approaches zero for infinite large values of t.

There are several ways to increase the reliability of a machine, such as design improvements, lubrication, cleaning, operator training, tuning, and replacing of worn machine parts. Apart from machine or process design improvements most of these actions can be categorised under the loosely defined term maintenance. A formal definition of maintenance is given by IEC 60050-191 (1996) as "*the combination of all technical and administrative actions, including supervision actions, intended to retain an entity in, or restore it to, a state in which it can perform a required function.*"

Machines have to be maintained in order to increase reliability and thereby avoid production disturbances. *It is therefore assumed that the purpose of a single maintenance action is to increase reliability.* I.e. $P(T_m > t) > P(T > t) \Rightarrow T_m > T$, where t is the operating time, T is the time to failure prior to maintenance and T_m is time to failure after maintenance.

Including the maintenance in the system scope creates an additional source of production disturbances. Maintenance itself is also a potential source of machine failures and may cause disturbances to production. In addition to maintenance, there may be failures originating from machine construction and varying quality of raw materials to be processed with the machines. These latter failure types are possible and even probable in a real world, but they are more or less related to the behaviour of the production process and the errors in machine design and manufacturing process, which are not included in the scope of this dissertation research.

To increase the reliability of machines, failures originating from the machines should be reduced. However, the absolute objective of failure reduction does not probably yield the most optimal results with regard to the financial objectives, because the costs of reliability may exceed the returns of reliability. Wireman (1998, p.1) defines the objective of maintenance in his definition of maintenance management as "*the management of all assets[2] owned by a company, based on maximizing the return on investment in the asset.*"

The motivation for maintenance is not the absolute reduction of the production disturbances but the optimisation of costs between maintenance and the failures. *The assumption is that the*

[2] In literature the term asset is often used to denote any physical object, such as device, equipment, machine, or even building. The term “asset” is a broader term than “machine” referring to any physical property that has been invested in. In this dissertation, the terms machine, component, equipment and asset are used interchangeably.

objective of maintenance as a whole is to minimise the costs of maintenance and failures. As a word, "cost" may include any damages whether financial, safety or environmental.

The relevant literature in respect to these assumptions will be reviewed in the following chapters.

4 REVIEW OF RELIABILITY AND MAINTENANCE LITERATURE

In this chapter, the basic maintenance terminology, the reliability paradigms, maintenance process activities and some maintenance business aspects are reviewed in order to build the foundations for a theory of maintenance systems.

4.1 TERMINOLOGY

The term maintenance includes various actions and tasks that aim to increase or to retain the reliability of the machines. A term often presented is *maintenance policy*, which refers to the categories of the maintenance actions applied on the machines. Depending on the industry and the applied maintenance paradigm the terms of the categories vary. Such terms include condition-based maintenance, failure-based maintenance, preventive maintenance, predictive maintenance, reactive maintenance and corrective maintenance (i.e. Horner et al., 1997; Jonsson, 1999; Moubray, 1997; Nakajima, 1989). Principally all the categories refer to the timing or methodology of the maintenance activity.

The main categorisation is maintenance activities that happen before and after a failure. Therefore, the terms *proactive maintenance* and *reactive maintenance* are used. Proactive and reactive maintenance may be *planned* or *unplanned*. This means that the work procedures of the maintenance action and its required resources are either planned or unplanned before the need for the maintenance action. A maintenance action for a failure that has never before occurred is difficult to plan beforehand. Therefore, reactive maintenance is often thought as a synonym for unplanned maintenance. However, planning for reactive maintenance can be done if the required maintenance procedures are known. For example, the replacement procedures and resource requirements of a light bulb failure can be planned even if the maintenance action is reactive.

Proactive maintenance action can be *preventive* or *predictive*. Preventive maintenance tries to prevent a failure before its occurrence with such activities as lubricating, cleaning or changing a wearing component in a machine. Predictive maintenance, also know as *condition-based maintenance*, tries to detect the machine condition automatically or manually, for executing the maintenance action based on the actual condition of the machine. *Scheduled maintenance* is a proactive maintenance action that has been scheduled beforehand according to a plan. Proactive maintenance can be scheduled, but reactive maintenance can never be scheduled in advance.

4.2 RELIABILITY PARADIGMS

According to the literature study there are four main reliability-related paradigms being applied, namely reliability-centered maintenance (RCM), total productive maintenance (TPM), reliability engineering (RE) and control engineering (CE). All the paradigms apply various methodologies and maintenance policies to the control of reliability. The origins of the paradigms are different, as well as their application domain and the viewpoint. RCM and TPM originate from industry practices, and reliability engineering and control engineering originate from mathematical and systems science. All these paradigms are reviewed briefly to be able to really understand the various approaches to reliability and how the industrial maintenance is being planned and controlled.

4.2.1 Reliability-centered maintenance

The history of RCM originates from the task force work of the US aviation industry in the 1960s and 1970s to improve safety and reliability of civil aircraft (Jardine, 1999). A sequence of guidelines and handbooks were published, namely MSG-1, MSG-2, and MSG-3 (Air Transport Association of America, 1993). United Airlines was sponsored by the US Department of Defence to write a report about the relationships between maintenance, reliability and safety, which became the foundation for RCM. RCM is a rather heavy framework for developing maintenance strategy. As a development methodology RCM answers to the following questions (Moubray, 1997): i) What are the functions and associated performance standards of the machine in its present operating context, ii) in what way does it fail to fulfil its functions, iii) what causes each functional failure, iv) what happens when each failure occurs, v) in what way does each failure matter in respect of the environment, human safety, losses, and expenses, vi) what can be done to predict or prevent each failure, vii) what should be done if a suitable proactive task cannot be found?

The core idea of RCM, as indicated by the questions, is that any physical machine or system has at least one function and the users have performance requirements for that function. The machine is considered as a system in an operating context, or environment.

The failure of a machine is its inability to do what its users want it to do. In other words, RCM defines the failure as a state of the machine that cannot be accepted by the user. A specific term *functional failure* is defined as "the inability of any asset to fulfil a function to a standard of performance which is acceptable to the user" (Moubray, 1997, p. 47). This definition emphasises the failure as being any state in which a user-defined performance standard of a function of the machine cannot be achieved. The definition separates failures from the physical properties of the machine. Even if the machine is physically damaged but can achieve the performance level that the user expects from the machine, there is no failure according to the RCM paradigm. On the other hand, a failure may occur due to changing requirements of the user without changes in the structural or functional properties of the machine.

By answering to the third question the RCM methodology tries to identify the events that cause the machine to go into a failed state. These events are called *failure modes*[3]. RCM distinguishes total failure, which is total loss of function, from partial failure, which is the inability to meet the performance standards even when the machine still functions. The failure event searching procedure, *failure modes and effects analysis* (FMEA), is performed for each functional failure. That is, for each possible failed state the causing events and the consequent events are identified for purposes of predicting the effects of failures. The failure consequences are identified in respect to human safety, environment, production operations, and repair costs in order to create a proactive strategy for preventing them. Due to the origin of aeronautics, the RCM methodology places human and environmental values before material values.

Some lightweight methods of RCM have been developed, such as PM Optimization (PMO) that starts from the existing proactive maintenance policies and tries to identify which failure events it is trying to prevent (Turner, 2001). This approach answers quickly to the first three questions of RCM. After that the same logic is followed as in RCM. A drawback of PM Optimization is that it may miss some failure scenarios that could be identified by the RCM methodology.

In summary, RCM acknowledges that the objectives for maintenance should be defined from the idea of what the machine does — not what the machine is. The focus of RCM is to use proactive tasks to eliminate the events that cause failures. The failure effects and consequences to the operation, safety and environment are assessed to prioritise the proactive maintenance tasks. As the primary value of RCM is human safety, the methodology is quite heavy in trying to

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[3] In this dissertation the term *failure event* that equals to RCM term failure mode is used

predict what *might* happen. Thus, it cannot be used very often. For example, the NASA (1996) guideline for facilities proposes an RCM analysis every two years.

4.2.2 Total productive maintenance

Total productive maintenance combines total quality management and proactive maintenance policies in order to achieve maximum production efficiency. The history of TPM originates from the preventive maintenance and reliability engineering research from the 1950s. The reliability engineering paradigm was combined with Japanese quality management in the 1970s. As a strategic management paradigm TPM emphasises the importance of quality and employee participation in maintenance management. The most central objective of TPM is the maximisation of the overall equipment[4] effectiveness (OEE), which is calculated by (Nakajima, 1988)

$$OEE = Availability\ (\%) \cdot Performance\ (\%) \cdot Quality\ (\%) \qquad (1)$$

where availability is the operating time of the available working time. Performance is the ratio of the actual production of the maximum production, and quality (yield) is the ratio of good products of the total production as shown in Figure 3.

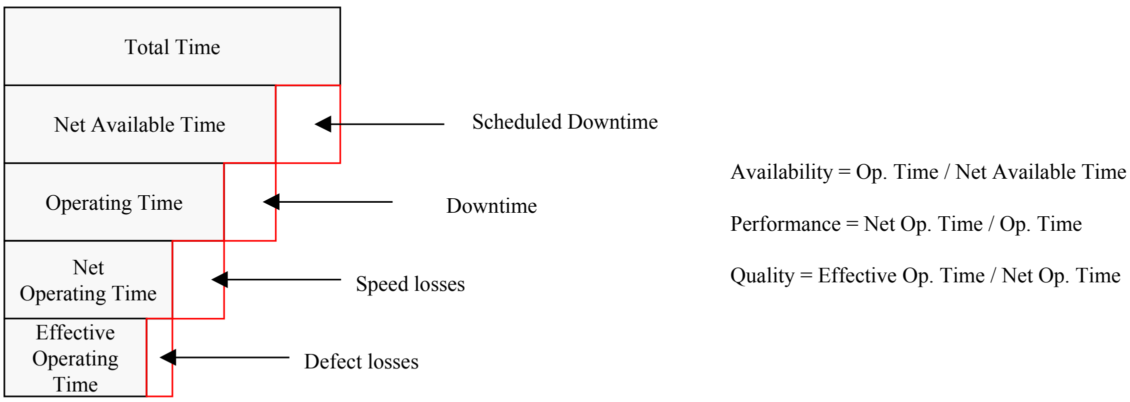

Figure 3 OEE Calculation (adapted from Nakajima, 1988, p. 25).

To achieve maximal OOE TPM tries to eliminate "the six big losses" that have a negative effect on the OEE. These losses are categorised in three groups: downtime, speed losses and quality defects. Downtime losses consist of machine failures and lost time to setups and adjustments. Speed losses consist of idling and minor stoppages due to disturbances in the machine operations and of reduced speed. Defects consist of process defects from scrap and reduced yield from machine startups.

The failures in TPM are known as breakdowns of two types: function-loss breakdown and function-reduction breakdown. The function-loss breakdown is a state "in which the equipment functioning stops." (Shirose and Gotō, 1989, p. 86) The function-reduction breakdown is a state in which the machine still operates but causes speed losses and defects. These definitions are very close to the failure and partial failure definitions in RCM. Nakajima (1989) makes a clear distinction between sudden failures and chronic failures. Sudden failures are the failures that happen randomly. Usually they are easy to detect because they change the status quo of the production capability of a factory. Contrasted to sudden failures, chronic failures are small, occur frequently, and they are hidden in the production system. They are considered normal, and therefore are not noted, or prevented. Thus, they can be found only by comparing the current

[4] In TPM the used term is "equipment", in the context of this dissertation, the words machine, part or component are used

status quo to the theoretical or optimal conditions. The causes of chronic problems, such as dirt and moisture, are not necessarily critical alone, but the causes often amplify each other. Therefore, TPM emphasises standardising the operating conditions by cleaning the machines, which also serves as inspection of the machines.

Proactive maintenance in TPM focuses on periodic inspections, planned restoration and routine maintenance (Miyoshi, 1989). The main information source of predictive maintenance is the inspections that serve both the planning for routine maintenance as well as restoration of the machines. TPM promotes the importance of machine operators in the basic maintenance activities, such as inspections and cleaning. This increases the possibility to identify failures before their consequences become too costly. The preventive maintenance program is derived from the statutory regulations, machine maintenance standards, breakdowns and work order history.

In summary, TPM tries to stabilise the operating environment of the machines by keeping them clean and at the same time by inspecting them with human senses. The absolute OEE goal aim at making it possible to detect chronic failures that could otherwise be undetected. Standard operating procedures help in making the maintenance actions more repeatable.

4.2.3 Reliability engineering

Reliability engineering is a well-established branch of mathematical and machine design science (i.e. Bukowski and Goble, 2001; IEC 60050-191, 1996; Endrenyi et al., 2001; Høyland and Rausand, 1994; Pulkkinen, 1994; Schneeweiss, 2001; Simola, 1999; Turner, 2002; Villemeur, 1992). The relation of reliability engineering to maintenance is characterised by Air Transport Association of America (1993, p. 2) in the additional note to the maintenance program objectives:

These objectives recognize that maintenance programs, as such, cannot correct deficiencies in the inherent safety and reliability levels of the equipment. The maintenance program can only prevent deterioration of such inherent levels. If the inherent levels are found to be unsatisfactory, design modification is necessary to obtain improvement.

Maintenance cannot improve the capability and reliability of a machine above the inherent levels of that machine. Therefore, the machine design and materials are the most significant factors when determining the maximum reliability of systems.

As a methodology, reliability engineering focuses on identifying causes, probabilities and consequences of failures to plan the relevant actions to reduce them. This is done by modelling physical systems and their reliability and failure characteristics with mathematical models or by using more qualitative decision analysis (Vatn, 1997, for example). The physical systems are often modelled with reliability networks or fault trees (IEC 61025, 1990), which describe the relations of the components and how failures of one component affect the operation of other components. The failure occurrence and duration probabilities of the systems and components are modelled by using probability distributions, such as Weibull, exponential and Gamma distributions. By using these models it is possible to estimate the lifetime and failure probabilities of components and the systems consisting of those components.

Reliability engineering makes some assumptions about the failures. The formal definition for the word “failure” is usually left out from the reliability engineering literature and mathematical models. Often, failures are considered as binary events that happen stochastically during the life cycle of the machine. The machine is either in failed state or not. The reliability engineering methodologies rarely present methodologies for handling partial failures. The main reason seems to be that it is very difficult to model the propagation of partial failures to other partial failures in the system of interest.

As a mathematical science, the focus is on the failure models and their applicability to different systems. Since the approach is probabilistic and focuses on estimating the average or asymptotic reliability of systems, this approach is being used by machine manufacturers who have the interest to enhance the maintenance and the inherent reliability of their products.

4.2.4 Control engineering

Dynamic system modelling and system control is a science of control and automation engineering. The process variables are controlled with mathematical algorithms, such as PID controllers (Åström and Hägglund, 2000). The controllers maintain satisfactory operations by compensating disturbances in the process. The used term for undesired system states is *fault* (Chiang et al., 2001).

Fault detection and diagnosis are important fields of research with the aim to keep the operators and maintenance informed about the status of the process and to diagnose the cause of possible faults. The three categories to detect an abnormal process condition are data-driven, analytical or knowledge-based methods (Chiang et al., 2001; Lewin, 1995). Data driven models operate purely on measured process data and reduce the measured data to lower dimension data without losing essential information of the original data. Analytical methods use mathematical models and parameter estimation to detect faults. Knowledge-based methods use causal analysis, expert systems or pattern recognition to detect faults.

The control engineering approach to regulate the failures is to control the production processes and compensate the disturbances in the production system. Therefore, a stable process should have some stochastic operating parameter limits or the operating parameters should follow dynamically modelled behaviour. A deviation of a process parameter from the statistical or modelled behaviour is a sign of an abnormal process state, which may indicate that a failure event has occurred.

The difficulty of the control engineering approach is that the industrial manufacturing and production processes are not always stable. When there is a change in the production plan or produced product the system may be in a labile state causing difficulties in control and wrong alerts.

4.2.5 Summary of paradigms

TPM and RCM reflect the cultural backgrounds of their origins. RCM is a forward planning re-engineering methodology, whereas TPM emphasises small continuous improvements by the plant employees. The focus areas are somewhat different: RCM focus on keeping the status quo of machines, and TPM focus on maximising the throughput of machines. Control engineering is not closely related to the other three paradigms and approaches failures from the viewpoint of systems control science, although some reliability-engineering approaches, such as proportional hazard model (PHM) use a combination of data-driven models with failure probability distributions (Kobbacy et al., 1997) and Markov-chains (Wiseman, 1999).

In summary, the formalised connections between RCM, TPM, reliability engineering and control engineering are surprisingly weakly defined although all the paradigms are often applied in production plants, at least partially. This is due to the slightly different scopes and objectives of the paradigms. The following Table 2 tries to capture the differences of these maintenance and reliability paradigms.

	RCM	TPM	Reliability Engineering	Control Engineering
Scope	Machine functionality	Machine efficiency	Machine durability	Machine controllability
Maintenance objective according to paradigm	Keeping the machine functionality at the required level	Maximising the machine capacity by equipment efficiency	Enhancing the machine life-time and reliability	Maintaining the production process state
Failure or failed state	Inability to fulfil user-required functional capability	Loss or reduction of a capability with regard to optimal performance	Loss of a function	Statistically abnormal process state
Life-cycle phase being applied	At the machine design and operation phase	At the machine operation phase	At the machine design phase	At the machine operation phase
Context	Single machines, users, and plant	Single machines, users, and plant	Multiple machines, users, and plants	Single production process
Applicable methods	Proactive maintenance by preventing failures before they first occur	Personnel participation in continuous improvement for preventing sudden and chronic failures	Design-out failures with enhanced component design and materials	Control of process states and compensation of disturbances by mathematical algorithms.

Table 2 Table of reliability paradigms.

4.3 MAINTENANCE PROCESSES

As an activity, maintenance can be described as a business process. The term is a bit fuzzy and overloaded. The idea of a business process concept is that there are several sequential activities that form an information processing chain. Sharp & McDermott (2001) define business process as "*a collection of interrelated work tasks, initiated in response to an event, that achieves a specific result for the customer of the process.*" This definition emphasises that the process instance is triggered by an event, and consists of work tasks to satisfy the customer needs. Sharp and McDermott (2001) mention that in some cases the information systems and business processes cannot be separated. The information system implements a business process and enables the process workflow. Therefore, it is important to understand the maintenance process in order to model the effects of information systems.

Detailed description of a maintenance process is difficult. The implementation of the process workflow depends on the applied industry and company. The process model in this chapter is derived from literature (Johnstone and Ward, 1981; Dhillon and Reiche, 1985), interviews (INTERVIEWS 8, 9, 12) and from observing the documentation of a computerised maintenance management system product (MRO Software, 2001). The model is general and should be suitable for describing most maintenance processes. Its informative value is not very high, but it should be accurate enough to provide an understanding of the activities in maintenance systems.

The triggering events for maintenance processes are i) reactive failure event, usually in form of a failure report or work request, ii) condition-based maintenance event, from inspections or automatic condition monitoring, iii) preventive maintenance event, from preventive maintenance program, and iv) backlog event, from a work queue that should have already been done.

The previous initiating events indicate that there is a queue of work to be done. This queue is filled with work orders arising from failures. The work orders are processed by the maintenance staff that maintain the machines. The failures may be predicted by inspecting the machines or by using automatic condition monitoring. Manual inspection is a periodic activity triggered by a "watchdog" subsystem that monitors the time or usage of the machine, thus creating a maintenance work order that is placed in the queue. Preventive maintenance is similar to inspections: The maintenance action is triggered by a time or usage monitoring system, and the order is placed in the queue. Several applications of the queuing theory have been presented in maintenance resource allocation (e.g. Komonen, 1998; Taha, 1992).

Depending on the viewpoint, the customer of the maintenance process is either the production process owner or the production machinery owner. The production process requires functional machines, and therefore the production process is directly affected by the quality and efficiency of the maintenance process. On the other hand, the machine owner has invested money in the machines and expects long-term profitability from the investment. The production process owner and machine owner are not necessarily the same organisation. There are situations where a machine is leased from a leasing company to a production plant, for example.

The main activities in maintenance are planning, scheduling and execution. Planning consists of planning the actual work activities and the resource needs, such as tools, materials and work skills for the maintenance task. Scheduling consists of arranging the maintenance tasks in the right order and time concerning the production plan and resource availability. Execution of the maintenance task consists of such activities as installation, inspection, modification, restoration and repair of the machines.

In addition to these there are some supporting activities such as recording failures, work requests, maintenance execution reports, machine configuration changes and administration of reporting, budgeting, engineering, regulatory compliance, and inventory control. In order to keep the models simple the supporting activities have been left out of the process flow diagrams. The modelled two process flows are presented in Figure 4 and Figure 5.

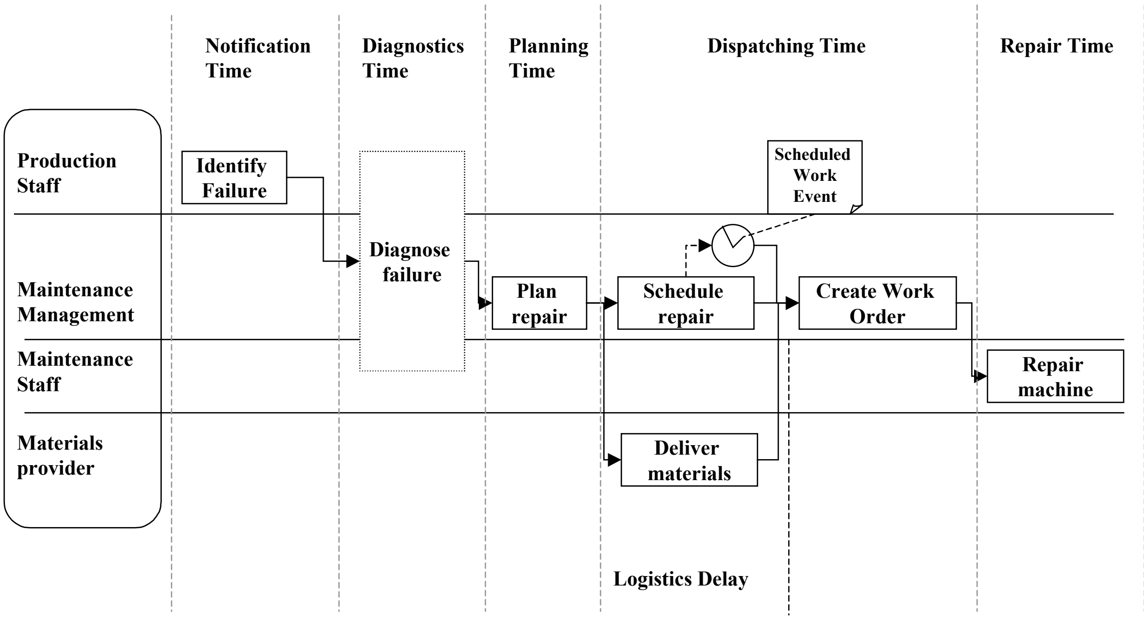

Figure 4 A reactive maintenance process flow diagram

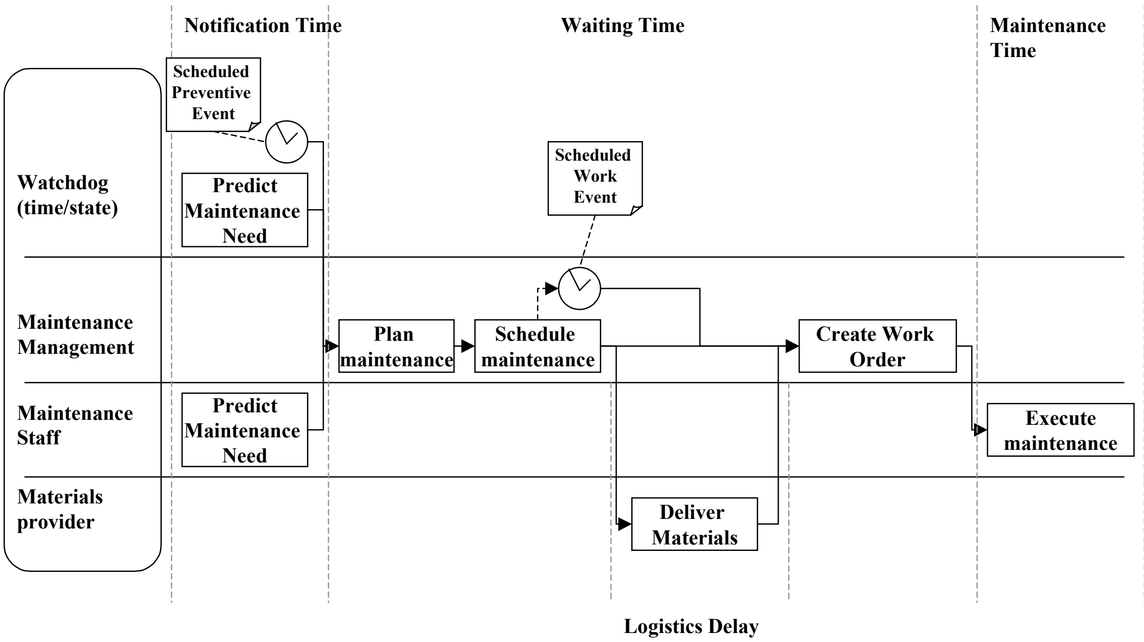

Figure 5 A proactive maintenance process flow diagram.

The reactive maintenance process in Figure 4 begins with a failure or possible failure identification. The failure is then diagnosed. Diagnosing is an activity that may require several participants from specialists to production personnel. After the failure is diagnosed, repair is planned and materials are ordered. After that, the repair is scheduled, and the work is ordered. When the materials are available the machine is repaired according to the schedule.

The process flow diagram indicates that the throughput, or cycle time of reactive maintenance is affected by the notification, diagnostics, planning and dispatching time as well as the repair time itself. Therefore, failure notification, diagnostics, planning, scheduling, or work order dispatching should be more efficient to increase the efficiency of the process. Logistics delay can be reduced by keeping a stock of materials available for maintenance.

The proactive maintenance process flow in Figure 5 does not include the diagnostics stage. In practice, this is not always true. When using condition monitoring there may be signs of future failures, which makes it possible to predict a failure. The symptoms may be so clear that there is no need for diagnostics, but if the symptoms are unknown or contradictory there may be a similar diagnostics stage as in reactive maintenance. Failure prediction marks the beginning of a process as well as the preventive event that is created according to machine operating time or other usage measurement. If the process is well designed and pre-planned, the waiting time from the event to the beginning of maintenance execution should be much shorter than in the reactive process. Also, the materials can be ordered *before* the failure occurs so that they are ready for use when needed.

The process flows indicate that proactive maintenance is quicker and more easily standardisable than the reactive process. However, the contents of the process planning and execution stages of proactive maintenance depend on the failure type. Furthermore, the feasibility of proactive and reactive maintenance is defined by the cost of failures and the maintenance, rather than the efficiency of the processes alone.

4.4 BUSINESS ASPECTS

Proactive maintenance can be seen as a method to convert variable costs of failures to fixed costs of maintenance. Maintenance is an expense to the owner of the machines, but also a business opportunity to the spare parts and maintenance service providers. The maintenance costs and revenues are the main drivers for controlling the reliability of machines and the efficiency of maintenance processes.

4.4.1 The costs and revenues of maintenance

File (1991) presents the costs and revenues from these two points of view as presented in Figure 6 and Figure 7.

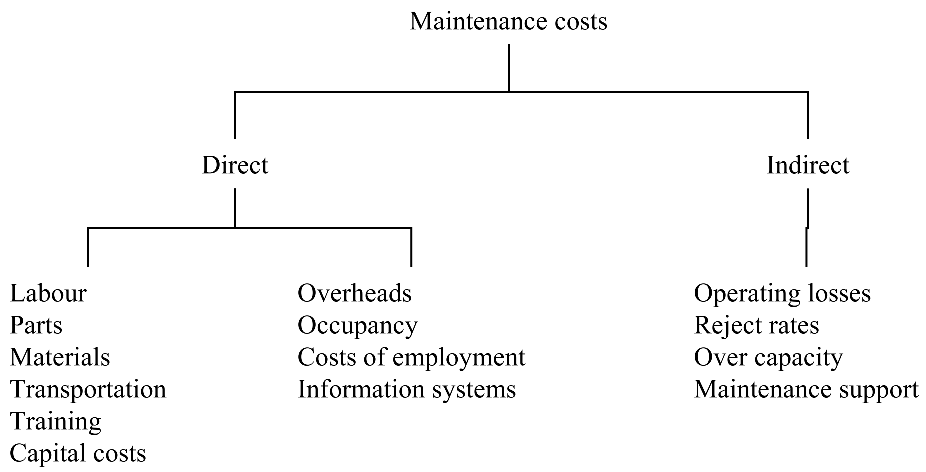

Figure 6 The costs of maintenance (File, 1991, p. 96).

The costs can be divided into direct and indirect costs. Direct costs are related to the efficiency of the maintenance processes and they are easier to calculate than indirect costs. Indirect costs are related to the effectiveness of the maintenance process to reliable production. Also, too high production capacity, or over-maintaining, as well as the supporting activities, such as production personnel support for the maintenance personnel, can be calculated as indirect costs.

Maintenance costs are often allocated to the maintenance department. MacInnes and Pearce (2002) claim that this alone may be a wrong way to allocate the costs. They propose that the costs should be allocated also to the machines. This helps in identifying the costs of machine ownership and in focusing the maintenance activities.

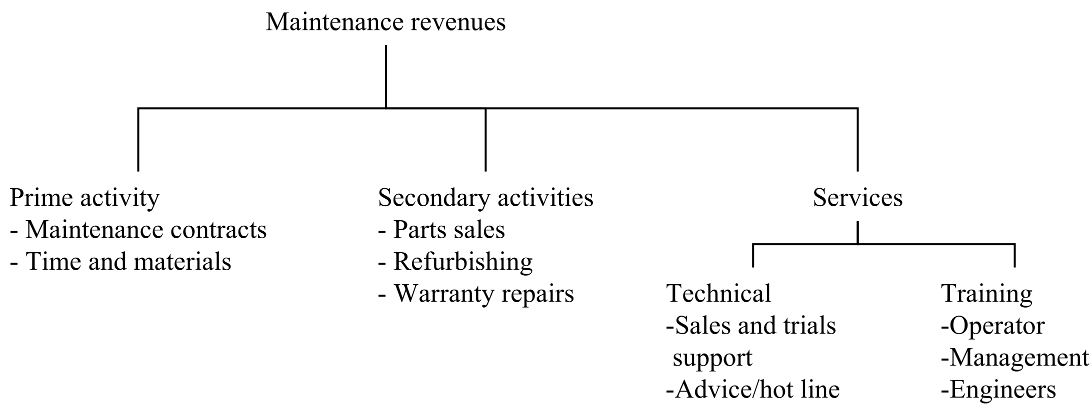

Figure 7 The sources of maintenance revenues (File, 1991, p. 97)

If maintenance is looked at as a revenue-generating business, the main focus is on the maintenance contracts, which are based on the work time and materials consumed or on the parts sales, repairs and refurbishing. The services, such as training or support, are a complementary source of revenues. A maintenance contract usually covers the normal work and materials and guarantees a specific service level with a fixed yearly price. Therefore, the maintenance service provider benefits from enhancing the maintenance processes.

5 SYSTEMS APPROACH TO MAINTENANCE

In this chapter, maintenance is approached from a systemic point of view. The assumption of systems approach is that there are many similar entities that behave similar way. Although failure processes of machines are more or less stochastic, the systems approach seems to fit conceptually into modelling component behaviour in failure and maintenance processes. However, the systems approach is not a common one. Contrary, the modelling and optimisation of maintenance strategies are usually based on control of stochastic systems (e.g. Høyland and Rausand, 1994) or on applying decision theory (e.g. Vatn et al., 1996; Vatn, 1997). The value of systems approach is in its capability to simplify complex problems and model the dependencies in a system. The drawback is the possible oversimplification and the assumed determinism in the models, which reduces the quantitative application of the models. However, in this research is the interest is more on the behaviour than in the optimisation of maintenance systems.

5.1 SYSTEMS

The exact definition of a system varies by author (Kerr, 1991; Klir, 1985; Laszlo, 1972; Turban and Aronson, 1998; Saaty and Kearns, 1985; Schoderbek et al., 1990; Weinberg, 1975). However, all definitions share a common idea of an interrelated set of *functions* and *structures* that serve *a purpose*.

According to Saaty and Kearns (1985), the purpose of a system is a behavioral concept and difficult to define. They system purpose may change over time or it may have several levels, such as long-time goals, short time objectives and ideal system states to approach in order to satisfy an objective. A man-made system serves the purpose of its designer or the system user. As an observer-related concept, a system may have several different interpretations, according to the observer. A system can always be considered a subsystem of some larger system.

5.1.1 Functions, structures and environments

System functions transform purposes into action. These actions thus realise the purpose. A function can be described as an aggregate of its states in space and time. The functions may be operating parallel and sequentially and the behaviour of the system functions affects the behaviour of other functions. A system that is factored to its subsystems will consist of a hierarchical set of functions. The functions are carried out by *flows*. The types of flows can be material, energy, information, or transformations from one state to another state. Structure is a set of constraints on flows in space and time. It consists of forms or parts that relate to one another to perform a function (Saaty and Kearns, 1985).

An environment always surrounds a system, and the system is separated from its environment by a boundary. The boundary can be physical, or time frame or some other limiting element (Turban and Aronson, 1998). The interconnections and interaction among the systems and their environment are called interfaces. The boundary between the system and its environment is not always clear, but blurred. A system is called open if it is very dependent on its environment. Fully closed systems are more theoretical than real, because the only known fully closed system is the universe. Closed systems do not need external energy or release energy to their environment. They also tend to attain maximum entropy[5]. Open systems exchange input and output flows with the environment, and may attain a time-independent steady state with the help of self-regulation.

5.1.2 Complexity and interdependencies

It is characteristic to systems that they are usually very complex, and the system components have a high number of strong internal connections. The complexity can be described with the number of interactions and interdependence (Saaty and Kearns, 1985) or the number of system attributes (Schoderbek et al., 1990). The elements are interdependent and the intensity of the dependencies varies.

The interdependence is symbiotic, if the systems are dependent on each other for their existence. The system consisting of subsystems can have emergent properties. That is, such properties that cannot be found or understood in subsystems since they are generated or amplified by interaction between the subsystem functionalities. Such a relationship is also called synergetic (Kerr, 1991; Schoderbek et al., 1990). Weinberg (1975) states as a rule that the whole is more than the sum of its parts, but also notes that the part is more than a fraction of the whole. The latter statement tries to remind that even if subsystems do not seem to have emergent properties, the subsystem may be a part of some other system or have an emergent property there which is not observable in the currently observed system. That is, a subsystem may serve several purposes and several systems.

To survive, a system must be adaptive in regard to the changes within itself or in its environment. The adaptation can occur either in the short run or in the long run. The forms of adaptability are either functional or structural. Short-run adaptation takes place through functional changes, whereas long-run adaptation occurs through structural changes. (Schoderbek et al., 1990). The adaptation can affect the internals or the environment of the system. In the latter case, the possibilities to control the changes are much more restricted than in the former case, because the system boundary restricts the possibilities to manipulate the environment. However, it may be possible to acquire environmental information, or information from inside the system to help in adapting the system.

5.1.3 Factoring and integrating systems

The method to understand and possibly to find some rules and model the system is to dissect it to smaller subsystems (Weinberg, 1975). To factor a system into subsystems Kerr (1991) suggests recursive top-down factoring to simpler systems that contain understandable processes. The boundaries and interfaces should be clearly defined. In a perfectly connected system, where all the subsystems are connected to each other, there are $n \cdot (n-1)/2$ interconnections, where n is the number of subsystems. This makes any such system very difficult to control. Simplification of the interconnections is therefore essential. Kerr (1991) provides two approaches to simplify subsystem interactions:

1. By forming clusters of subsystems that interact with each other by using a specialised interfacing system. The clusters interact by using the interfacing system. A division manager who acts as a representative of his/her organisation can be regarded as an interfacing system
2. By decoupling subsystems to avoid interaction analysis. Decoupling can be done by using buffers, slack resources or standard procedures. Heylighen and Joslyn (2001) call these methods as passive mechanisms to dampen disturbances in a system.

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[5] Entropy here refers to statistical entropy, a measure of system variety defined by the possible states the system can be in.

Inventory is an example of a buffer. It reduces or eliminates randomness in a production chain to propagate backward or forward, and makes control of the systems easier. Slack resources are capacity that is not used until the normal capacity is unavailable, e.g. a stand-by equipment or personnel. Standard procedures aim at standardising the informational inputs and outputs of a system to eliminate the sources of ambiguity and misunderstanding.

Sometimes it is feasible to integrate systems, i.e. when clustering systems instead of decoupling them. Miller, Rosenthal and Vollman (1986) have defined three types of integration in manufacturing environments. Technical integration involves establishing physical connections between the functional areas. Procedural integration uses common data and has a consistent interpretation of that data between the functional areas. Goal integration uses the same information to achieve common goals or an objective.

5.1.4 Control systems

To guide the system toward its goals there must be a control decision-making system that controls the controlled element in the system. Classical cybernetics, which studies the control and communication of systems, recognises three paradigms of goal oriented system control: open-loop or information-less paradigm, feed-forward paradigm, and feed-back paradigm (Wiener, 1961). The difference is which source information the decision-making element uses: no source information, the same input information as for the controlled element, the output information of the controlled element, or some combination of them (Klir, 1985, p. 366).

According to Ashby's (1957, p. 206) Law of Requisite Variety, the larger the variety of actions available to a control system, the larger the variety of external perturbations and internal states it is able to compensate. The law states that only variety in the regulating system can force down variety due to the controlled system. The law has two implications (Umpleby, 2001): *First, there must be a control system that equals the variety of the controlled system. Secondly, the amount of appropriate selection that a control system can perform is limited by the amount of information available about the controlled system.* The law is a logical law applicable to a given set of possible states and the actions on those states, not an empirical law that is derived by observing a real system.

5.1.5 Maintenance activities as a system

There have not been many studies about maintenance as a system. Kerr (1991) briefly notes that maintenance can be divided into tactical planning of preventive maintenance and operational control of the execution of the maintenance itself. He suggests that the loss of capacity due to planned and unplanned maintenance should be known for planning the maintenance, as well as the complete history of the occurred failures and their frequencies.

It is also difficult to separate the production process and the maintenance processes. The approach Jonsson (1999) takes is not to separate maintenance from production, but to consider maintenance as a part of the production process, as shown in Figure 8. The maintenance in this model creates production capacity, which is secondary input for the production process, and the production creates maintenance need, which is secondary output of the production process. Jonsson's (1999) research results indicate that companies that integrate maintenance and their production strategy have a better competitive position.

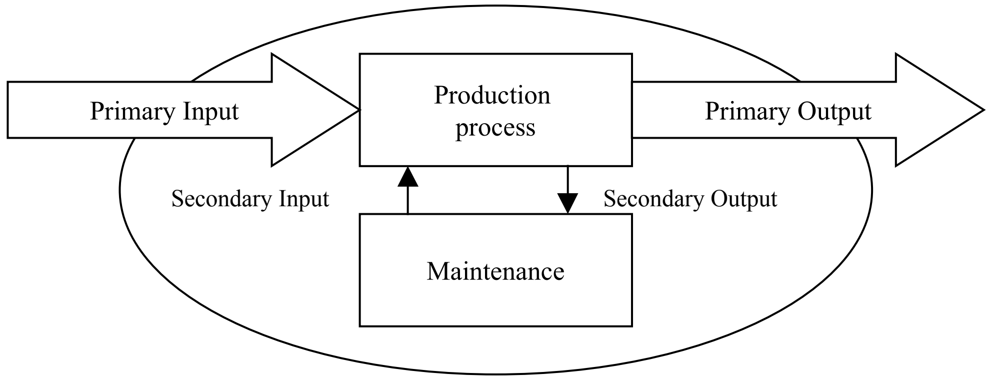


Figure 8 The production and maintenance processes (Jonsson, 1999, p. 26).

Lee (2001) presents a more idealistic approach. His focus is on an overall machine optimisation and management system that is enabled by an intelligent machine. The system closes the loop between maintenance and the production as shown in Figure 9. The proposed system should include the machine model that includes the wear and degradation process, diagnostics and fault detection algorithms. The actual equipment condition should be possible to measure or simulate. A maintenance model, including a supply chain and management model should exist. The machine and the maintenance model should be refined according to the maintenance and equipment condition history. Also, a rough production process model should be included in the system to manage and simulate the relations of the production process to the equipment and the maintenance process.

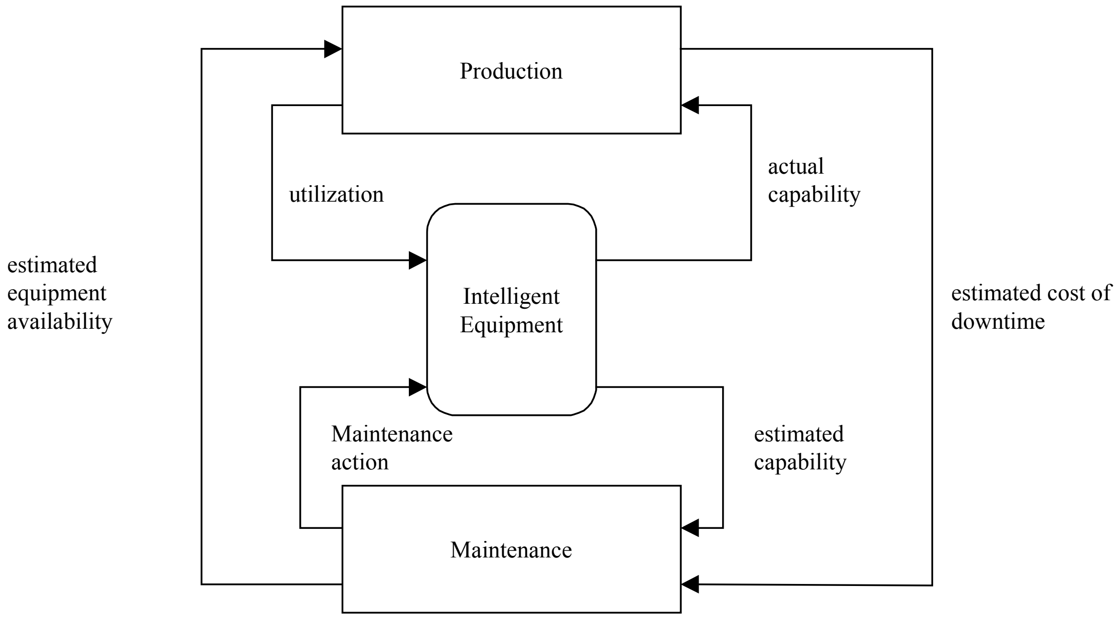


Figure 9 An enterprise-wide smart machine optimisation and management system. Modified from Koç and Lee (2001).

5.1.6 Machine reliability and maintenance system effectiveness

Allen (2001) distinguishes the approaches to study the effect of maintenance into either physical machine health or maintenance system effectiveness itself. In the first approach, all those actions are considered that reverse the effects of machine ageing over the component life-cycle. This makes it possible to clean the effect of maintenance to the machine. The drawback is that the every single maintenance action should be tracked over the total life-cycle of a component in a constant process environment.

In the latter approach, the machine age is calculated backward from the failure to the moment the machine was take into use or renewed. This approach does not take into account each maintenance task but the overall maintenance on the machine. Thus, any ad-hoc maintenance is considered as an external influence on the maintenance system. The question that Allen (2001) raises is whether to *model the reliability of the controlled system* (reliability engineering) or *model the effectiveness of the control system* (RCM, TPM). The difference is in the application of the information.

5.1.7 Summary

Maintenance can be considered as a control system for controlling the reliability of machines in a process environment. The variety of possible states is constrained by the maintenance actions. Preventive maintenance can be considered as feed-forward control and reactive maintenance as feed-back control. Condition-based maintenance reacts to the signs of possible future failures, and is therefore is a mixture of reactive and preventive maintenance. Consequently, condition-based maintenance represents neither pure feed-forward nor pure feed-back control. If the preventive maintenance schedule is changed according to the occurred failures, the maintenance system adapts its behaviour with a higher level of feed-back control.

Because machines are open systems exchanging materials, energy and information with their environment, their control is complex and rather unpredictable. Ashby's (1957) Law of Requisite Variety suggests that the more there is information about the machines the more possibilities there are to select the appropriate maintenance action to control the reliability.

5.2 MAINTENANCE SYSTEM PERFORMANCE METRICS

The objective of this research is to model maintenance systems and the effects of condition monitoring. The operation of a maintenance system must be measured to model the effects of condition monitoring and to be able to control the system. This chapter reviews some of the maintenance system metrics that could be used as the controlled variables.

5.2.1 Efficiency and effectiveness

Turban and Aronson (1998) propose that systems should be measured with both *effectiveness* and *efficiency*. They define effectiveness as the degree to which the goals are achieved. Effectiveness is concerned with the results and outputs of the system. Efficiency is a measure of inputs to achieve outputs. In other words, effectiveness is about doing the right things, and efficiency is about doing the things right. Sharp and McDermott (2001) propose several process metrics such as the number of times the process has been executed, the process cycle time, the cost per execution, cost of defects, and the ratio of good output versus bad output.

Johnstone and Ward (1981) describe metrics for the maintenance system measurement, such as the number of personnel accidents, maintenance budget variance, maintenance cost per machine, maintenance cost as percent of capital investment or percent of machine uptime, workload backlog, overtime ratio and emergency work ratio of total work. Middleton and Stevens (1999) define three business types: cost-constrained, capacity-constrained and requirements-constrained. For each of these they suggests different primary metrics: costs, OEE and quality rate. Wireman (1998) describes several other metrics, including also those that measure the usage of computerized maintenance systems. He also notes that a common mistake in measuring efficiency is using only the input values of the maintenance process, such as the number of work orders completed and maintenance personnel as percentage of total personnel.

5.2.2 Overall Equipment Efficiency

Jonsson (1999) suggests that maintenance effectiveness should be primarily measured with the OEE metrics of TPM. According to Jonsson (1999), the strengths of OEE lie in its simplicity and supporting quality management, continuous improvement and internal efficiency measurements. OEE calculation presented by Nakajima (1988) does not take planned downtime into account. The practice varies, and some authors calculate planned downtime in the OEE availability (e.g. Jonsson, 1999).

Bonal et al. (1996) suggest metrics that combine the OEE calculation and investment costs of the machines. The goal is to maxims the utilisation of the constraining bottleneck machine of a production line, i.e. the efficiency of the machine in respect to the investment costs. Otherwise the productivity improvements could be lost because of production bottlenecks. Moubray (1997) claims OEE to be misleading focusing on achieving the maximum performance from a machine regardless of what the performance requirements are. In addition, he states that the costs of quality losses, performance losses and availability losses are not financially comparable. The costs of scrap include raw materials plus the lost profits, whereas performance and availability losses include only profits. Therefore the quality, availability and performance rates would not be multiplicative.

5.2.3 Availability

By definition (IEC 60050-191, 1996) reliability is a measure of what the ability of a machine to perform a required function for a given time interval is. Availability is a measure of what the ability of a machine to perform a required function at a given instant of time is. These terms have quantitative relationships (US Department of Defence, 1982; IEC 60050-191, 1996) as defined by the following inherent availability equation

$$A_i = \frac{MTTF}{MTTF + MTTR} \tag{2}$$

where MTTF denotes the mean operating time to failure, and MTTR denotes the mean time to restore or repair. MTTF is a measure of machine reliability and durability: the longer the operating time between the failures the more reliable and durable the machine is. MTTR is a measure of machine maintainability, which tells how much time it takes to restore a machine to the working state in optimal conditions. Operational availability is defined by

$$A_o = \frac{MTBM}{MTBM + MDT} \tag{3}$$

where MTBM denotes the mean operating time between maintenance, and MDT denotes the mean downtime caused by maintenance – or lack of maintenance. MTBM is a measure of the proactive and reactive maintenance frequency of the machine. MDT is a measure of how long time the maintenance takes on average.

The difference between (2) and (3) are that inherent availability A_i is mainly affected by the machine design. The design affects the reliability (MTTF) and maintainability (MTTR) of a machine, which can be seen as the maximum in inherent availability of the machine. Operational availability A_o represents the availability of the machine in its operating context. Both MTBM and MDT of A_o calculation are affected not only by design, but also by spare parts availability, the applied maintenance policy, and other operational constraints. NASA (1996, pp. 3/20-3/21) defines the availability metrics as follows:

Inherent Availability Ai
(1) The probability that a system or equipment, when used under stated conditions in an ideal support environment will operate satisfactorily at any point in time as required.
(2) Excludes preventive or scheduled maintenance actions, logistics delay time and administrative delay time.

Operational Availability Ao:
(1) The probability that a system or equipment, when used under stated conditions in an actual operational environment will operate satisfactorily when called upon.
(2) Includes active maintenance time, logistics delay time and administrative delay time.

5.2.4 Proposed effectiveness and efficiency metrics

Turner (2002) criticises the informative value of MTTF. In his opinion, the MTTF is in practice difficult to calculate. The MTTF information is usually not available by failure type or component level, and the machine components may be replaced by maintenance and therefore have an effect on the MTTF. In addition to these arguments Turner states that the maintenance of the machine, in fact, aims to prevent failures before they occur, and therefore MTTF and A_i calculated for any machine in operation are unreliable. In other words, he sees the drawbacks in applying MTTF in reliability modelling (see Chapter 5.1.6). For similar reasons, the US Department of Defence (1982) suggests that the inherent availability A_i should be used only in factory acceptance tests, not in measuring the operational reliability of machines.

However, MTTF can be used in maintenance system effectiveness measurement. This is because in reliability engineering the effect of maintenance must be cleaned from the MTTF calculation, but in measuring maintenance system the effect of maintenance must be included in the metrics. The MTTF reveals the effectiveness of the maintenance programme in a certain operating context for a machine under it, and therefore enables control of the maintenance system. *Therefore, in this dissertation it is proposed that MTTF can and should be used as the maintenance system effectiveness metrics.*

Machine reliability is affected also by other factors than maintenance, such as machine design. Therefore, high reliability is not absolutely achieved by effective maintenance unless the other affecting factors make high reliability possible.

Successful control of a maintenance system requires measurement of both the system outputs (effectiveness) and inputs (resources). The operational availability equation (3) and some variants of the OEE equation (1) include the proactive maintenance downtime factor, but the other required input resources, such as materials or labour costs of the maintenance system, are not included in the metrics. Consequently, this results into a single objective to take as much capacity out of the machines as possible in regard to calendar time. Therefore, the usage of such metrics in maintenance system control yields optimal results only temporarily, e.g. when there is not enough production capacity.

Efficiency is defined in this research as a measure of the ability to use the available resources to generate the required output. Efficiency can be measured by the required input resources, such as time and money used in the maintenance system with regard to the reliability that the maintenance system generates. Reliability has an effect to the number of failures and amount of downtime and therefore *the proposed efficiency metrics is the cost of maintenance and failures*. In practice, the costs must be normalised. For example, the cost of human injuries and environmental hazards should be normalised so that they can be compared to direct and indirect monetary losses.

5.2.5 Availability of source data for the metrics

In the real life, there is a problem of how to collect the information to calculate the metrics. There are numerous mathematical models in reliability engineering that can be used in estimating machine lifetime, the effect of maintenance on machine reliability and much more. As mathematical models they are valid, but real-life calculations with these models face the problem of definitions and accuracy of the source data. The definitions and the accuracy of measuring such quantitative maintenance system metrics as the number of failures, operating time and downtime vary by paradigm, observer, available number of samples and data collection methods. Therefore, a mathematical reliability engineering method will yield results that are comparable only to results of similar reliability paradigms, definitions and data collection methods. Thus, MTTF, OEE, or A_o of a machine cannot be compared to the MTTF of other machine unless the definitions, reliability paradigms and data collection methods are similar.

In practice, there seems to be no easy way to gather and calculate accurate operation information from machines, especially the uptime and stand-by time information. Several papers in a Finnish national technology programme report (TEKES, 2001) pinpoint difficulties or suggest automated data collection methods for acquiring the availability data (Foster Wheeler Energy, p. 22; Konola, p. 36; Mäkitalo, p. 54; Välisalo, p. 67). The methods in the report mainly utilise data from the production and maintenance personnel by using special reporting systems or the reports in the maintenance systems. Depending on the organisation, industry, plant policies, technology, culture, and maintenance process the source data was gathered and the results were achieved in different ways, case by case, machine type by machine type.

5.3 FAILURES

What seems to be differing in the various reliability paradigms and methodologies is the definition of basic maintenance terms. The semantics of words is not exactly the same in the different approaches to reliability. If the definition of a single word that separates a fully working machine from a non-working one is weak, how is it possible to know when a maintenance action is needed? Even standards have contradictions: IEC 60050-191 (1996) defines failure as an event, whereas SAE J1011 (1999) defines failure as a state.

5.3.1 Failure states

The systems theory suggests that a system function is defined by its states and the state changes. This is in parallel with RCM and TPM thinking, where the failures are system states. Therefore, it is assumed that a failure is a state. I.e., failure state $S_f \in S$, where $S = \{S_0, S_1, \ldots, S_n\}$ is a set of possible system states.

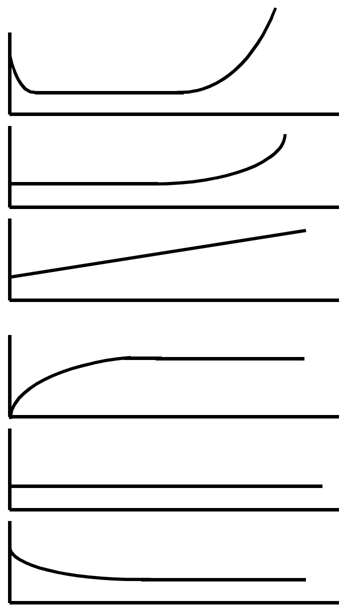
The systems approach argues that any system state is observer-specific (Ashby, 1957; Weinberg, 1975). That is, for observers A and B the failure states $S_{fa} \in S$ and $S_{fb} \in S$ may differ so that $S_{fa} \neq S_{fb}$. This does not state that the objectivity of observations is a sufficient condition for objective failure definition, but it helps in understanding why possible system states should be modelled. It also helps in understanding the RCM/FMEA approach in which the possible failure states are explicitly defined. Only if the failure state is explicitly defined, can the failure state be objectively observed and proactive control actions planned. However, the state definition, e.g. that temperatures of over 50 degrees mean failure, still remains subjective.

In practice, a production system is a man-made system with a purpose. Therefore, the failure state is always defined by a user. A production system may have several users, or stakeholders, having different viewpoints and attitudes concerning the purpose of the system. Therefore, the user is merely a role of an organisation, and the failure definitions are not necessary person-specific but role-specific.

5.3.2 Failure patterns

RCM-related studies (Moubray, 1997; Allen, 2001; Turner, 2002) suggest that increasing the number of maintenance tasks does not necessary increase the reliability of a machine. The studies show that in the aircraft and marine industries most of the failures occur because of components that do not show any ageing but only infant mortality and constant failure probability after that. The more maintenance and replacements of these components are done, the more unreliable the systems become.

Figure 10 shows six generic failure patterns of components during their life. A notable characteristic is that only 8-29 % of failures are age-related in such a way that the failure rate increases with age. The rest of the failure rates are constantly random or present infant mortality, which results in that no scheduled restoration can improve the reliability of the component.



UAL 1968	**Broberg 1973**	**MSP 1982**	**SUBMEPP 2001**
4%	**3%**	**3%**	**2%**
2%	**1%**	**17%**	**10%**
5%	**4%**	**3%**	**17%**
7%	**11%**	**6%**	**9%**
14%	**15%**	**42%**	**56%**
68%	**66%**	**29%**	**6%**

Figure 10 Four studies of failure rates as functions of component ages referred by Allen (2001). UAL and Broberg were studies about aeroplanes, MSP about ships, and SUBMEPP about military submarines.

Figure 10 shows that the frequency of occurrence of the failure patterns is highly specific to context and the observation method. Both Allen (2001) and Moubray (1997) note that the first "bathtub" curve is a result of a combination of other failure patterns, consisting of failure events of infant age, a period of random failures and sudden wear-out. Allen (2001) also suggests that the third, constantly increasing failure pattern may also be a combination of multiple sudden wear-out failure events of the second type. Generally speaking the more components in a system, the more types of failure events it will have. If the system is thoroughly tested and run in after installation, the design and installation errors are not shown and there are less 6th type infant mortality failures.

5.3.3 Failure causes and effects

There is also a difficulty in differentiating the failure cause and effect. A manufacturing system, whether a machine or a production line, usually comprises several components. Each component has a certain inherent reliability and is exposed to external or internal failure events. These components form a reliability network that defines the total reliability of the system. There may be an almost infinite number of dynamic, static, operational, logistical, electrical, mechanical and chemical connections that define the interdependencies of the network. The failure event of one component may cause failure effects that look as failure events to other components. The failure event may therefore propagate through the system causing a flow of failures for the following components. E.g. a wear-out of an air compressor filter causes dirt to block a pneumatic actuator which stops a production line.

The two failure events are dependent if and only if $P[E1 \cdot E2] \neq P[E1] \times P[E2]$ (Villemeur, 1992). That is, if the joint probability of two failure events does not equal the product of individual probabilities of the events. According to Villemeur (1992) the categories of dependent failure events are common cause events that have the same direct cause, and events that create intersystem or intercomponent dependencies such as a failure of a redundant component. The common cause event types can be divided into design, construction, operating and maintenance procedures or environmental effects. Villemeur (1992) refers to several nuclear and aviation failure databases indicating that the common cause failure events comprise 4-9 % of all the failure events. Design errors are the most dominant (40-50 %) among the common cause failure event types, followed by operating errors (30-45 %) and manufacturing and assembly errors (10 %).

The division of dependent or independent failures is highly specific to context and the observation method. Generally speaking, a failure event that seems to be random is not necessarily random, but may just be out of the methodological or observational accuracy. Therefore, any comparison or judgement about failures or their causes should be very careful.

5.3.4 Partial failures

The concept of partial failures is well acknowledged by RCM, TPM and control engineering, but not often noticed in reliability engineering. Partial failures are usually considered as performance degradation or deterioration, and therefore modelled mathematically as continuous dynamical systems, which is not in the field of study in reliability engineering. Instead, Markov chains (Bukowski and Goble, 2001; Endrenyi et al., 2001; Wiseman, 1999) and lately also Petri Nets (Schneeweiss, 2001), have been used to model the development and probability of occurrences of system states.

Endrenyi et al. (2001) present a simple Markov chain-based model between the random total failures, deterioration (partial) failures and proactive maintenance with two figures presented in Figure 11. A simplification of continuous deterioration with intermediate discrete states makes the failure process easier to model. There are two ways of defining the intermediate states: either by operating time, which is an approximation of the real state, or physical signs, which requires periodic inspections or continuous condition monitoring.

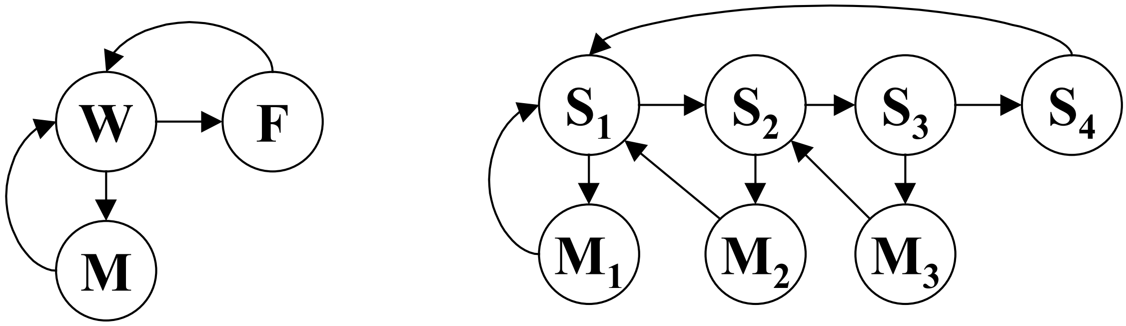


Figure 11 State diagrams for total and partial failures (Endrenyi et al., 2001) W:working state; F:failed state; S:state; M:maintenance state.

The problem in this kind of a presentation is in deciding in which of states S_1-S_4 the machine is considered failed. In the RCM approach the user may decide that S_3 is a failed state. In reliability engineering S_4 is considered definitely a failed state and S_1 definitely a working state. In TPM it is agreed as in RCM that S_3 may be a failed state, but the aim is to remain in state S_1.

5.3.5 Subjective state definitions in the maintenance paradigms

In practice, there must be several organisations and paradigmatic approaches involved with a production system. Emergency repairing, predictive maintenance, preventive maintenance, system optimisation and operational system control all try to control the system states. The allowable and satisfactory system states, however, differ in the various paradigms. Figure 12 tries to capture the paradigmatic approaches to the control of system states.

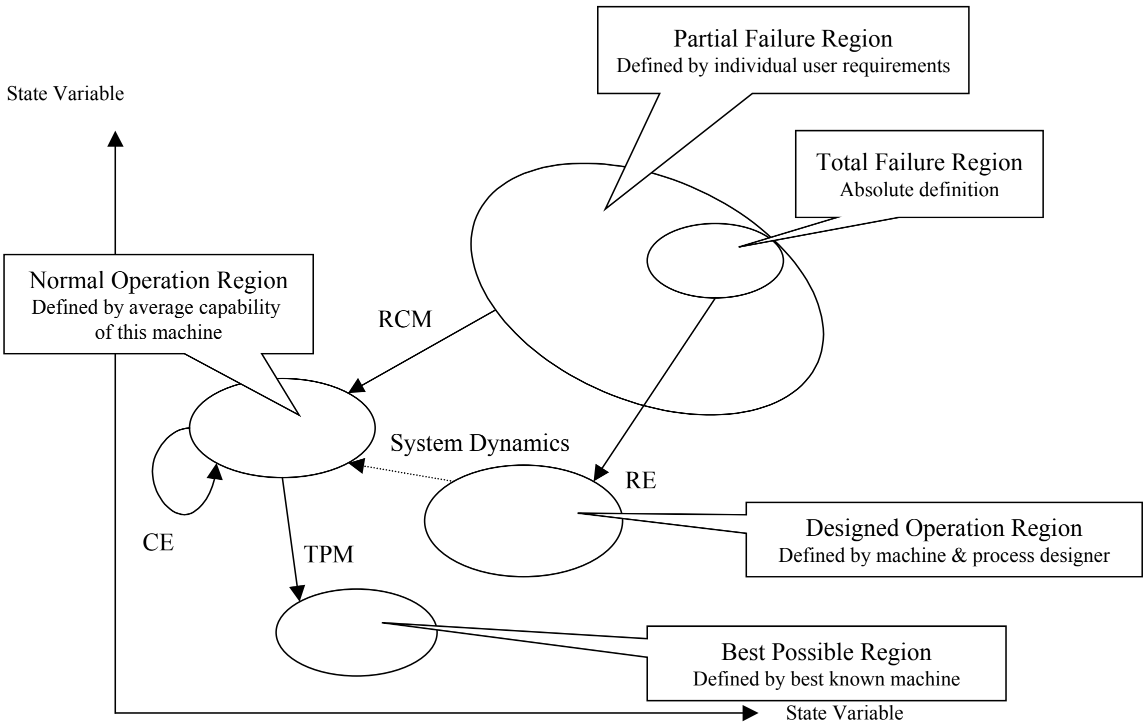


Figure 12 Paradigmatic approaches to the control of system states. TPM tries to move the operating state to optimal region, control engineering tries keep the status quo, RCM tries to keep the operating state away from failure region, and reliability engineering tries to keep the designed operating state. A total failure, meaning the total loss of a function, is the only common failure state for all the paradigms. The solid arrows describe the system control approaches emphasised by each paradigm and the dashed arrow is a system- dependent drift. In reality, there may be more than two states defining the system state.

5.4 EFFECTS OF INFORMATION IN FAILURE AND MAINTENANCE PROCESSES

It was stated earlier that the number of appropriate maintenance action types the maintenance system is able to use is limited by the information available of the machines under maintenance. The statement is discussed in this chapter.

5.4.1 The observability and reversibility of black-box system states

Imagine that the machine or production line state is not observed other than after the actual failure occurrences. Proactive control, i.e. preventive maintenance, would require a model of the system failures.

If the internal states of the system are not known, the system can be modelled as a black box, that has only two states. In that case, nothing needs to be known about the system internals. The system seems to exhibit time-dependent behaviour or behaviour dependent on some other external variable of the binary state changes, and can therefore be modelled with the help of stochastic models. An example is the reliability engineering approach in which a machine is either failed or not failed. A common approach to model such failures is to take the operating time as the independent variable, and the failure rate as the dependent variable. The failure patterns shown in Figure 10 are based on such models.

If the failures are binary states, then the application of a stochastic failure model for preventive maintenance requires that a maintenance action restores the failure totally or to some definite pre-failure state. In other words, the maintenance action can return the system only to the beginning of the hazard curve or to some definite point along that curve as illustrated in Figure 13. This reduces the number of appropriate maintenance action types, and suggests a total restoration of the system.

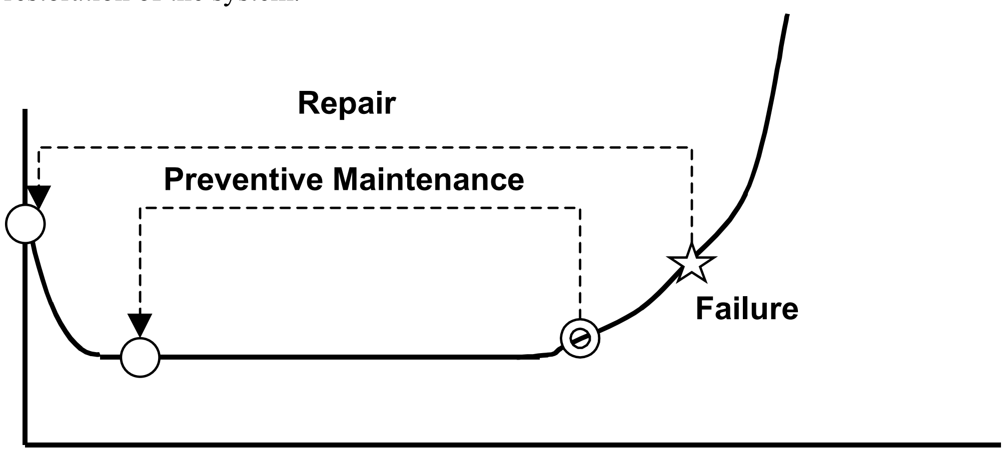


Figure 13 In black-box systems it is assumed that maintenance always returns the system to the hazard curve and that the form of the curve does not change due to maintenance.

The challenge in complex systems is that if the sub-systems are renewed separately, the whole system will not be in the same state after the maintenance as it was before maintenance and the model cannot be used in preventive maintenance programming. Therefore, the systems should be divided into subsystems and the subsystems should be modelled separately.

5.4.2 Condition monitoring

If the system is monitored with a condition monitoring system, the system becomes a white or a grey box system. In that case, the condition monitoring method restricts the variety of possible observable system states. The knowledge of which monitored system states are considered failure states must exist in order to prevent the system from failing. The control engineering paradigm assumes that a given system state should be maintained and therefore uses no explicit definition of *each* failure state, but an explicit definition of the preferable operating state. Consequently, the explicit definition of the preferable operating state excludes all the other states and therefore becomes an explicit definition of one failure state.

According to Shannon (1948) by acquiring enough information even over a noisy transmission channel it should be possible to obtain accurate information of a system state, and therefore control the variety in the system states with the help of a given model. A system, in which the system states are stochastic and the observations take place trough a stochastic process as well, could be estimated by modelling the system with some advanced system identification methods, such as hidden Markov models (Rabiner, 1989), proportional hazards models (Wiseman, 1999) or stochastic filtering such as Kalman filters (Drécourt, 2003). Even though the human brain does not operate similarly to computers, there is no doubt that a human brain can also create similar system models unconsciously. Therefore, an experienced mechanic may know quite accurately when the machine is going to fail based only on the machine age or human-sensible parameters. On the other hand, a human error may affect the observation of the states. To rely on human perception as an observation channel increases the risk that a person does not recognise the system state or reports the observed system state subjectively. If the condition monitoring is automated, the human transmission errors are reduced. Therefore, automatic condition monitoring should help in developing better proactive maintenance programs regardless of the applied modelling method.

The increased number of monitored system states makes it possible to apply a wider range of maintenance actions than in an unobserved system. This is because the maintenance actions may change the system state to a wider range of states, and the condition monitoring makes it possible to know the exact state of the system. In practice, the human senses are such condition monitoring systems. Therefore, more maintenance actions than in a theoretical unobserved system should be expected in a real maintenance system. If electronic condition monitoring methods that are able to sense system states beyond the human senses are applied, the number of possible maintenance actions could be even wider than without electronic condition monitoring methods.

Bukowski and Goble (2001) have defined a term *diagnostics coverage* to describe the probability that a failure state can be recognised by a diagnostic system. Thus, any condition monitoring method should be able to increase the diagnostic coverage. Because condition monitoring increases the amount of information about the machines, there are more possibilities to choose the right moment to undertake the correct maintenance action. Any misinformation, false diagnostics or measurement inaccuracy reduces the possibility to select the correct timing and type of maintenance action. In a perfect condition monitoring system the all the states are observed correctly.

For the purposes of this dissertation term observability[6] is defined as *the conditional probability that a machine state is observed correctly*. I.e., $P(o=s|s)$, where $s \in S = \{S_0, S_1, \ldots, S_n\}$ is the true state and $o \in S$ is the observed state. In a perfect condition monitoring system the conditional probability $P(o=s|s)=1, \forall s$.

The assumption is that the data provided by the condition monitoring system is used as an input for the maintenance system. A condition monitoring system without usage is worthless.

[6] Note that the definition of observability differs from the mathematical definition (Wolovich, 2000) in mathematical control theory.

5.4.3 Condition-based maintenance actions

Condition monitoring does not facilitate the system modelling. The level of modelling granularity can be much finer in systems under condition monitoring than without condition monitoring.

The question is why model a system if it is under condition monitoring? The answer is that condition-based maintenance reacts to possible failures and prevents them from happening. The preventive part of condition-based maintenance needs a model of the failure process. If the condition monitoring is perfect and the failure prediction can be done early enough, then the maintenance system is able to prevent all the failures. I.e, the failure states are avoided (MTTF = ∞) only when $P(o=s|s)=1, \forall$ s, and when $t_f>t_i$, where t_i is the initiation delay of the maintenance action and t_f is the shortest transition time between any working system state and any failure state in S.

Under these conditions any maintenance action that reduces the variety — or constrains the system state from being in the failure state — would be enough. But to know when and how to act, the effects of *both* the maintenance actions and the failure processes on the system state transitions should be modelled, implicitly or explicitly.

If the condition monitoring is not perfect then the system may enter in an unknown system state as a result of variability in the maintenance actions. Furthermore, if not using condition monitoring, a repeatable maintenance action is the only possibility to know the system state for modelling failure transition time. In that case, it is even more important that the maintenance action is repeatable and always results in a known system state. I.e. let $M = (M_0, \ldots, M_n)$ and $X = (X_0, \ldots, X_n)$ be pairs of maintenance actions and the resulting system states $X_{0\ldots n} \in S$. In case where $P(o=s|s)=0$ the system state is known after maintenance only if conditional probability $P(X_j|M_j)=1, \forall j=0, \ldots,n$. That is, perfectly repeatable maintenance is needed to "reset" the system to a known state in order to model the system transitions.

In practise, when using condition monitoring the observability $P(o=s|s)$ is between $]0,1[$. Therefore, observability, maintenance action initiation time and repeatability affect the maintenance effectiveness, i.e. MTTF.

5.4.4 Information creation in failure and maintenance processes

Failure and maintenance processes are information processes. That is, the processes change the input information into output information. The failure and maintenance processes are irreversible in regard to information. A failure process loses information of the cause of the failure, and a maintenance process loses information of the failure state. Generally speaking, it is not usually possible to detect the input information by observing the output information of the information process.

However, according to Losee (1998) the irreversible processes also produce information about the process itself. That is, a human being may be able to model the process and the required input information. By observing the failure states after failures and the operating states after maintenance it is possible to get information about the behaviour of those processes. If possible, the input information of the processes should be available, to help understand the processes. E.g. it is useful to have failure reports before executing a maintenance action, and pre-failure system status reports after failures to get information about the failure and maintenance processes. It is also possible to estimate the possible outputs with the given inputs if there is a finite set of possible processes. That is, with a detected system state it may be possible to predict the failure state. The existence and behaviour of the processes may be difficult to estimate, and therefore an experienced human is needed to create the scenarios.

To explicitly define the failure states and to develop a proactive maintenance strategy it is possible to begin from the existing maintenance actions, as in PM Optimization, from the occurred failure states, as in TPM, or from the scenarios of possible failure states, as in RCM. The information creation processes in the maintenance paradigms are different from each other.

6 SYSTEM MODELS I-V

Maintenance systems appear to be very difficult to describe in written text. In this chapter, the maintenance systems are therefore modelled with several methods in order to capture the complexity and various views to the maintenance systems.

6.1 OVERVIEW OF SYSTEM MODELS I-V

Five models were developed during the research. Two of them are qualitative models describing the relations of the entities and activities in the system. Three of the models are quantitative for modelling the stochastic and dynamic behaviour of the maintenance systems. The overview of the models is presented below.

Model I	**Knowledge model** A unified modelling language (UML) domain model of failure and maintenance concepts for sharing the knowledge constructs developed in the literature study and theory part of this dissertation.
Model II	**Control activities model** An applied Gorry-Morton framework (Gorry and Morton, 1989) for understanding the decision making and control activities in maintenance systems.
Model III	**Stochastic maintenance system model** A stochastic simulation model for studying the effect of condition monitoring on the availability and total costs of maintenance
. Model IV	**Dynamic maintenance system model** A dynamic simulation model for studying the effect of condition monitoring and the maintenance quality on the reliability and maintenance worker allocation.
Model V	**Dynamic supply chain model** A dynamic simulation model for studying the effect of remote condition monitoring information feedback on the spare parts supply chain.

6.2 SYSTEM MODEL I: A UML DOMAIN MODEL OF FAILURE AND MAINTENANCE CONCEPTS

6.2.1 Purpose of the model

The primary purpose of the model is to share the knowledge acquired during the research. The secondary purpose is to develop a high-level conceptual domain model for future information system development projects.

6.2.2 Knowledge, ontology and information communication

To develop a knowledge model, a definition for knowledge should be stated. Kerr (1991, p. 65) describes the knowledge about an environment or domain "*as the set of organised constructs possessed by an individual at any particular time in relation to a particular environment or domain*". Any new data that modifies the knowledge structures of the recipient is regarded as information. The knowledge is communicated between individuals by using messages that convey abstract symbols with some syntax. The recipient can convert the symbols to knowledge only by understanding the message syntax and by interpreting the symbols against an existing set of mental constructs. An identical set of constructs, a shared context, is required between the sender and the receiver to fully transfer knowledge. Two persons cannot have a fully identical set of mental constructs, which makes full knowledge transfer impossible.

However, an explicit knowledge representation with the help of text or images may help in improving the context sharing and therefore the communication of the information. Also, subjective activities, such as failure diagnostics cannot be automated if the mental constructs of the human decision making have not been modelled.

6.2.3 UML as a knowledge modelling methodology

From the point of view of information systems development this dissertation can be regarded as an analysis of maintenance activities. Analysis is the first phase in information system development. As an activity, the analysis consists of investigation of the problem and the requirements. The difference between the analysis and the design is that the analysis does not take into account how the system should be implemented but only what the system does. The value of standard software engineering methodologies should be acknowledged in analysing the existing information systems or in analysing the requirements for new information systems. To serve the secondary purpose of the model, the knowledge should therefore be represented in a format familiar to software engineering to enable its further usage in future information system development projects.

A commonly used notation in software engineering is defined by UML. UML can be regarded as a knowledge representation format, as well as a software design notation. The use of UML in the analysis makes it possible to use unified process (UP) (Larman, 2002) as a software development method. The dissertation research methodology does not enable the application of the unified process as such. Instead, one of the central concepts was picked from the unified process: the domain model.

The domain model is a description of things of interest in the real world and consists of a set of conceptual classes, their associations and attributes modelled with UML class diagrams. Larman (2002, p.129) defines domain models as "a visual dictionary of the noteworthy abstractions, domain vocabulary, and information content of the domain." Comparing to the knowledge definition in Chapter 6.2.2 the domain model represents a knowledge model. The classes in the domain models show real-world concepts. The domain model is an analyst's view of the domain, and it should be distinguished from the design view of the software classes. However, the domain model can be used in designing the software classes of the implementation. Therefore, the domain model communicates information about the domain and reduces the representational gap between the software implementation and the mental domain concepts of the analyst.

6.2.4 Validation of the UML model with a knowledge modelling tool

The UML domain model has one major drawback in domain modelling: No class instances can be defined. That is, an instance such as "oil change" cannot be defined for a concept named "maintenance action". This makes it difficult to assess the validity of the model. Therefore, the UML model was developed with the help of a special knowledge modelling tool (Protégé-2000 v1.7 from Stanford University). After changing the model in the knowledge modelling tool and entering some sample class instances, the same changes were made to the UML model. Then the UML model was simplified, and the same changes were made in the knowledge modelling tool. This modelling methodology was surprisingly powerful. The knowledge modelling tool made it possible to test the model with instance data, which helped in refining the model.

6.2.5 The UML domain model

The resulting UML domain model is presented in Figure 14.

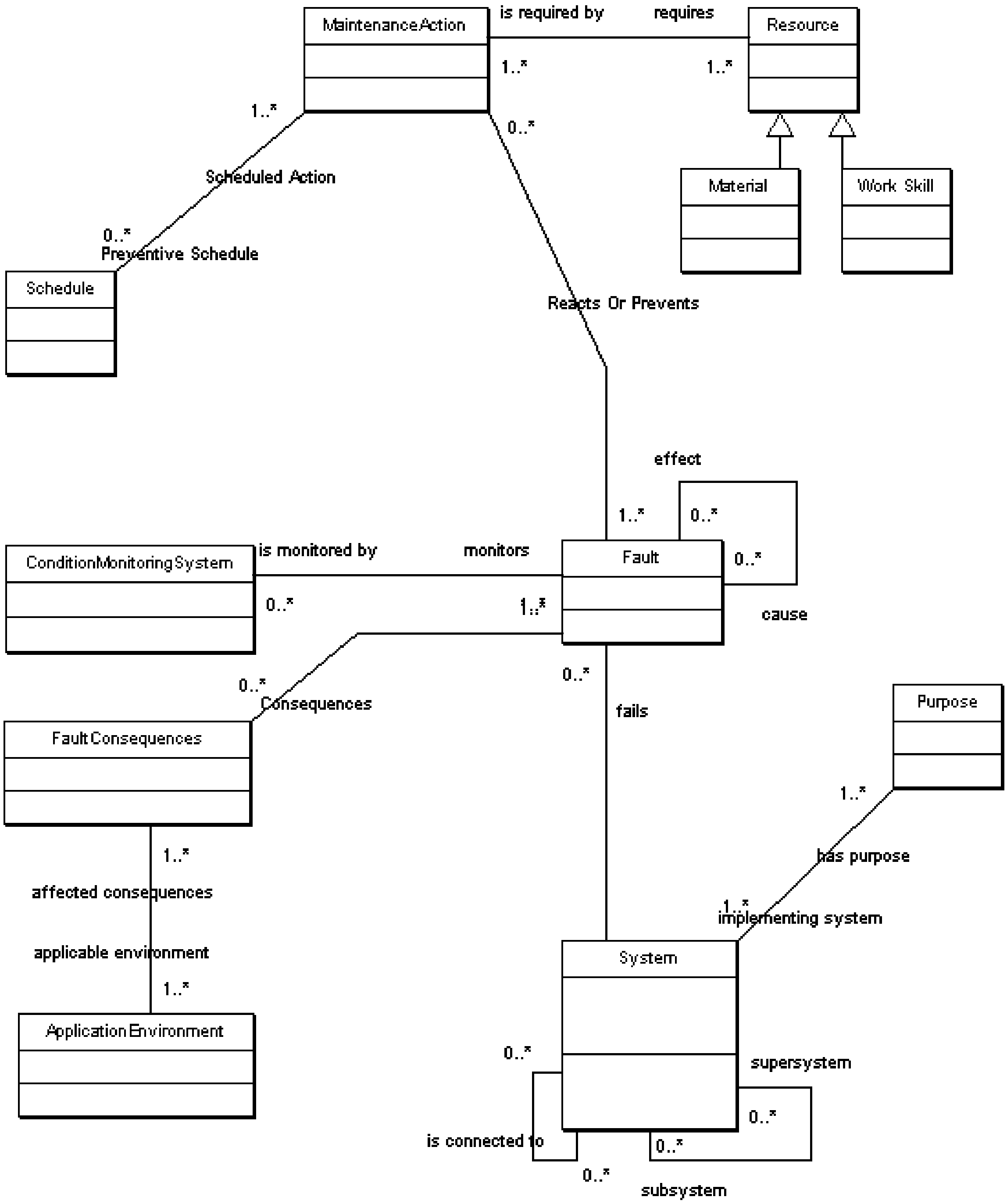


Figure 14 A domain model of failure and maintenance concepts.

The central concept is the system. A system can be connected to and from zero or more systems representing the logical arrangements of the system. In other words, an engine may be connected to an exhaust system. A system may have zero or more sub- and supersystems. That is, a production line may consist of machines, and the machine may be a part of several production lines. Each system has at least one purpose, that is the reason for the existence of the system. A purpose may be implemented by at least one system. E.g. the purpose to generate power can be implemented by a combustion engine or a gas turbine. A system may fail to a fault (failure state) or due to a fault (failure event). An example screenshot of the system concept from the knowledge modelling tool is shown in Figure 15. The structure is identical to the UML domain model.

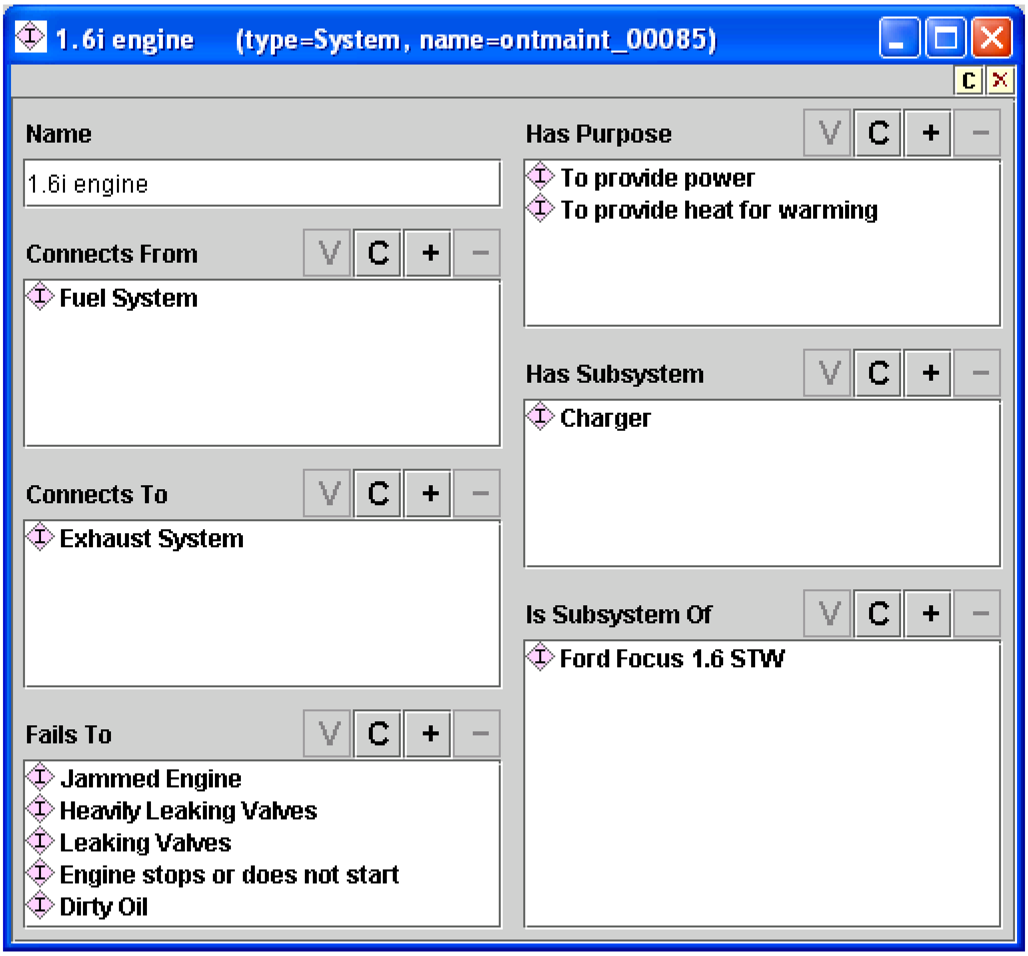


Figure 15 A realisation of the system concept as represented by the knowledge modelling tool.

A fault represents both failure states and failure events. When entering instances in the knowledge modelling tool the distinction between a failure state and failure event was so unclear that the separation between them was very difficult. Instead, a less informative concept, namely fault, was used. In other words, a fault is a possibility for or an existence of a failure event or state. The idea that both state and event are kinds of faults is bit confusing. However, an event represents a state change. Therefore, an event can be described with the resulting state or a state with the event. It is just semantics to think with failure occurrences or existences. In the model, a fault may cause zero or more consequent faults, or a fault may be caused by zero or more faults. Each fault may have zero or more consequences, and each consequence is caused by at least one fault. A consequence is applicable in at least one environment. E.g. a total loss of pulp production capacity is applicable only in the paper making process. In an application environment there may be several fault consequences. An example screenshot of the fault concept from the knowledge modelling tool is shown in Figure 16.

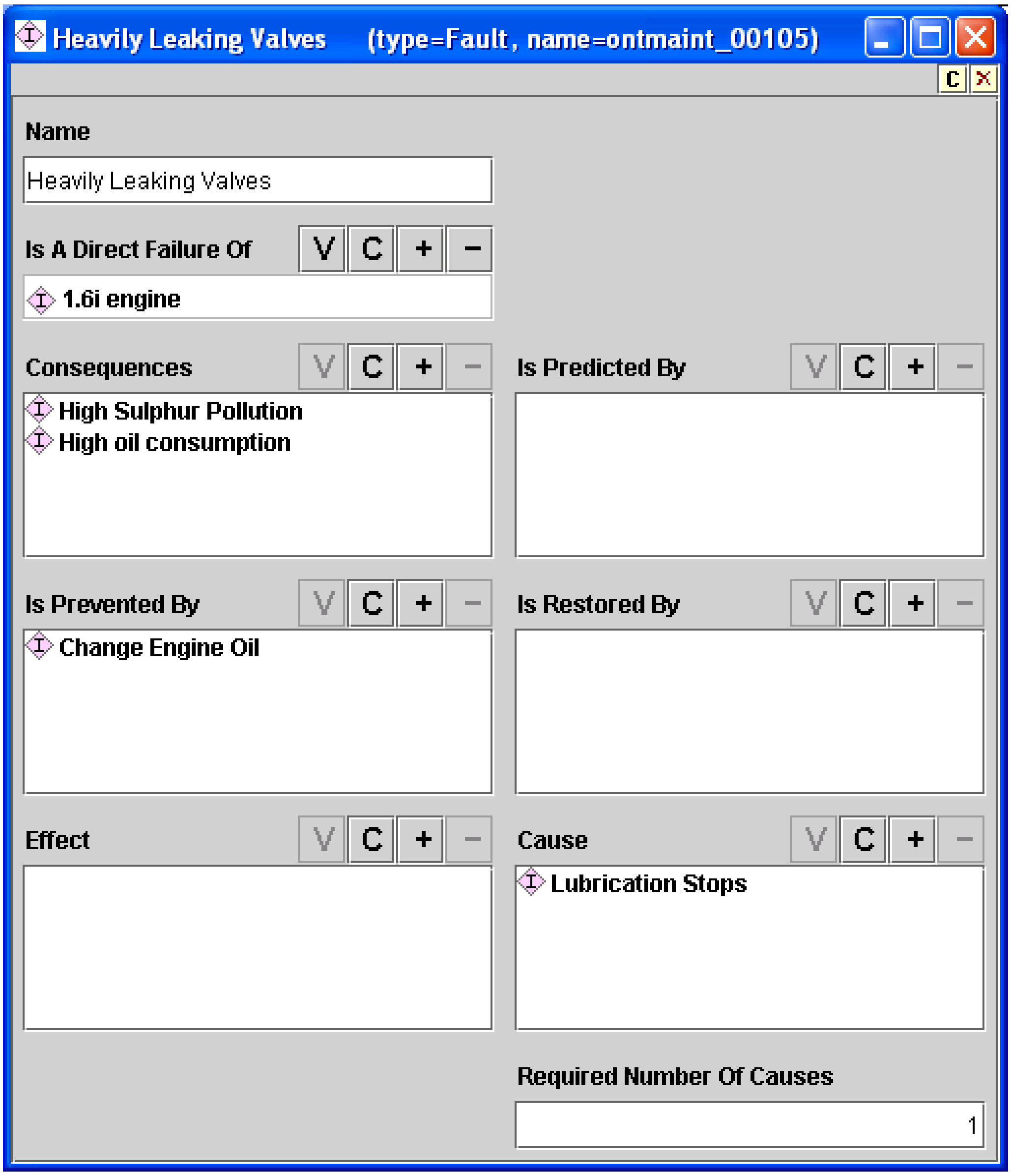


Figure 16 A realisation of the fault concept as represented by the knowledge modelling tool.

A condition monitoring system strives to monitor at least one fault, and a fault can be monitored by zero or more condition monitoring methods. A maintenance action reacts to or prevents at least one fault. Each fault must be reacted or prevented by zero or more maintenance actions. A maintenance action requires at least one resource. A resource can be either material, such as spare parts or tools, or the work skills of a worker. A resource must be required by at least one maintenance action. Each maintenance action may have zero or more schedules. A schedule, e.g. once per year, schedules at least one maintenance action. An example screenshot of the work skill and schedule concepts from the knowledge modelling tool is shown in Figure 17.

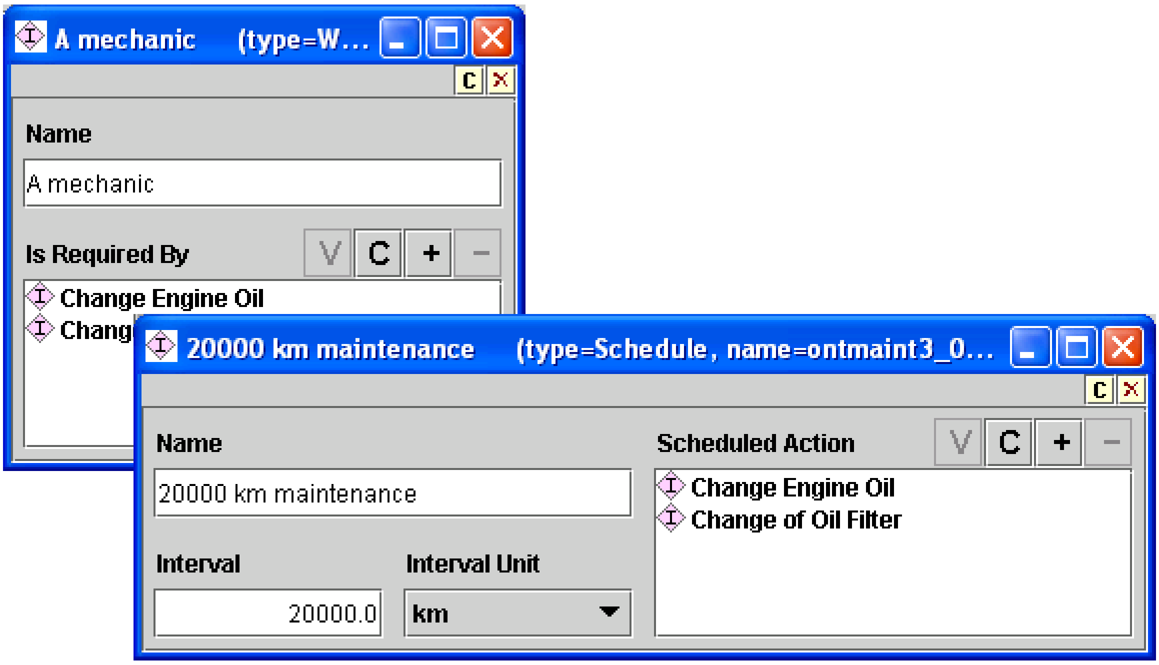


Figure 17 A realisation of the work skill resource and schedule concepts as represented by the knowledge modelling tool.

The explicit definition of faults in the domain model refers to the RCM/FMEA thinking in which the failure consequences cannot be defined if the failure state is not defined. Contrary to RCM/FMEA the system is defined with a purpose rather than a function. However, a function or a set of functions is needed for achieving the purpose. As stated earlier, a fault can be a cause or an effect of other faults. The thinking here is aligned with the fault tree analysis (FTA) method defined in IEC 61025 (1990). In the knowledge modelling tool the user can begin from any system purpose or fault and create a fully compatible model to FMEA and FTA.

6.2.6 Summary

The presented knowledge model defines a structure for maintenance system models. The modelling tool helps in creating a realisation of such a maintenance system model and ensures that the system is valid. If there are discrepancies between the model and the actual system, either one or the other is not valid. Therefore, the realised model should be modified according to reality or the reality can be analysed and corrected. By adding quantitative failure and maintenance models and by connecting the tool to a CMMS it would be possible to create an efficient real-time maintenance planning tool.

6.3 SYSTEM MODEL II: A GORRY-MORTON INFORMATION SYSTEMS FRAMEWORK

6.3.1 Purpose of the model

The failure and maintenance processes are very complex and unpredictable despite the vast variety of methodologies and paradigms that can be applied to control the processes. The applicability of information technology depends on how much human intelligence can be replaced with artificial intelligence (AI) and what kind of requirements AI places on the availability and quality of the information for making the necessary decisions.

The UML domain model presented in Chapter 6.2 presents the knowledge constructs of maintenance systems. The constructs, however, do not tell how the maintenance systems are controlled. The purpose of the model is to understand the complexity of decision making and control activities in maintenance systems.

6.3.2 Artificial intelligence

Even though the scope of this research does not cover the implementation of information systems, some characteristics of intelligence should be defined in order to understand the control possibilities of maintenance systems.

According to Turban and Aronson (1998) artificial intelligence is concerned with two basic ideas. Firstly, it involves understanding what intelligence is by studying the thinking processes of humans, and secondly, it deals with representing those processes in computers. The signs of intelligence include learning and understanding, responding quickly to a new situation, using reasoning in solving problems, making sense of contradictory messages and applying knowledge to manipulate the environment. Kaplan (1984) has defined several important commercial advantages of artificial intelligence over natural intelligence: AI is more permanent, offers ease of duplication, can be less expensive than natural intelligence, is consistent and thorough, can be documented, can execute certain tasks much more quickly than a human, and can perform certain tasks better than most humans. However, according to Kaplan (1984) natural intelligence has several advantages over AI: Natural intelligence is creative, enables people to benefit from and use sensory experience directly, and human reasoning makes use of a wide context of experiences and brings that to work on individual problems.

Natural intelligence enables people to recognise relationships between things, sense qualities and spot patterns to make relationship recognising possible. These are very difficult to program in AI. Kaplan's (1984) definitions suggest that the problems that an AI system can solve must be well structured and repetitive. Complex and unstructured problems require human intelligence.

6.3.3 The Gorry-Morton framework

The most complete knowledge and system-control related information system model found during the literature study was a framework for management information systems of Gorry and Morton (1989). The framework shown in Table 3 is based on the problem classification into structured and unstructured types, as well as the time-horizon of the decisions.

	Operational Control	**Management Control (Tactical planning)**	**Strategic Planning**
Structured	• Accounts receivable • Order entry • Inventory control • Production scheduling	• Budget analysis • Short-term forecasting • Variance analysis – overall budget	• Tanker fleet mix • Warehouse and factory location • Mergers and acquisitions
Unstructured	• Cash management PERT/COST systems	• Budget preparation • Sales and production planning	• New product planning • R&D planning

Table 3 Management information systems framework (Gorry and Morton, 1989).

A structured problem is one in which the intelligence, design and choice phases of the problem solving are structured. In other words, there are algorithms or decision rules that make it possible to find the problem, design the solution alternatives, and select the best solution. Operational control systems include repetitive and pre-programmed actions that deal with accurate, internal and current or historical data, whereas strategic planning is long-range, infrequent, predictive and uses mainly aggregated and external data. Typical corporate information systems reside on the upper left corner of the framework. The information systems that deal with unstructured problems are usually decision support systems.

The main problem in implementing an information system in structured operational areas is to adapt the existing model to the organisation. Information system design in the unstructured areas is more involved with the structuration and modelling of the problem and the problem solving process rather than the implementation problem. The modelling and structuring of the unstructured problems make it possible to automatically or semiautomatically solve problems that would otherwise require a human expert. Gorry and Morton (1989) emphasise the importance of understanding the critical decisions made by the organisation in order to create information systems that deal with unstructured problems.

According to Schoderbek et al. (1990, p. 118) "*decision making and control are similar, if not identical managerial activities. Both activities are initiated and maintained through communication.*" This statement suggests that the entire framework of Gorry and Morton is essentially a control system framework with regard to the control time horizon of the system and the degree of structure of the control decisions.

6.3.4 Applying the Gorry-Morton framework to maintenance systems

According to the literature study, the framework of Gorry and Morton (1989) has not been applied to maintenance systems. Therefore, maintenance-related concepts and methodologies were placed in the framework in order to analyse both the time frame and control decision complexity of the system. Inspired by the version of the original framework Turban and Aronson (1998) present in their book, an additional column named "applicable methods" that describes what kind of methods exist to make decisions or to help make them in maintenance systems was added. The resulting framework with transitions from reactive to preventive maintenance, and from preventive to condition-based maintenance is presented in Table 4.

	Operational Control	Tactical planning	Strategic Planning	Applicable Methods
Structured	• Work order entry • Cost reporting • Condition monitoring	• Maintenance direct costs budgeting	• Inventory and workforce planning	• Quantitative models • Analytical models • Operations research
Semistructured	• Maintenance workflow control • Inventory control • Root cause analysis	• Preventive maintenance work scheduling • Fault tree analysis • Maintenance work planning	• Failure effects and consequence analysis • Run-to-failure or use preventive maintenance	• Descriptive models • Process and event models
Unstructured	• Failure diagnostics • Machine repair	• Failure prognostics	• Failure mode analysis • Long-term maintenance planning	• Heuristics • Decision support systems • Expert systems • Neural networks

Table 4 A maintenance information system framework and the transitions from reactive (lower-left circle) to preventive maintenance (middle-right circle), and from preventive to condition-based maintenance (upper-left circle).

By analysing the framework it is obvious that CMMS functionality lies on the operational-tactical timescale dealing mostly with structured-semistructured issues. Condition monitoring is also a structured activity in the operations control, because it is frequently repeated and focuses on the current state of the system. Preventive maintenance is semi- or unstructured and affects future system states in the medium or long-range time horizon. Therefore, when operating with structured and current information, condition monitoring may enable more accurate maintenance activities than preventive maintenance. However, the diagnostics and prognostics of the failures still remain on the unstructured level implying that human intelligence is needed in deciding what kind of actions a detected system state requires.

RCM and TPM seem to be paradigms that deal with semistructured and unstructured problems in the failure-maintenance system, whereas reliability engineering and control engineering are structured approaches. Therefore, a mix of the methods and paradigms in real-world maintenance is necessary. Without applying several different methods and paradigms the control of the system would be difficult because of the missing decision making methodologies. Ashby's (1957) statement that only variety in the regulating system can force down variety due to the controlled system applies in the failure and maintenance processes. This also implies that there is no "silver bullet", e.g. a paradigm, policy or methodology, that would solve all the problems related to maintenance systems.

6.4 SYSTEM MODEL III: A STOCHASTIC MAINTENANCE SYSTEM SIMULATION MODEL

6.4.1 Purpose of the model

The stochastic simulation model applies reliability engineering paradigms and can be used to calculate the approximate effect of reactive, preventive and condition-based maintenance on the total maintenance costs, reliability and operational availability. A comparison of differences in the maintenance policies caused by cost-, reliability- and availability-driven maintenance system control can therefore be made. The novelty of the simulation model is the possibility to mix both condition-based and preventive maintenance policies to simulate operational availability and costs. The model can be partly verified with a numerical calculation method presented prior to the simulation model.

6.4.2 Overview and assumptions

The basic assumption of the model is that the single unit system under maintenance always returns functionally and structurally to as good as new. In addition to that, the model applies only to one failure state of that component. The application of the model to some machine or production line requires explicit definitions of the failure states. The modelling and simulation tool was Mathcad 2001i by Mathsotft Inc. The full model is presented in Appendix B: Model III in Mathcad 2001i format.

The simulation model assumes that the occurrence of the failure state follows a two-parameter Weibull rate (NIST/SEMATECH, 2002)

$$\lambda(x) = \frac{\beta}{\eta} \cdot \left(\frac{x}{\eta}\right)^{\beta-1} \tag{4}$$

and the cumulative probability of failures follow a cumulative Weibull distribution function (NIST/SEMATECH, 2002)

$$CDF_w(x) = 1 - e^{-\left(\frac{x}{\eta}\right)^{\beta}} \tag{5}$$

where x is the time in days, β is the shape parameter and η is the scale parameter. The Weibull distribution is a special case of extreme value distribution (Høyland and Rausand, 1994) and is widely being used in modelling failure probabilities because of its flexibility in curve fitting. All the major failure patterns including decreasing, constant and increasing failure rates can be modelled with the Weibull distribution. Also, the Weibull parameters for generic machine types are commercially available (Barringer, 2003). Application of other probability distributions is possible, since the simulation does not use the analytical properties of the Weibull distribution.

The simulation model assumes that there is some average utilisation (Ut) of the machine in relation to calendar time. In case of a failure the mean repair time will be MTTR days, and proactive maintenance, i.e. condition-based and preventive maintenance, takes on average MTTM days to execute. The cost information needed includes

- component price (c_{co})
- repair work costs (c_{re})
- proactive maintenance work costs (c_{ma})
- daily lost capacity expenses of proactive maintenance (cd_{cap})
- daily increased operating expenses caused by a failure (cd_{op})
- daily increased quality expenses caused by a failure (cd_{qu})
- daily lost capacity expenses caused by a failure (cd_{car})

Therefore, the long-run mean yearly total costs of maintenance is given by

$$fc(n,m) = \left(c_{co} + c_{ma} + cd_{cap} \cdot MTTM\right) \cdot n + \left[\left(cd_{op} + cd_{qu} + cd_{car}\right) \cdot MTTR + c_{re} + c_{co}\right] \cdot m \quad (6)$$

where n is the number of proactive maintenance actions and m is the number of repairs during a year.

6.4.3 Numerical method of a preventively maintained system

With a given maintenance interval MTBM in operation days and failure rate function (4) it is possible to calculate both the number of failures and the number of preventive maintenance actions. The model is suitable for verifying this particular simulation model, although a more elegant solution for calculating the failure and maintenance frequencies can be derived from the renewal theory (Høyland and Rausand, 1994, p. 292).

The calculation assumes that the preventive maintenance action changes the failure rate to the same level as a new system after each MTBM operating days. This is described by the following cumulative distribution function (Virtanen and Hagmark, 2002) if a Weibull distribution is applied:

$$CDF_M(MTBM, x) = 1 - e^{-\int_0^x \lambda(\mathrm{mod}(x, MTBM))dx} \quad (7)$$

where mod(x, MTBM) represents the modulo operator that takes the remainder on dividing x by MTBM. This results in a curve type shown in Figure 18.

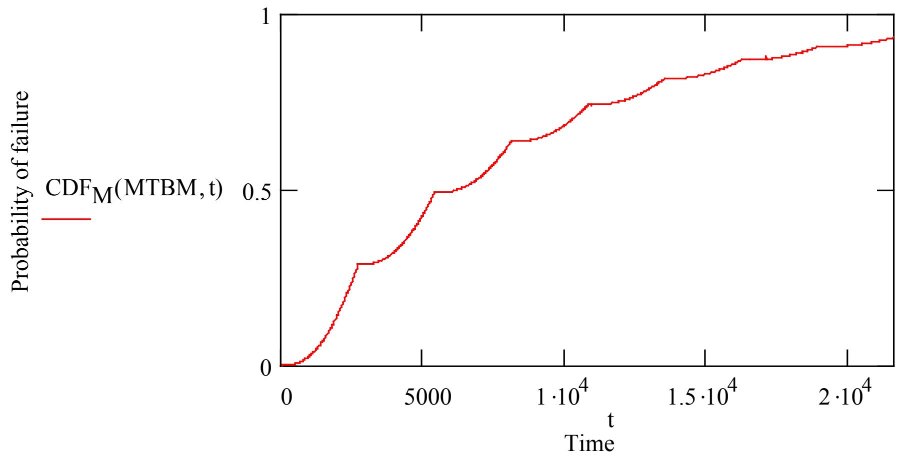


Figure 18 Cumulative failure probability of a preventively maintained Weibull system (7) with MTBM=2700, β=2.5, η=4167.

The mean time to failure (MTTF) needed in the calculation is given by numerically integrating the reliability function from zero to infinity (Høyland and Rausand, 1994)

$$MTTF = \int_0^\infty [1 - CDF_M(MTBM, x)]dx \tag{8}$$

The MTTF value does not equal the MTTF of a *machine* but the MTTF of the *function* that may be implemented by several machines replaced by preventive maintenance.

The probability that a failure is observed during the first MTBM interval is CDF_M(MTBM, 1·MTBM)-CDF_M(MTBM,0). The probability that a failure is observed during the 2nd MTMB interval is CDF_M(MTBM,2·MTBM)-CDF_M(MTBM, 1·MTBM) and so on. By multiplying the probabilities by the respective number of maintenance actions gives the expected value for the number of preventive maintenance actions per failure (mf):

$$mf = \sum_{i=0}^{\infty} [CDF_M(MTBM, (i+1) \cdot MTBM) - CDF_M(MTBM, i \cdot MTBM)] \cdot i \tag{9}$$

which can also be written as

$$mf = \frac{n}{m} \tag{10}$$

where n and m are the number of preventive and reactive maintenance actions during a year.
The mean calendar time to reach the first repaired failure (MTTFR) is given by

$$MTTFR = n \cdot MTTM + \frac{MTTF}{Ut} + MTTR \tag{11}$$

where Ut is the average machine utilization. The number of reactive maintenance actions, and therefore the number of failures during a year is given by

$$m = \frac{365}{MTTFR} \tag{12}$$

The group of the three previous equations (10, 11, 12) can be solved to calculate number of reactive maintenance actions during a year:

$$m = \frac{-\left(\frac{MTTF}{Ut} + MTTR\right) + \sqrt{\left(\frac{MTTF}{Ut} + MTTR\right)^2 + 4 \cdot mf \cdot MTTM \cdot 365}}{2 \cdot mf \cdot MTTM} \tag{13}$$

With m it is easy to calculate the n with the help of (10), and the yearly costs of maintenance with (6). For analysis purposes also the operational availability is defined according to Chapter 5.2.3:

$$A_o = \frac{365 - (m \cdot MTTR + n \cdot MTTM)}{365} \tag{14}$$

It is assumed that the production process is operating 24 hours per day and 7 days per week. If not, then the MTTR and MTTM as well as the number of production days, 365, should be adjusted according to the production schedule. No method for calculating OEE is presented because the quality and capacity losses are calculated directly with the cost function.

The numerical calculation method presented in this chapter is suitable to reactive-preventive maintenance, but the effect of condition monitoring is difficult to implement in the presented equations. Also, the numerical calculation of integrals and sums is quite slow. Therefore, the method presented in this chapter was used only to verify the simulation results of the simulation model presented in the next chapter.

6.4.4 Simulation model of a preventively maintained system under condition monitoring

Usually, condition monitoring is assumed to be able to detect the failure state 100 % reliably (i.e. Dieulle et al., 2001; Maillart and Pollock, 2002) or the condition monitoring reliability is assumed time-invariant (Bukowski and Goble, 2001). Also, condition-based maintenance is usually assumed to replace preventive maintenance as the maintenance policy. In reality these assumptions are not always valid. For example, paper roll bearings are sometimes replaced even if they are under condition monitoring. This implies either that the condition monitoring method is not fully reliable or that the condition monitoring detects the failure too late.

In the simulation model, condition monitoring is assumed to be able to detect the future failure state with some certainty (DC) [0 % ...100 %], which is called diagnostic coverage (Bukowski and Goble, 2001). If the failure is detected, the detection time (DT) is the time between the found indication of a future failure state and the actual occurrence of the failure.

In reality, there is likely to be some dependence between DT and DC. That is, the mean detection time is longer with higher diagnostics coverage, and vice versa. But, because it may be possible to adjust the sensitivity of the diagnostics there may be an increasing number of false diagnostics alarms if DC and DT are increased. These aspects are not included in this model but considered later in Model IV.

In addition to cost parameters in the previous chapter, there is an additional cost of one condition monitoring inspection (c_i), and the monitoring interval parameter, mean operating time between inspections (MTBI). If using automatic condition monitoring as assumed in this research, both c_i and MTBI can be approximated as zeros. If applying the model in highly integrated process industries where a machine can be maintained only during some fixed maintenance breaks, there must be some factor that defines what the average time is from the detection of a failure to the next possible moment when the maintenance can be executed without interrupting the process. This time interval, mean operating time to arrange a maintenance break (MTTAM), may also be defined by the availability of suitable spare parts or maintenance planning and scheduling delay.

The simulation model uses two-parameter Gamma probability distribution

$$PDF_{\Gamma}(x) = \frac{\lambda^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x} \qquad (15)$$

where α is the scale parameter, λ is the rate parameter and Γ is the Gamma function to model the probability of detecting the failure DT days before its occurrence. Use of other distributions is possible, e.g. Beta distribution, which is very flexible and suitable for modeling expert estimated data (Fente et al., 1999). In the simulation, the distribution is formed by user-given parameters for mode (the peak value), median, 10 % and 90 % confidence levels for the detection times. The mode value is fixed as it is easiest to estimate (Fente et al., 1999). The least squares method is used to fit the Gamma distribution to the given points. An example of such distribution is given in Figure 19.

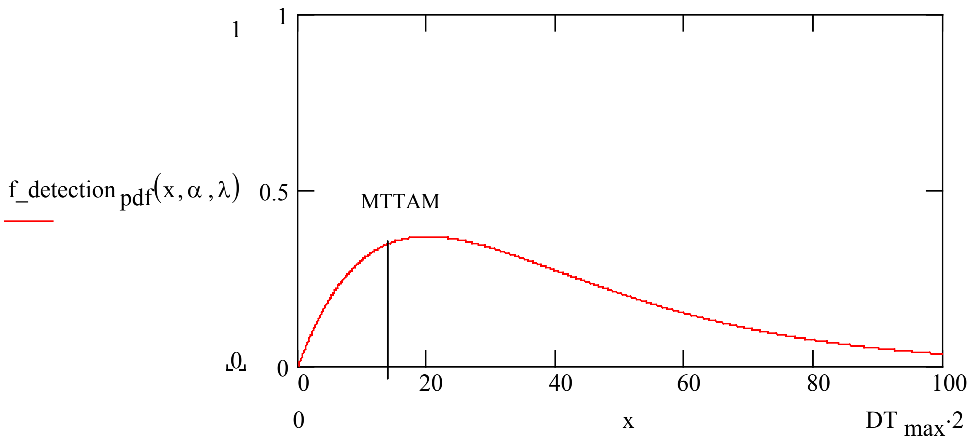


Figure 19 A Gamma probability distribution (15) with scale parameter α=2 and rate parameter λ=0.05 to model the failure detection time as a function of probability. The curve area on the right of the MTTAM line defines what the probability is that the failure is detected earlier than the time it takes to arrange maintenance (MTTAM=15 d).

An inverse of the cumulative Weibull failure distribution (5) as well as an inverse cumulative Gamma distribution are used in the simulation by feeding random probabilities between values 0 and 1 to the functions. The functions return the simulated operating time to the next failure and the detection time to detect the failure. The simulation proceeds as follows

1: take a random number between 0 and 1 and simulate the next failure time in operating days by using an inverse function of Equation 5 in respect to time x and sum it to previous failure or maintenance time
2: determine the next preventive maintenance by adding mean operating time between failure (MTBM) to previous failure or maintenance time
3: if the simulated failure time is before the next preventive maintenance time, that is the system is going to fail, then

> 4: take a random number between 0 and 1
> 5: if the random number is less than DC, that is, the diagnostics detect the failure, then
>
> > 6: take a random number between 0 and 1 and use inverse cumulative Gamma distribution to simulate how many operating days before the failure it is detected
> > 7: adjust the time of detection by selecting the next condition monitoring time defined by the mean operating time between inspections (MTBI) from the previous failure or maintenance time
> > 8: if the failure time minus detection time is greater than the mean calendar time to arrange maintenance (MTTAM) then
> >
> > > 9: the system fails at the failure time because the maintenance cannot be executed before the failure
> >
> > else
> >
> > > 10: the predictive maintenance time is the detection time plus MTTAM
>
> else
>
> > 11: the system fails at the failure time because the diagnostics cannot detect the failure

else

> 12: the preventive maintenance is executed before the failure and the maintenance time is given by the previous failure or maintenance time plus MTBM

13: go back to step 1 until enough maintenance and failure events have been simulated

It is possible to count the number of proactive maintenance actions from the simulation results and apply (6) and (14) to calculate the average total costs of the maintenance and the average operational availability of the system.

6.4.5 Simulation results

To study the effect of condition monitoring a fictive electrical motor was used with Weibull failure curve defined by β=2 and η= 4166.667 (Barringer, 2003) which analytically calculating gives as the mean time to fail MTTF=3696.933 operating days. The preventive maintenance interval MTBM was set at 2700 operating days and the diagnostics coverage DC at 75 % of the failures detected, if applied. Both the maintenance (MTTM) and repair (MTTR) take 5 calendar days. The cost information used was as follows:

- motor price c_{co}=10,000
- repair work costs c_{re}=2,000
- proactive maintenance work costs c_{ma}=1,000
- daily lost capacity expenses in case of proactive maintenance cd_{cap}=0
- daily increased operating expenses caused by a failure cd_{op}=0
- daily increased quality expenses caused by a failure cd_{qu}=0
- daily lost capacity expenses caused by a failure cd_{car}=10,000

The proactive maintenance is not assumed to cause any capacity loss expenses (cd_{cap}=0) to contrast the differences between cost and availability-driven maintenance system control. The cd_{cap} would be significant only in a situation where the proactive maintenance would cause loss of sales. In case of repair or maintenance the motor is replaced with a renewed one. The repair work is assumed more expensive than proactive maintenance because of the overtime work costs. Proactive maintenance is assumed to be arranged immediately (MTTAM=0), so that the detection time curve has no effect.

Four maintenance policies were studied: reactive only, preventive only, condition-based and preventive, and condition-based only. The results are presented in Table 5 and Figure 20 with 1,000,000 years of simulation.

	A_o	Costs / year	MTTF (days)	Failures / Year
Reactive	99.892 %	4892.0	3696.8	0.079
Preventive	99.838 %	3023.7	8631.3	0.034
Preventive & CBM	99.837 %	1735.4	34576.9	0.008
CBM	99.891 %	1880.3	14770.5	0.020

Table 5 Simulation results of four different maintenance policies.

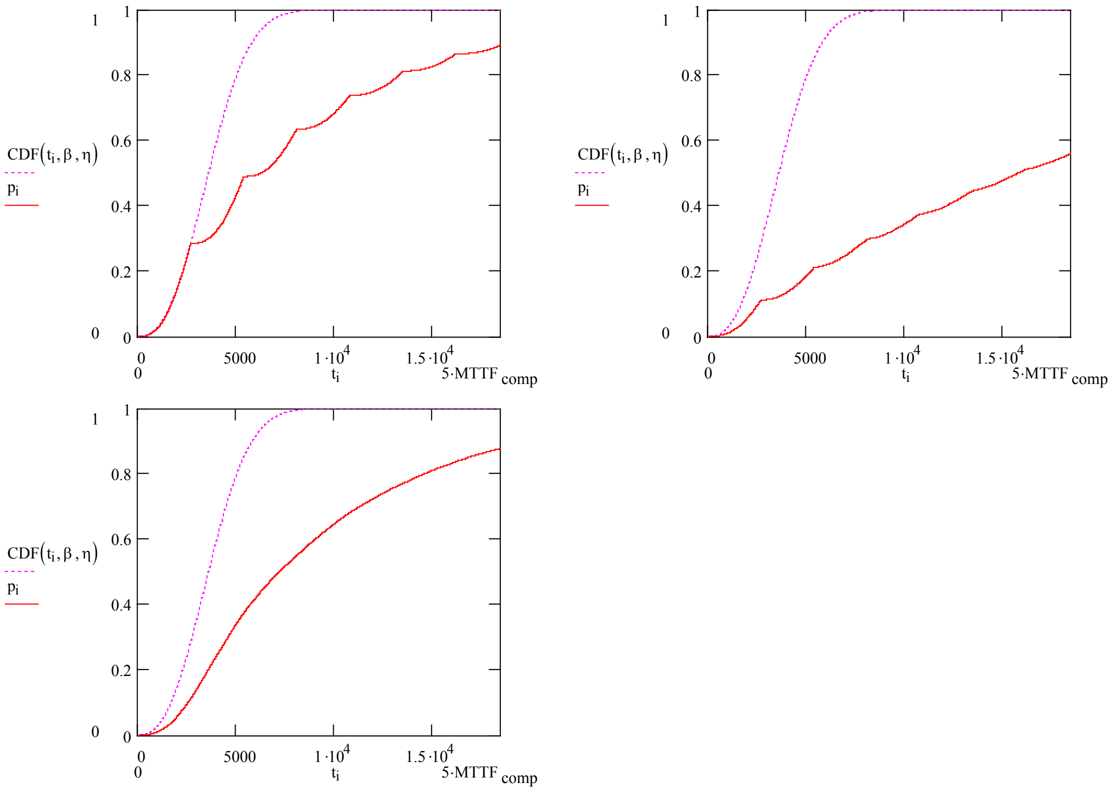


Figure 20 The simulated cumulative failure probability distributions (solid lines) of preventive only (upper-left), preventive & condition-based (upper-right), and condition-based only (lower-left) policies compared to numerically calculated reactive policy (dotted lines) from (5).

If using operational availability as the efficiency metrics, the optimal policy is reactive and the most inoptimal one is a combination of preventive and condition-based maintenance. On the other hand, using total costs as the metrics reverses the situation: the optimal policy is the combination of preventive and condition-based and the most inoptimal one is the reactive maintenance policy. The reason for that is the different weighting of the failures and proactive maintenance. If using MTTF (reliability) as the metrics, the optimal and inoptimal policies are the same as in using costs as the measurement method. This is because, similarly to MTTF calculation, the applied cost data does not calculate the downtime caused by preventive maintenance in as a cost.

The optimum values for both the costs and MTTF are achieved when the diagnostics coverage is 100 % and the maintenance can be arranged immediately (MTTAM=0). In that case the costs are 876.2, operational availability is 99.891 % and MTTF is infinite. The lower operational availability than in reactive maintenance is explained by the fact that the diagnostics detect the failure some time before its occurrence. This leaves some safety margin in the average lifetime of the system, which cannot be used in production as opposed to the case of reactive maintenance that utilises the all the possible production time.

The failure rate was increasing, so these results do not apply to decreasing and constant failure rates. Decreasing and constant failure rates cannot be reduced by preventive renewals. In these cases, condition-based maintenance is the only option to reactive maintenance, except for the situation where the failure cause is not affected by the system design. In that case, it may be possible to prevent the failure event with some external preventive action, such as operator training.

The simulation results imply that the method of measuring the maintenance process can radically affect the maintenance policy selection. Especially, *if operational availability is used as the efficiency metrics and the condition monitoring is not perfect, then there is a risk to* *overvalue condition-based maintenance over preventive maintenance and reactive maintenance over condition-based and preventive maintenance.*

6.4.6 The effect of limited time to diagnose

If using 15 days as the mean operating time to arrange maintenance (MTTAM) and the detection time curve shown in Figure 19, the numerically calculated percentage for the components that could not be proactively maintained in time would be 17.3 % of the detected failing components. Therefore, with 75 % diagnostic coverage, 62.0 % of all the failures could be avoided. This could be used as an approximation of diagnostics coverage with zero days MTTAM to get similar results.

In highly integrated process industries the MTTAM is defined by the scheduled maintenance breaks. The production process cannot be stalled right away if condition monitoring indicates failure. In highly parallel production systems, such as cell production, there are no such restrictions. Therefore the MTTAM is merely defined by the spare parts availability and the throughput time of the maintenance process workflow. In the previous example, dropping the MTTAM from 15 days to 10 days increases the percentage of avoided failures from 62 % to 68.2 %.

Reduction of the maintenance process throughput time and condition monitoring have an amplifying effect on each other to increase reliability in situations where the maintenance process cycle time limits arranging a maintenance break. However, the scale of the amplification is dependent on the detection time, diagnostics coverage and the maintenance process throughput time.

6.4.7 Summary

In the example simulation, the application of condition monitoring increased reliability compared to the reactive and preventive maintenance policies. However, the condition-based maintenance with limited diagnostics coverage (observability) was not the optimal policy.

The presented model used only one failure type so the comparison between maintenance actions was not done. However, if preventive replacement or renewal was the only maintenance action, adding additional failure types to the model would reduce the effectiveness of preventive maintenance even more. This is because prevention of one failure type with renewal would be quite likely inoptimal in regard to other failure types.

The example simulation shows that the measurement metrics of maintenance system affect the applied maintenance policy. Such metrics as operational availability seems to favour irrational maintenance policies that are usable only in special cases.

Because the detection time DT reduces the ability to do the maintenance action on the detected failure in time, it is feasible to shorten the maintenance process throughput time with such technologies as computerised maintenance management systems in order to reduce the production losses in case of failures.

6.5 SYSTEM MODEL IV: A DYNAMIC MAINTENANCE SYSTEM SIMULATION MODEL

6.5.1 Purpose of the model

The purpose of the model is to analyse the effect of the control system, condition monitoring, maintenance repeatability and worker resources to the dynamics of maintenance systems. Of the presented models, this is dynamically the most complex one. The model is based on the theory part and models derived so far. The dynamics cannot be predicted from the equations that define the model structure, and therefore the model helps in revealing the behaviour of maintenance systems.

6.5.2 Dynamic modelling

Dynamic models have their roots in system thinking and system control with information feedback. The origins of the applied modelling method are in the classic Forrester (1961) book. The modelling method emphasises studying the effect of the system structure and decisions on the behaviour of the system. The three basic modelling elements are *levels* that describe the state of the system, *rates* of flows that connect the levels and *decision functions* that control the rates. Levels accumulate the incoming and outgoing rates, e.g. they represents such concepts as liquid tanks, stocks of materials or awareness levels. Rates represent instantaneous flows of materials, money, orders, persons and equipment. These flows are interconnected by information networks which are also systems of levels, rates and decision functions. The decision functions represent policies in the system, which define how the levels (system state) affect the rates.

6.5.3 Simplifications and assumptions in dynamic modelling

Common approaches to model failures and maintenance of production systems are to use either stochastic simulation or Markov state-space models. These approaches are feasible considering that the maintenance systems are by nature probabilistic and they may contain several possible states. Although stochastic simulation is very flexible with the application of various probability distributions, the drawback of stochastic simulation is usually its heavy requirements for computing power. Markov models are efficient, but they have limitations with life- and maintenance-time distributions and with taking into account trends such as seasonal changes.

Dynamic simulation models are good what comes to modelling non-linear dynamic systems with large amounts of objects that flow from a state to another. In that case it is not feasible to analytically calculate or stochastically simulate the state of each single object in the system. Although the events in the maintenance systems may be discrete, such as sudden unexpected failures, there are lots of continuous and interacting processes, such as degradation and repairing of machines and moving the spare parts from a location to another. Therefore, continuous approximations can often be made. The probabilistic nature of failures is "noise" from dynamic simulation point of view. The proportion of noise becomes smaller and smaller compared to the average failure rate when the number of independent machines increases. Therefore, the maintenance system is simplified so that the stochastic behaviour of failures is assumed as a deterministic function of the average age of the component population. The maintenance and repair times are assumed similarly deterministic without probabilistic behaviour, because the variability is very small compared to the overall system delays. The fundamental difference compared to the stochastic simulation and Markov models is that instead of tracking the states of each component, the interest is in the number of components in each state and in the flow rates between the states. Because the model is continuous there may be fractions of components in each state.

The dynamic models are usually adequate to describe the behaviour of the simulated process. However, the correctness of the model structure and outputs is very difficult to show, even in cases where actual data of process parameters and outputs is available (Graham et al., 2002). The presented model makes no exception in that sense. Use of the model in real maintenance system optimisation would require more rigorous analysis and calibration of the model parameters.

6.5.4 Model overview

The model was developed with Vensim PLE v5.0 by Ventana Systems Inc. and is presented in full in Appendix C: Model IV in Vensim 5.0 text format. The modelled system is a fictive one, but should nevertheless roughly represent maintenance of deteriorating machines that have infant failure characteristics caused by poor maintenance and repair repeatability. The system parameter values are selected so that they could represent a real system — except for some values that are set intuitively too small or too large to make the system behaviour clearly visible.

6.5.5 Component failure and maintenance model

The system maintains a set of components. They can be thought to be of the same type representing a group of machines being maintained by a machine manufacturer. The components may be in states $S_0 \dots S_8$ that are defined by the number of components in that state. A simulator view of the component model is presented in Figure 21. The component states and the characteristic delays defining the system dynamics are presented in Table 6.

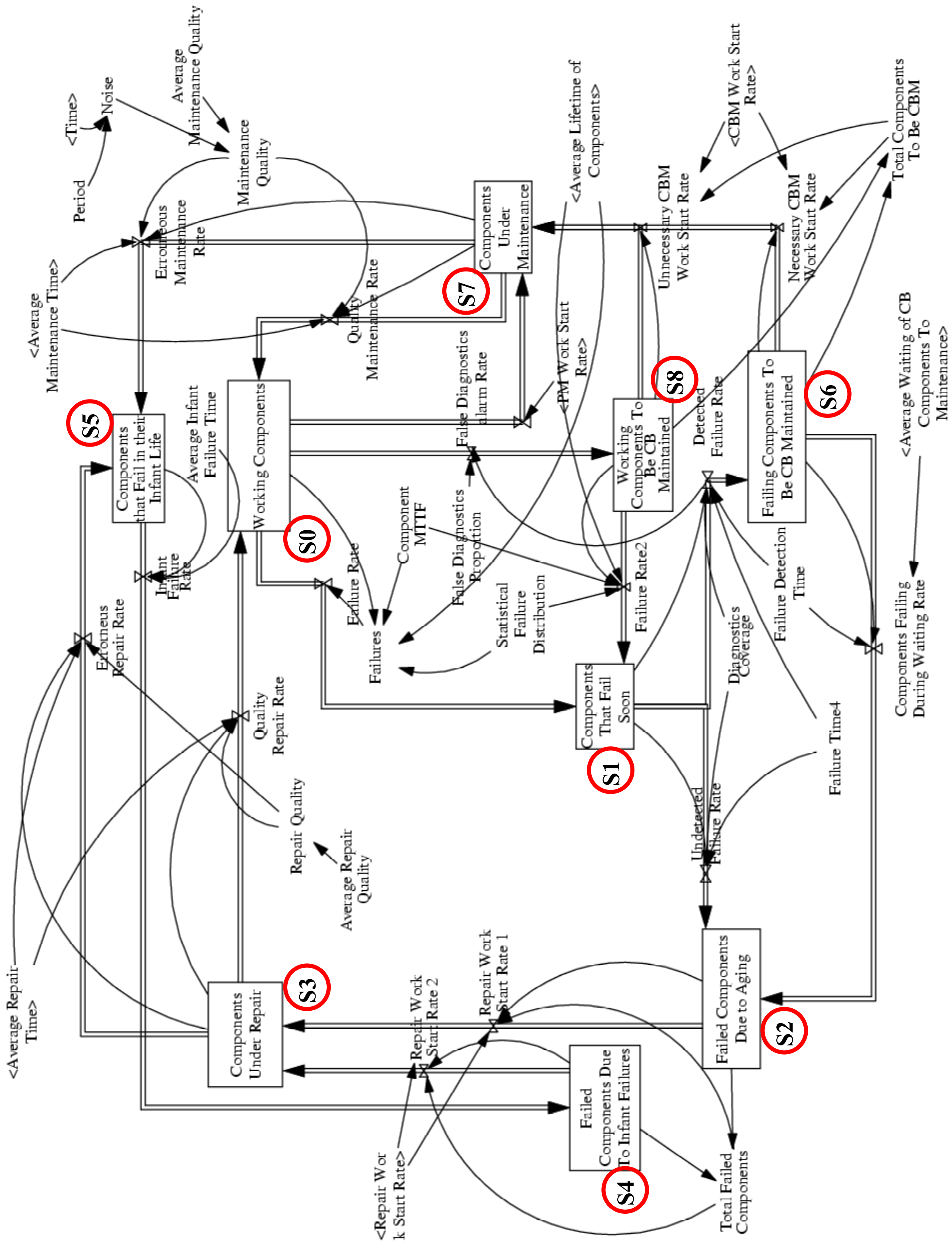


Figure 21 The component model as seen in the simulator. Rectangles represent levels, valve symbols represent flow rates, curved arrows represent information between decision functions, and elbowed arrows represent possible paths between the levels. Repair work start rate, PM work start rate and CBM work start rate are calculated in a worker allocation model.

State	Description	Characteristic state delay
S_0	Number of working components	Defined by the average age of components by equation (16) and the renewal delay by equation (19)
S_1	Number of components that fail soon	12 weeks failure delay
S_2	Number of failed components due to deterioration	1 week administration delay
S_3	Number of components under repair	3 weeks repair delay
S_4	Number of failed components due to infant failures	1 week administration delay
S_5	Number of components that fail in their infant life	5 weeks infant failure delay
S_6	Number of failing components to be maintained	1 week administration delay and 8 weeks detection delay
S_7	Number of components under maintenance	4 weeks maintenance delay
S_8	Number of working components to be maintained	1 week administration delay

Table 6 The component states and the characteristic delays.

6.5.6 Worker allocation model

The components are being maintained by a 30-person group of workers who can be in three modes: idling, repairing, and executing proactive maintenance. The respective states are $W_0 \ldots W_2$ that are defined by the number of workers in that mode. The state for the preventive and condition-based maintenance actions is the same (W_2) and requires one worker and four weeks to complete. Repairing (W_1) can be done in three weeks, but requires on average two persons to complete. The administrative delay from start to end of a maintenance or repair task is one week. This time is spent in such activities as travelling, diagnosing the failures, and reporting the maintenance tasks. A simulator view of the worker allocation model is presented in Figure 22. The worker allocation states, characteristic delays and number of workers required to complete are presented in Table 7.

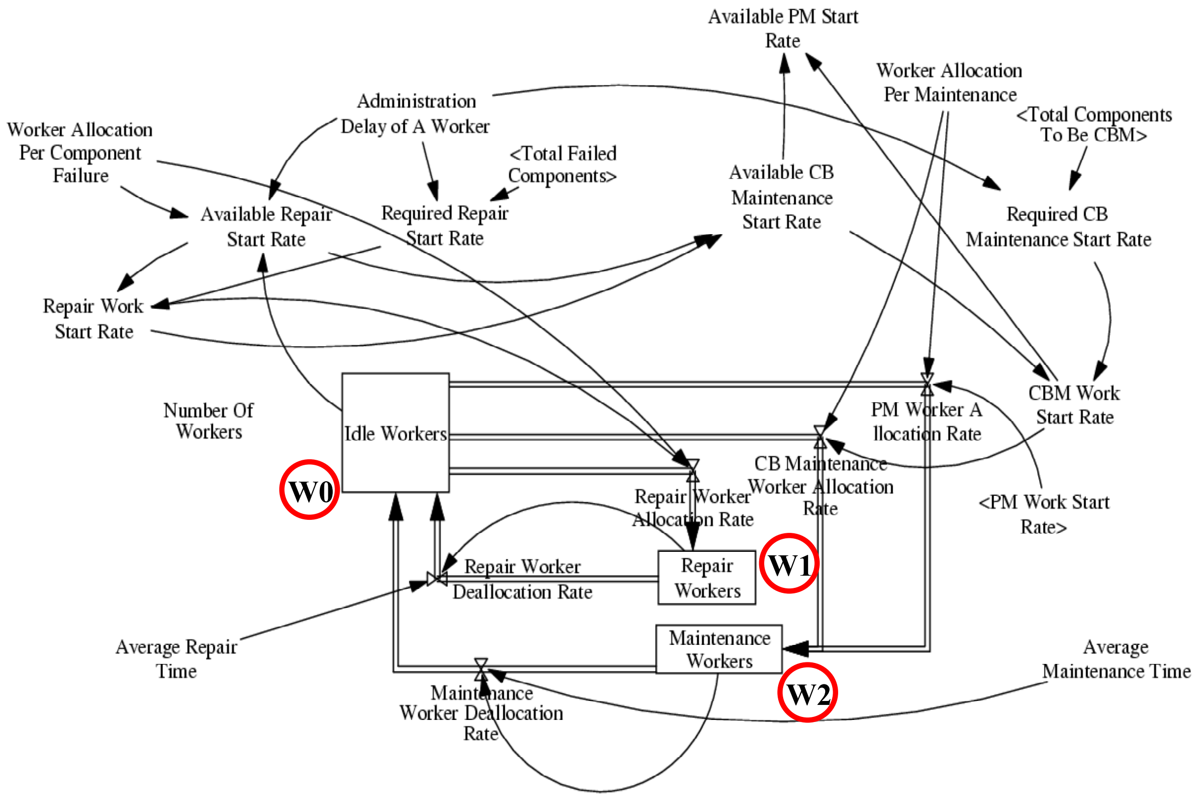


Figure 22 The worker allocation model as seen in the simulator. PM work start rate is defined in the control model.

State	Description	Characteristic state delay	Workers required to complete
W_0	Number of idle workers	1 week administration delay	
W_1	Number of repair workers	3 weeks repair delay	2 workers
W_2	Number of proactive maintenance workers	4 weeks maintenance delay	1 worker

Table 7 The worker states, the characteristic delays and the required number of workers.

6.5.7 Deterioration failure process

It is assumed that there are one thousand components (C=1000) in the system. They are normally in a working state (S_0). However, due to deterioration they fail. The failure rate is a function of the average age of the components in operation. This is a rough simplification and does not take the age distribution of the components into account, but nevertheless illustrates the effect of the population age on the failure rate. The deterioration failure process is defined with a modified Weibull failure rate

$$\lambda(x,c) = c \cdot \frac{\beta}{\eta} \cdot \left(\frac{x}{\eta}\right)^{\beta-1} \qquad (16)$$

where x is the average age of the components and c is the number of working components.
The used shape and scale parameters β=5 and η=566 make the curve steeply increasing to denote the effect of the high average age on the failures. Equation (16) and the shape and scale parameter values are fictive. The failure process can be considered to be formed from c equally

old components that each have a failure pattern defined with a Weibull failure rate where $\beta=5$ and $\eta=566$, which make the component MTTF equal to 520 weeks. A ten-year lifetime for an industrial machine is quite common (Barringer, 2003).

The component state changes from working components (S_0) to components that fail soon (S_1) according to the deterioration process. The components that fail soon (S_1) fail in average 12 weeks unless detected by an automatic condition monitoring and diagnostics system that has an average 8-week fixed detection time before the failure. If the diagnostics does not detect the failure, the component fails to the failed components due to deterioration state (S_2) after eight weeks.

6.5.8 Repair process

The failed components are taken under the components under repair state (S_3) if there are two workers available for that. The repair takes three weeks plus one additional week for administrative delays. If the repair is successful, the component is restored back to the working components state (S_0). Thinking this way, the components are restored without the use of materials. Or, one may think that the component represents a function that can be in the previously described states, and the maintenance restores the function with the help of spare parts or new components that are immediately available from a local inventory.

6.5.9 Repeatability of repair actions

The repair may be unsuccessful with 10 % probability, in which case the component is taken into operation but is in the components that fail in their infant life state (S_5). In other words, the repeatability of the repair is 90 %. The average time the components operate in that state is five weeks after which the component fails to the failed components due to infant failures state (S_4). The component is again repaired if there are two workers available. The selected repeatability rate may be too low if it were compared to the repair repeatability of real systems. However, the system behaviour is more easily visible with such parameter value selection.

6.5.10 Condition-based maintenance process

If the condition monitoring system detects the deterioration failure, the component is put in the failing components to be maintained state (S_6). If there is one worker available for condition-based maintenance, the component is moved to the components under maintenance state (S_7). In any case, the repair has a higher priority than condition-based maintenance and may cause a shortage of worker resources to condition-based maintenance of the components. The condition-based maintenance has, however, a higher priority than preventive maintenance. From the components under maintenance state (S_7) the component proceeds as in preventive maintenance described in the next chapter. The condition monitoring may be tuned to be too sensitive and cause false alarms. This is modelled as a fixed ratio of the detected failures rate. In case of false condition monitoring alarms the component is moved from the working components state (S_0) to the working components to be maintained state (S_8). The user cannot observe that state, so the components in that state are processed with the same priority as the failing components to be maintained (S_6).

6.5.11 Preventive maintenance process

To prevent the deterioration failures the maintenance system may renew some proportion of the working components to decrease the average age of the components. The components are changed to the components under maintenance state (S_7) if there is one worker available for preventive maintenance. In any case, the repair and condition-based maintenance have a higher priority and may cause a shortage of worker resources to preventive maintenance of the components. The maintenance succeeds with 95 % probability, i.e. the repeatability of the maintenance actions is 95 %. After successful maintenance the component is returned to the working components state (S_0). If the maintenance is not successful, the component is moved to the components that fail in their infant life state (S_5) and consequently, it will participate in the repair process.

6.5.12 Preventive maintenance control model

Selecting a predefined preventive maintenance interval in the model is based on the assumption that there is some target control variable. This kind of an optimum setpoint value may come from such a model as presented in Chapter 6.4. In the model the controlled variable is defined by

$$Y = C - (n_r + n_{fd} + n_{fi}) \tag{17}$$

where C is the total number of components, n_r is the number of components being repaired (S_3), n_{fd} is the number of components that have failed because of deterioration (S_2) and n_{fi} is the number of components failed because of infant failures (S_4).

Considering the scope of this dissertation in process industries, the indirect costs of failures are assumed relatively high compared to the costs of proactive maintenance. Therefore, proactive maintenance is preferred and the components under proactive maintenance are not included in (17). That is, the goal is not to control the operational availability but the reliability (MTTF).

The logic is to take the controlled reliability variable Y and compare it to a setpoint of a desired value. The difference, or error, between the actual value and the setpoint is controlled by changing the preventive maintenance rate of the working components. The error equation is defined as

$$E = Y - S \tag{18}$$

where S is the setpoint number of components, or the reliability target.

Selection of the preventive maintenance interval proceeds as follows: if the error E is positive, increase the maintenance interval to decrease reliability and therefore reduce Y. If the error E is negative, decrease the maintenance interval. If the error E is zero, then the required level is achieved and no control action is needed. Control of the interval is continuous but the changes are assumed very small. In practice the randomness in the failure process makes it difficult to estimate the actual error value. Therefore, the measurements must be filtered to obtain the real error E.

The selected approach to model the control logic is a proportional-integral (PI) control algorithm (Åström and Hägglund, 2000) that is commonly used in industrial process control. The use of the PI-algorithm does not imply that in reality the preventive maintenance is controlled by using a PI-algorithm. Merely, the PI-algorithm simulates the real world decision making and learning in which the system reliability is controlled with the help of some heuristic and mental processes. Usage of both proportional and integral control parameters filters high-frequency error signals out and ensures that the error will eventually be zero. A derivative parameter is not used because its prediction capability by linear extrapolation is not very effective in slow processes.

Error E is used to control the renewal delay, e.g. the weeks to renew all the components, with the PI equation (Åström and Hägglund, 2000) in parallel form:

$$R(E) = MAX(MIN(0.7 * MTTF + E \cdot G_p + \int E\,dt \cdot G_i, MTTF), 0.4 \cdot MTTF) \qquad (19)$$

where the MTTF of a component is 520 weeks, $G_p = 100$ is the proportional error gain and $G_i = 2$ is the integral error gain. In other words, the error of one component causes one hundred weeks' change in the renewal delay, and one component-week integral error causes two weeks' change in the renewal delay. These values were selected by testing the system so that there is some, but not excessive oscillation in the preventive maintenance work start rate. Thus, the system is appropriately tuned.

The minimum and maximum rates for the renewal delay are 0.4·MTTF and 1·MTTF of the component to prevent too long or short renewal delay. These limits are set by reasoning that the preventive maintenance frequency cannot be too high or low. The initial renewal delay is 0.7·520 weeks equalling to changing all the working components in 364 weeks. A simulator view of the control algorithm is presented in Figure 23.

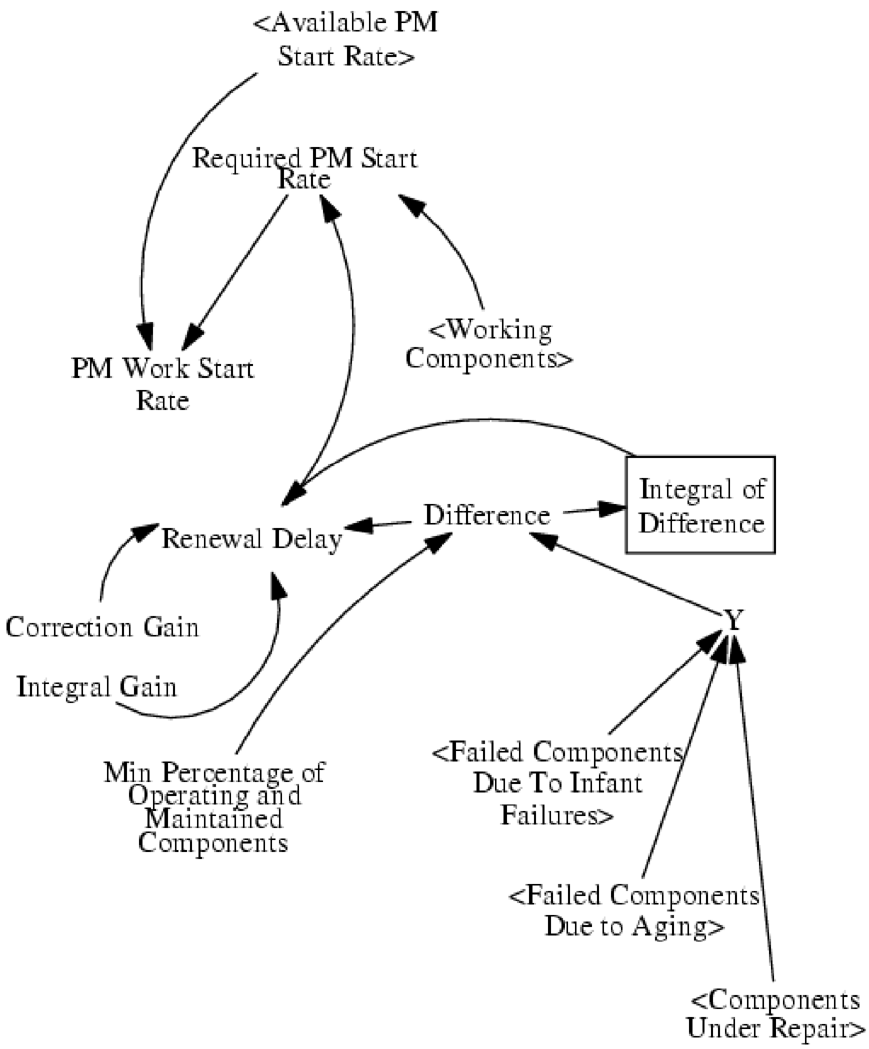


Figure 23 The simulator view of the PI-control algorithm. Setpoint S is set by adjusting the target percentage for operating and maintained components (Y).

6.5.13 Analysis of the system behaviour

The system is started from a situation where all the components are new and in the working state (S_0). The controlled variable Y=997. In other words, only three components should be under repair or waiting for repair. The simulation time is 3120 weeks equalling 60 years.

As shown by Figure 24 the system stabilisation takes almost thirty years. In the beginning the components are new and no preventive maintenance is needed. However, the number of deterioration failures increases quickly when the average age of the components increases. This is compensated with a heavy preventive replacement policy, which causes the average component ages to drop. The behaviour of the preventive maintenance work start rate starts to oscillate. The highest amplitudes of the start rate for the preventive maintenance work are cut because of the limits defined in (19), and because of the shortage of workers for preventive maintenance. Between week 980 (year 19) and week 1221 (year 23) there are not enough workers to do the required preventive maintenance. The system seems to be too slow.

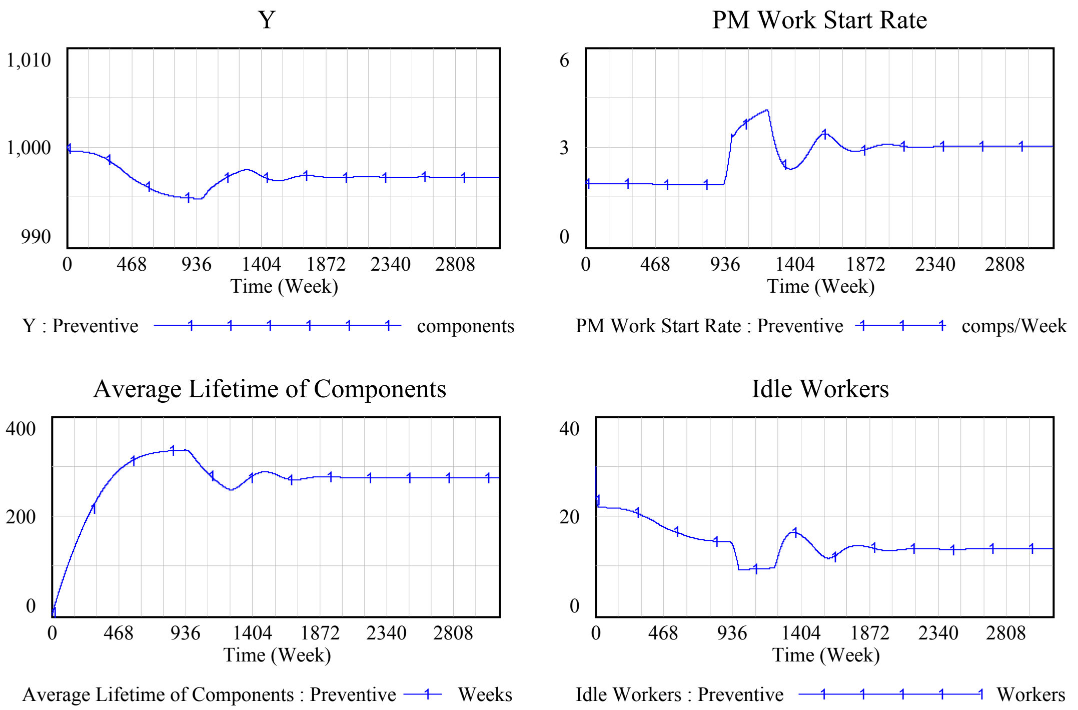


Figure 24 Controlled reliability variable Y, preventive maintenance work start rate, average lifetime of components and number of idle workers, G_p = 100 and G_i = 2.

It is difficult to make the system fast and stable by adjusting the gains, as shown in Figure 25 in which the $G_p = 50$ and $G_i = 5$ make the system oscillate heavily.

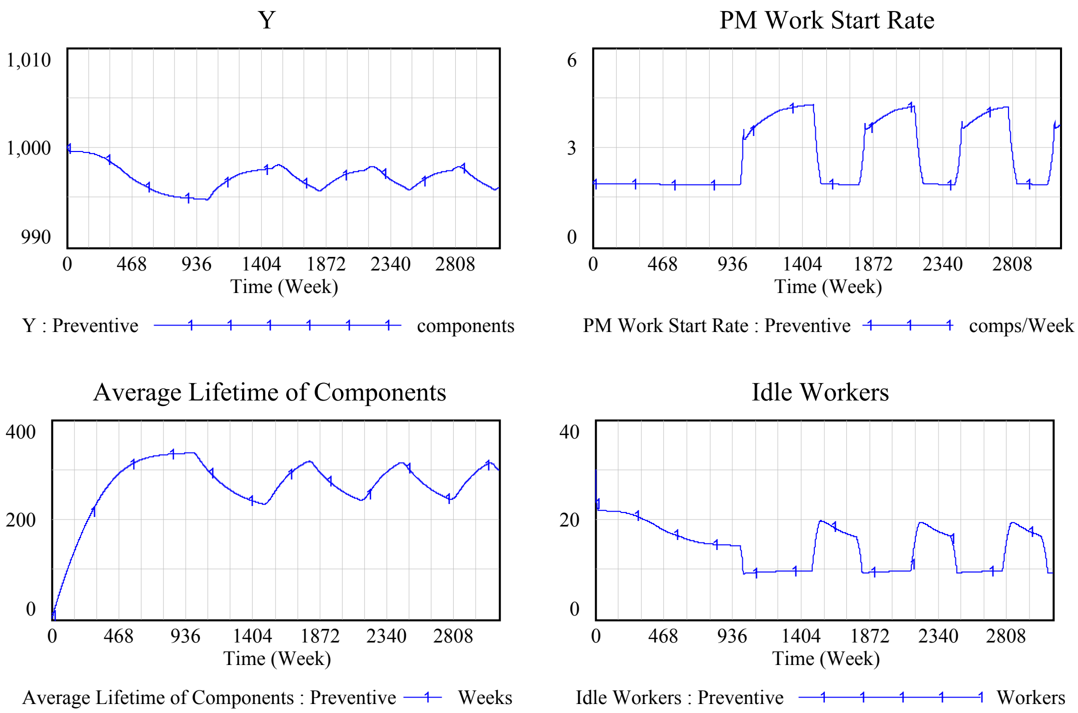


Figure 25 Controlled reliability variable Y, preventive maintenance work start rate, average lifetime of components and number of idle workers, G_p = 50 and G_i = 5.

The problem seems to be that a fixed reliability target in this kind of a slow system is very difficult to achieve. A practical solution is not to try to attain a specific level of reliability but to reach for a certain minimum level of reliability. If the minimum level is exceeded, no changes to the preventive maintenance program should be done. A modification of (18) presented as

$$E = \min(Y - S, 0) \tag{20}$$

was used to study this approach. The modification causes any positive error to be ignored. Consequently, better reliability than the desired level causes no change in the control. The setpoint of 997 components becomes the minimum reliability target. The resulting renewal delay and PM work start rates when $G_p = 50$ and $G_i = 5$ are presented in Figure 26.

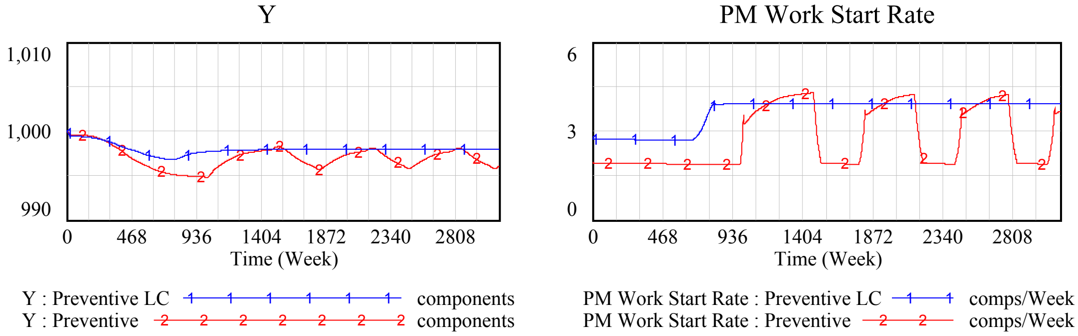


Figure 26 Controlled reliability variable Y and predictive maintenance work start rate with modified error equation (20) (Line 1) compared to the original error equation (18) (Line 2), G_p = 50 and G_i = 5.

There are 997.9 components in operation or under maintenance, which is over the required level. The system becomes much faster, since the PM program is adjusted in three years, with only minor oscillation. The drawback is that because (20) ignores positive errors, reduction of the reliability target does not have any effect on the start rate of the PM maintenance work. Therefore, in reality, there should be top and bottom allowed limits for the control variable Y. The oscillation is caused by continuous control towards the desired (optimally efficient) reliability. Therefore it can be hypothesised that reaching and keeping an optimally efficient maintenance program with preventive maintenance in slow failure processes is very difficult or impossible.

As good and realistic as the modified equation (20) seems to be, it is left out from further analysis and the original equation with G_p = 50 and G_i = 5 is used to amplify the system behaviour for analysing the system dynamics.

6.5.14 The effect of repair and maintenance repeatability on the system dynamics

The importance of preventive maintenance and repair repeatability is very high in this kind of a system. If the maintenance actions are not repeatable, the component states after maintenance actions are not known. In the simulation a failure in repeatability results in infant failure state (S_5) that cannot be detected by the condition monitoring system.

In the simulation, the reliability is controlled with the help of preventive maintenance, but the preventive maintenance may not be repeatable, which reduces its effectiveness and increases infant failures. Poor repair repeatability, in turn, reduces the effectiveness of reactive work and increases also infant failures. Therefore, poor repeatability of repair and condition-based maintenance amplify the number of failures and poor repeatability of preventive maintenance dampens its effectiveness.

The amplification and dampening can be reduced by either increasing the quality of repair and preventive maintenance or by reducing the number of deterioration failures. The reduction of deterioration failures takes place through preventive maintenance, which increases the number of infant failures. If the quality of repair and preventive maintenance cannot be increased, a control action out of the system scope, such as better component design, is required.

If the repair and maintenance quality is 100 %, i.e. fully repeatable, the system behaves as shown in Figure 27. Because the preventive maintenance does not cause infant failures, the deterioration failures are increased with a slower rate. The preventive maintenance is more effective and therefore the number of failures decreases more rapidly. Consequently, the amplification of the system is lower and the system is easier to control. In fact, the system control does not take into account that there are two failure types: infant failures caused by maintenance errors and deterioration failures.

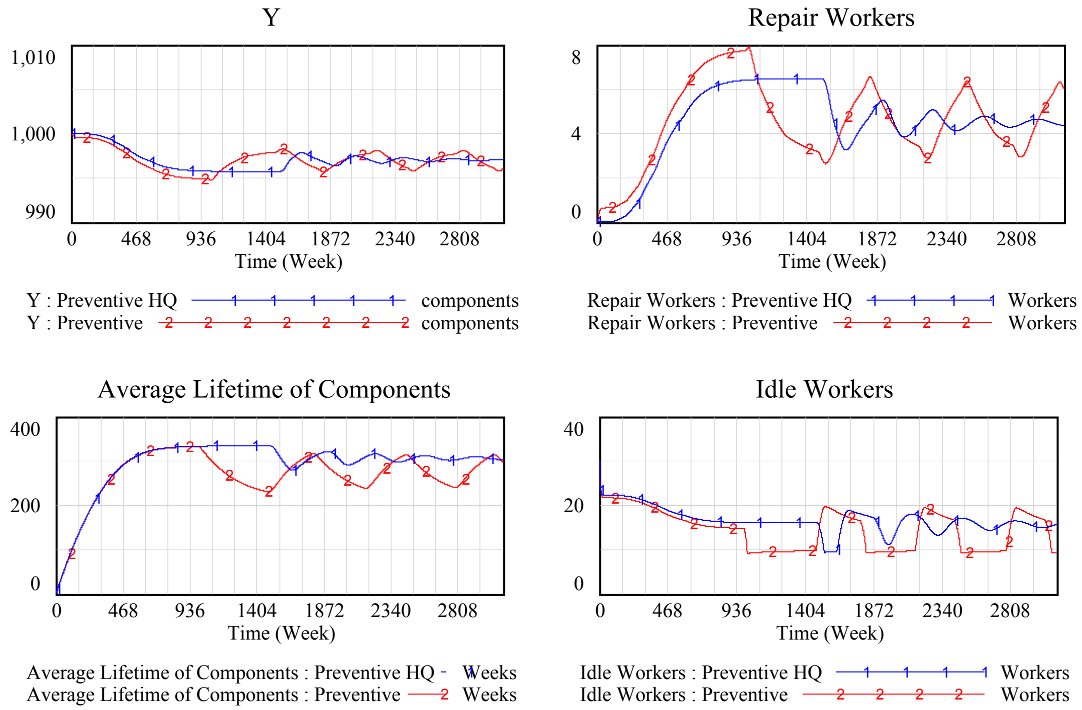


Figure 27 Controlled reliability variable Y, number of repair workers, average lifetime of components, and number of idle workers with 100 % maintenance and repair quality (Line 1) compared to 95 % maintenance and 90 % repair quality (Line 2), error equation (18), G_p = 50 and G_i = 5.

6.5.15 The effect of condition monitoring on the system dynamics

The installation of a condition monitoring system shifts a certain proportion of the reactive maintenance actions to proactive maintenance. Therefore, increasing the diagnostics coverage reduces failures, which further dampens the amplification caused by poor repeatability of repair. However, possible false diagnostics alarms cause unnecessary condition-based maintenance actions. If successful, these actions decrease the average age of the components and therefore decrease the number of deterioration failures. If unsuccessful, the number of infant failures is increased. If the increase of the infant failures is lower than the reduction of the deterioration failures, the false alarms increase reliability. In case of a constant failure rate, no preventive maintenance can increase reliability. In that case, false diagnostics increases the number of failures if the maintenance repeatability is not 100 %. If the failure rate is decreasing false diagnostics increases the number of failures in any case. *In other words, perfect condition monitoring dampens the reliability oscillations caused by imperfect repeatability of the repair work.*

The effect of 15 % diagnostics coverage without false alarms is shown in Figure 28. The system oscillation is dampened. Some of the repair workers are moved to condition-based maintenance and less preventive maintenance is required. Increasing the number of false alarms up to 20 times the detected failures did not have any other effect than increasing the system reliability and reducing the average age of the components. A test with a constant failure rate showed that the reliability was reduced if there were false alarms.

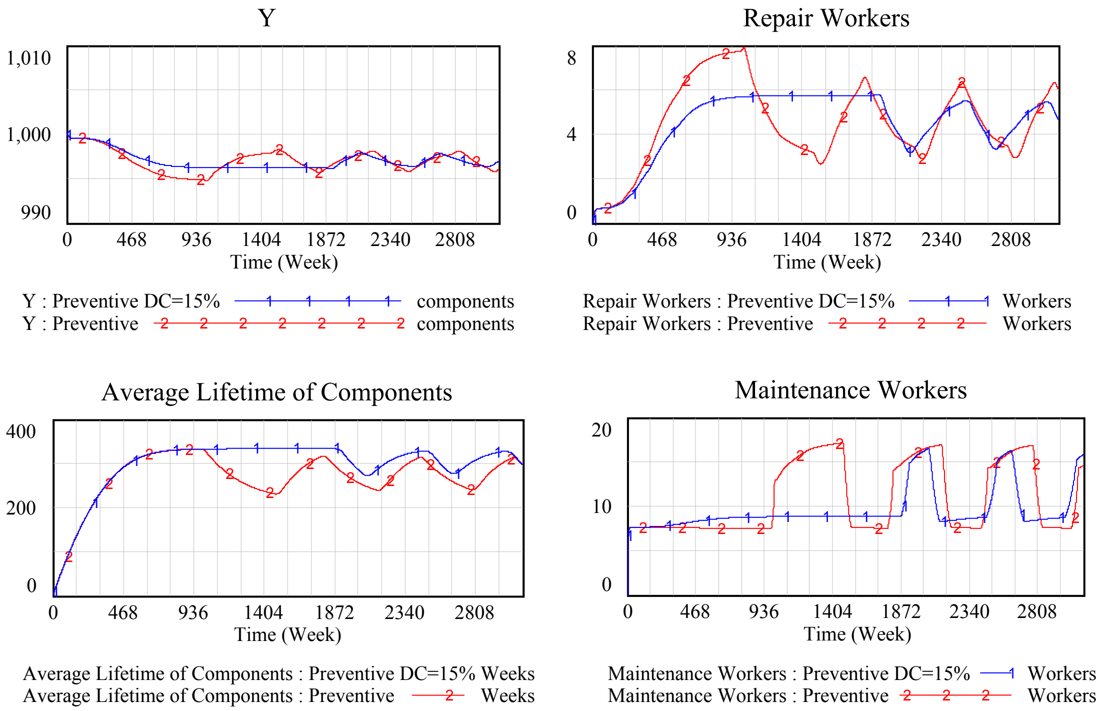


Figure 28 Controlled reliability variable Y, number of repair workers, average lifetime of components and number of maintenance workers when diagnostics coverage is 15 % (Line 1) compared to 0 % diagnostics coverage (Line 2), error equation (18), G_p = 50 and G_i = 5.

6.5.16 The effect of insufficient work resources on the system dynamics

Preventive maintenance controls the reliability. Because preventive maintenance has the lowest priority of the maintenance work, a sudden increase in deterioration or infant failures may lead to a shortage of resources in preventive maintenance. In this case, the system controllability is reduced until the failures have been repaired. Thinking in a systemic sense, this means that the coupling of preventive maintenance via the deterioration failure process to reactive maintenance is reversed so that reactive maintenance is coupled to preventive maintenance via a shortage of work resources.

In Figure 29 there are 35 maintenance workers instead of 30 maintenance workers. The target reliability is achieved sooner because there are enough maintenance workers, which makes it possible to do more preventive maintenance work. The reduction rate is the same because the deterioration failure process defines the dynamics of decreasing reliability.

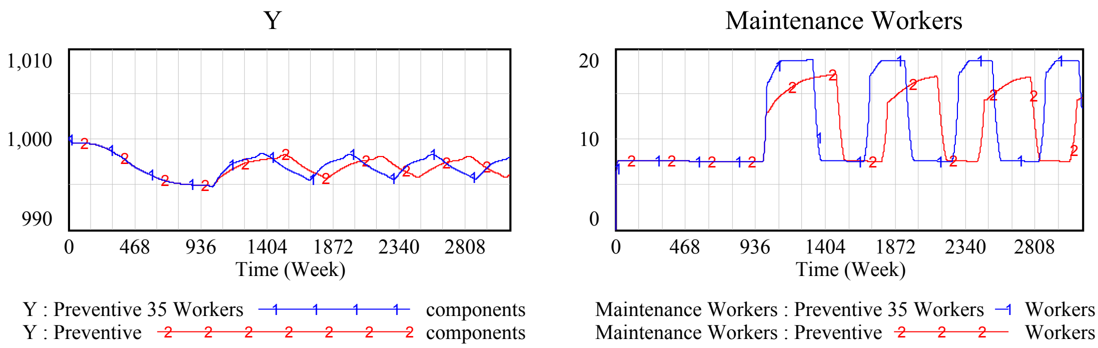


Figure 29 Controlled reliability variable Y and preventive maintenance workers when a total of 35 workers (Line 1) are available compared to 30 workers (Line 2), error equation (18), $G_p = 50$ and $G_i = 5$.

6.6 SYSTEM MODEL V: A DYNAMIC SPARE PARTS SUPPLY CHAIN SIMULATION MODEL

6.6.1 Purpose of the model

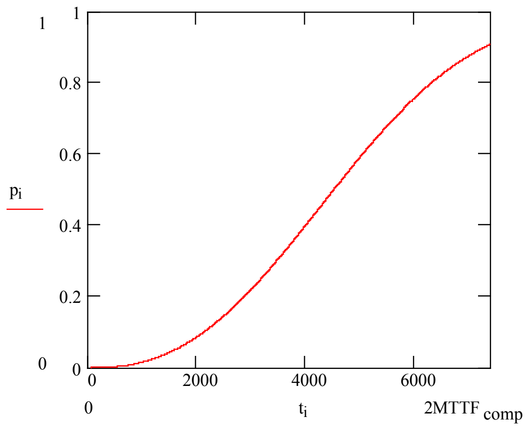
The model in this chapter was inspired by a rather heuristic methodology described by MacInnes and Pearce (2002). They propose that the spare parts supply chain should be designed according to the criticality of the parts as well as their reliability. Because the demand for the spare parts is initiated by the failures and proactive maintenance of the parts, the demand for these indirect materials is more difficult to estimate than the direct materials required in the production process. MacInnes and Pearce (2002) state that no more spare parts should be produced than what is consumed. Otherwise the materials in the supply chain are buffered, which causes fluctuations in the inventory levels.

With this model it is possible to study, but not necessarily to predict, what kind of effects remote condition monitoring could have to the supply chain dynamics. The model extends beyond the operative maintenance system described so far, and can be seen as a curiosity from the maintenance system point of view. However, to a machine manufacturer the model may give an idea of a new and concrete application of remote condition monitoring. The full model is presented in Appendix E: Model V in Vensim 5.0 text format.

6.6.2 Spare parts demand as a stochastic process

The example case in model III can be used to illustrate the spare parts demand that a single machine causes to the supply chain. The stochastic model is presented in Appendix D: Model V consumption analysis in Mathcad 2001i format.

As shown in Figure 30, the spare part demand is much easier to predict when the part is under preventive maintenance policy. Condition-based maintenance does not change the curve much from reactive maintenance, because it is the part reliability that defines the form of the curve. According to Figure 30, preventive maintenance makes the demand for spare parts and other resources more predictable when there is only one part.



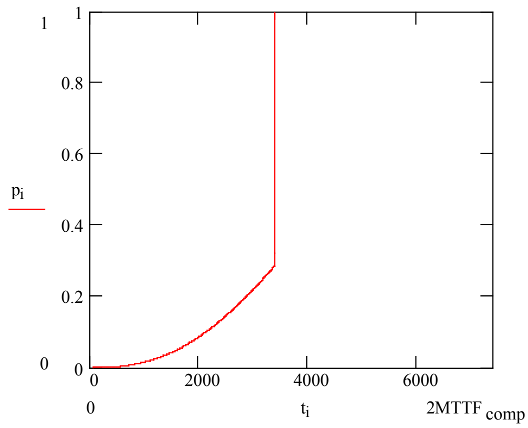


Figure 30 Probability of spare part demand of reactive (left) and preventive (right) maintenance policies.

The more there are part usage locations that the supply chain serves, the more evenly and randomly the failure and maintenance intervals will be distributed. Therefore, it can be assumed that when there are several part usage locations, the demand interarrival times for a spare part are exponentially distributed as presented in Figure 31. That is, with many parts operating, failing and being maintained independently the interarrival times converge to an exponential distribution with a mean value that equals the mean life time of the parts divided by the number of the parts — regardless of the applied maintenance policies.

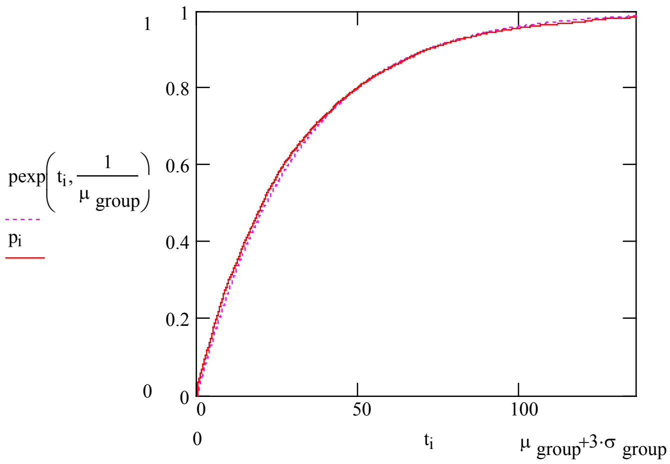


Figure 31 Analytically calculated exponential demand interval (dotted line) and simulated demand interval (solid line) in calendar days of 100 parts for 1000 years under condition monitoring and preventive maintenance. The average failure interval μ_{group}=30.853 is calculated from simulation. μ_{group} ≈ 1/100 · mean failure or maintenance interval 3070.991 for one part. The visible error comes from inaccuracy of the numerical simulation.

The inventories use buffering to match the uncertainty in the demand and supply. Therefore, the interarrival times between the orders that an upper stream inventory sees from each served downstream inventory can be modelled with a Gamma distribution. The distribution parameters are defined by the demand that the downstream inventory sees and the order quantity (OQ) that the downstream inventory uses. With OQ=1, the demand interval follows an exponential distribution, with OQ>=1 the demand interval follows a Gamma distribution. According to the central limit theorem with OQ >> 1, the demand interval can be approximated with a normal distribution, where mean = OQ · mean of the exponential distribution and standard deviation is sqrt(OQ) · mean of the exponential distribution. All these are special cases of a Gamma distribution.

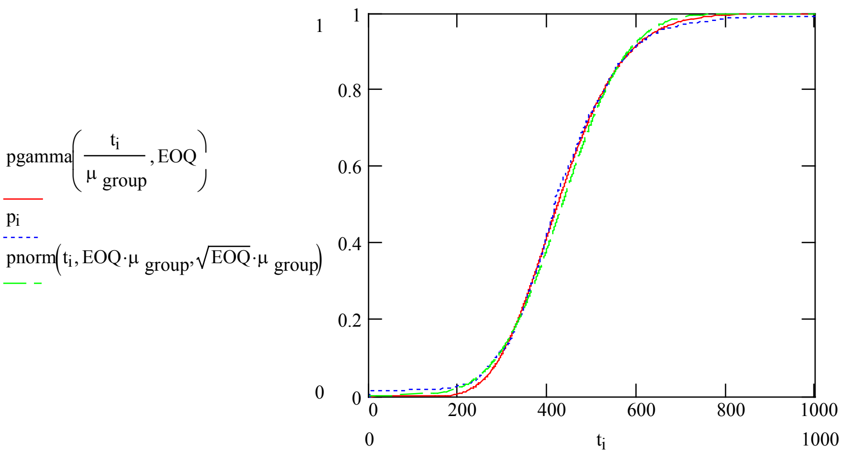


Figure 32 The Gamma distribution, simulated and normal distribution of the demand interval from a downstream inventory that an inventory sees when the downstream inventory buffers its demand with EOQ = 14 spare parts. μ_{group}=30.853.

The order quantity is defined by the inventory control strategy of each inventory as well as by the demand the inventory sees. Because any inventory probably serves several downstream inventory or part usage locations, it can be assumed that the order interarrival times for orders at any inventory are exponentially distributed. That is, the order interarrivals follow a Poisson process.

6.6.3 Modelling supply chains

The model presented in this chapter can be used to study the information sharing of consumption information to dynamic behaviour of the supply chain. The model is based on the classic Forrester (1961) industrial supply chain model. The various modelling methodologies and issues of supply chains have been studied quite extensively (i.e. Angerhofer and Angelides, 2000; Beamon, 1998). Similar dynamic supply chain models have been developed by Anderson et al. (2000) for the capital goods industry and by Anderson and Morrice (1999) for the service business and custom manufacturing. The effect of information sharing on demand variability in supply chains has been empirically studied by Lee et al. (1997) and quantified by Chen et al. (2000a, 2000b) with analytical calculations of stochastic behaviour.

Lee et al. (1997) define four reasons for demand variability: demand forecasting errors, order batching because of inventory optimisation, excess purchases because of quantity discounts, and preparation for supply shortages. In the models of Chen et. al (2000a, 2000b) the main variability-causing factors are the demand smoothing time window and the delivery lead time from order to arrival. Additionally, Chen et al. (2000a) show that demand information sharing will reduce supply chain variability. According to Forrester (1961), the variability stems from the system dynamics, which is caused by delays in the information and material flows, as well as from the management control decisions made according to the available information. Specifically, in the supply chains, the fluctuation is caused by lead times, safety stocks and the materials in transit.

The Forrester approach has not been applied in studying the effect of information sharing on supply chain behaviour prior to this dissertation. Similar simplification and approximation principles defined in chapter 6.5.3 apply to this model as well. The purpose is not to track the state of the individual parts but the amount and flows of the parts in the supply chain. It would have been possible to use some other modelling methodology such as queuing theory (e.g. Taha, 1992), but this would have missed the possibility to model the dynamic behaviour of the system.

6.6.4 Model overview

The presented model is a simplified version of the Forrester (1961) model. The simplifications mean that the orders from the downstream inventories to the upstream inventories are transferred and processed immediately. The delay times are also different from Forrester's model. There were two reasons for the simplification: firstly, electronic orders have been introduced and taken into use in industrial supply chains, and secondly, the problem is not to model the effect of the order processing but the effect of the information provided by remote condition monitoring for the system. The model parameters are fictive, but not unrealistic, serving the purpose of the model.

The model was developed and simulated with Vensim PLE v5.01 by Ventana Systems Inc. A simulator view of model is presented in Figure 33 and a simplified version of the system model is presented in Figure 34. The system models a supply chain consisting of three levels of inventories: manufacturer inventory (Level 1), regional distributor inventories (Level 2) and plant inventories (Level 3).

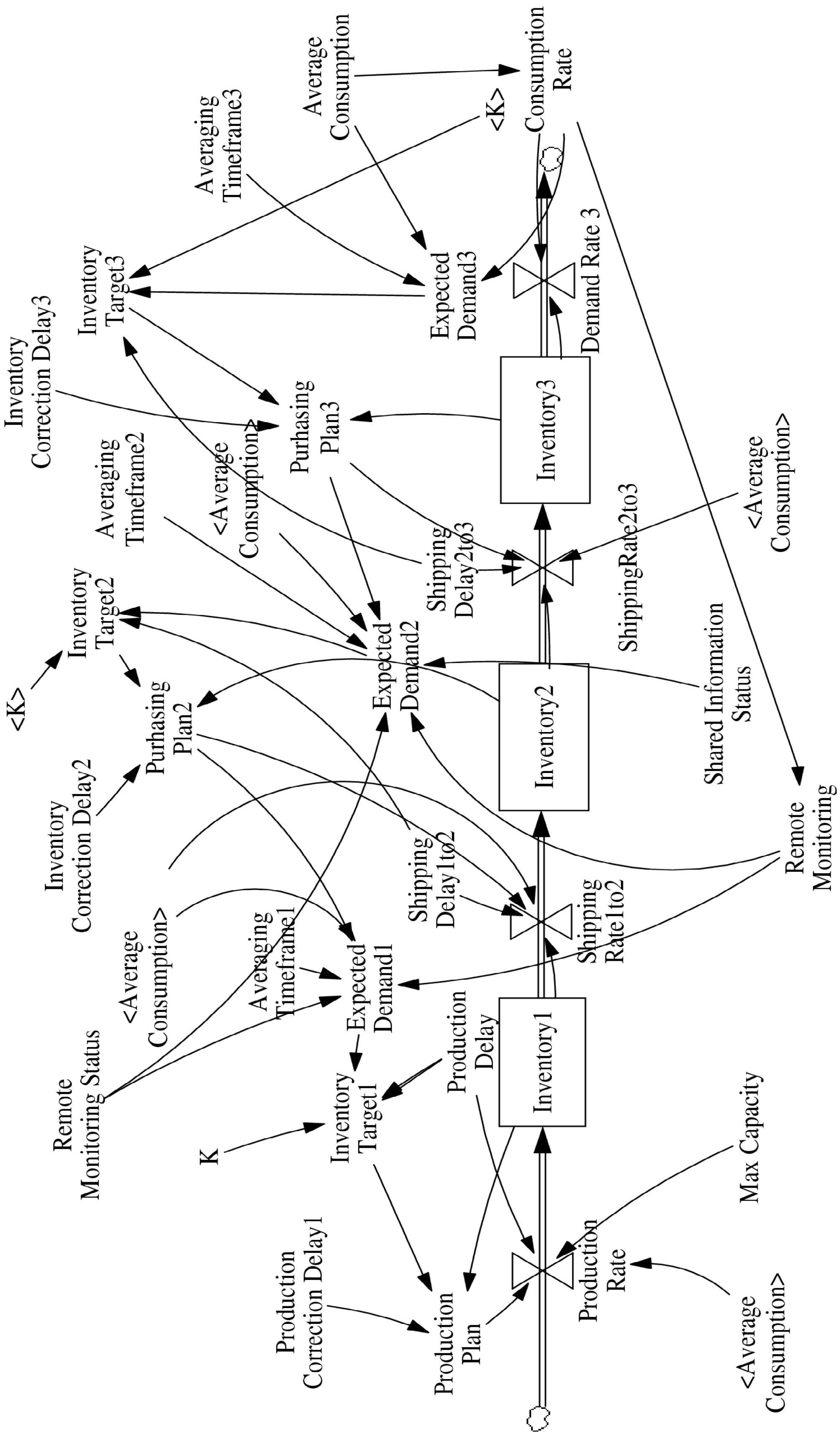


Figure 33 The supply chain model as seen in the simulator.

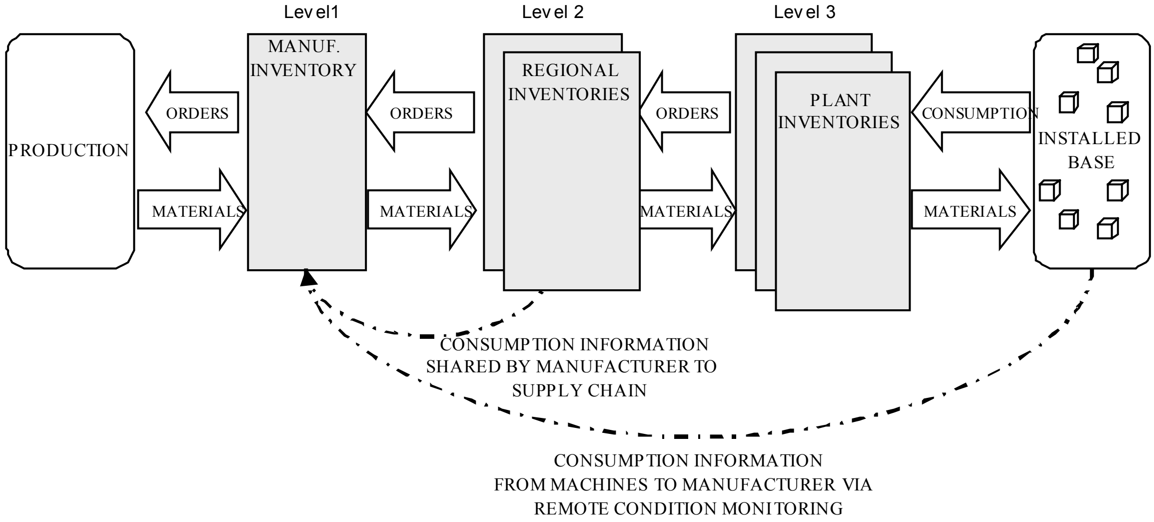


Figure 34 A simplified view of the supply chain model.

It is assumed in the model that there is an installed base of 90,000 parts. Each part has a failure type that is prevented or reacted to by replacing the part with a new one. The mean lifetime of the parts is 3,000 calendar days. Therefore, the parts are replaced at the average rate of 30 parts per day. The plant inventories store some parts as an insurance stock. The assumption is that the spare parts are not stocked by the maintenance on the factory floor after taken from the inventory. If the insurance stock falls below a predefined limit, an order is placed with a regional parts provider. If the stock of a regional inventory falls below a predefined limit, an order is placed with the manufacturer. An economic order quantity (EOQ) model (Beyer and Sethi, 1998) or similar is used to determine the inventory levels and order quantities. The manufacturer inventory uses a similar order quantity strategy to order parts from its production department that has a maximum production capacity of 37.5 parts / day, which is 25 % more than the average demand.

Because an inventory must serve very reliably the next level inventories, the inventory level must be kept high enough to compensate the randomness in supply and consumption to maintain the required service level. Therefore, there are always more parts in the supply chain than the average consumption would require. There are also some parts under transportation between the inventories, which can be seen as a supply pipeline that must be filled or emptied if the average consumption rate changes. Each inventory notes that there may be random fluctuation in the orders. Therefore they smooth the number of orders with 3rd order exponential smoothing, that weights more the recent consumption, to estimate the average demand. The difference between the desired inventory level and the actual inventory level is corrected after some time, defined by the average time to accumulate a demand that equals the order quantity (OQ) amount of parts. This correction time can also be seen as the delay that corrects the difference between the desired and actual inventory. E.g. a 10-day correction delay corrects the difference at the rate of 10 %/day. The orders are processed immediately and sent to the next level inventory. The transportation takes some time, which is modelled with 3rd order delay. The inventory target is modelled with

$$I_t = K \cdot D_e \cdot T_d \qquad (21)$$

where K is the safety factor for random fluctuation, D_e is the estimated demand / day, and T_d is the transportation delay from the upper stream inventory or the delay of the production process.

The dynamics of the system is defined by the safety factor K=2.5 and by the delays of the system presented in Table 8.

	Delay Length
Level 3 3rd order smoothing delay	21 days
Level 3 inventory correction delay	14 days
Level 2 3rd order smoothing delay	35 days
Level 2 inventory correction delay	28 days
Level 3 3rd order smoothing delay	56 days
Level 3 inventory correction delay	40 days
Production delay, 3rd order	21 days
Transportation delay from level 3 to 2	14 days
Transportation delay from level 2 to 1	7 days

Table 8 System delays.

6.6.5 A study of the system dynamics

The system starts from equilibrium and the dynamics is tested with two input data:

- 5 % (1.5 parts) sudden increase in consumption after 100 days of simulation
- a Poisson consumption process that is approximated according to the central limit theorem with a normally distributed random daily consumption with a mean of 30 and a variance of 30 parts/day

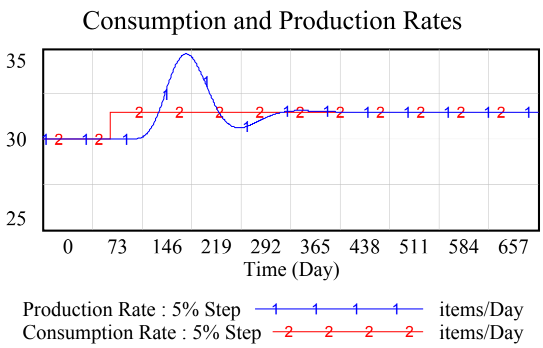
The system is studied in three modes (Figure 34):

1. in *a normal supply chain mode*, in which each inventory estimates the average consumption and operates independently of other inventories
2. in *an informed mode* in which the installed base of parts is connected via remote condition monitoring to the manufacturer inventory which uses the real-time consumption information as the consumption estimate
3. in *a fully informed mode* in which the installed base of parts is connected via remote condition monitoring to the manufacturer inventory and the manufacturer shares the consumption information with the downstream inventories. The plant inventories see the actual consumption anyway, so there is no need to connect the consumption information to them.

The input data is the same for all three system modes. The parts are named inventory items in the simulation.

6.6.6 Step response results in the normal supply chain mode

The consumption rate of the inventory items is 30 until day 100, after which the consumption increases suddenly to 31.5 items/day. The results are shown in Figure 35.



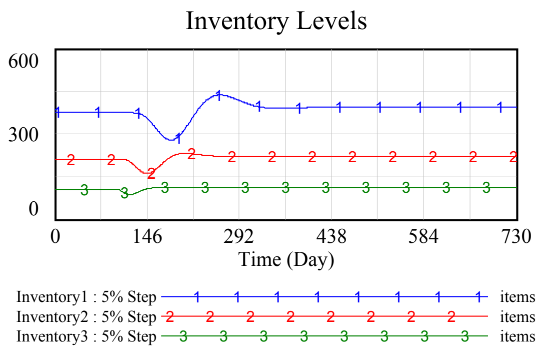


Figure 35 Step responses of the consumption and production rates (left) and the inventory levels (right).

Level 3 inventories go down until the correction of the inventory levels reaches the new target inventory levels. Level 2 inventories are reduced because Level 3 inventories order more items than before to match the increased demand, and also because the number of items in transportation is increased as well as the safety stocks of Level 3 inventories. The correction of Level 2 inventories causes too many stocked items at Level 2 because the need to increase the number of items being transported between Level 2 and Level 3 inventories and the increase of the safety stocks of Level 3 inventories are satisfied. The overshooting of Level 2 inventories is then corrected by Level 2 correction. Because of Level 2 safety stocks and the increased transportation pipeline content between Levels 1 and 2, the undershooting and overshooting of Level 1 manufacturer inventory is even greater than Level 2 inventories. The manufacturer production tries to satisfy the inventory levels and adjusts its production rates according to its inventory targets. In the example case, the 5 % step increase to 31.5 items in the demand rate on day 100 caused a maximum of 34.719 and a minimum of 30.609 parts to be produced per day as shown in Table 9.

Day	Demand	Production	Difference
0	30.0	30.000	0 %
100	31.5	30.000	0 %
211	31.5	34.719	10.22 %
290	31.5	30.609	-2.83 %

Table 9 Step response of the production rates in a normal supply chain mode.

The production rate reaches its peak value on day 211, which is 10.22 % higher than the actual demand. The undershooting happens more than half a year later on day 290 and is 2.83 % less than the actual demand.

6.6.7 Step response results in the informed and fully informed mode

In an informed mode some, but not necessary the whole population is installed with remote condition monitoring technology, that detects when a new part is taken into use. The machine manufacturer estimates the real demand from the consumption information to set the target inventory level.

The use of consumption information directly in the production planning was tried, but two problems emerged: Firstly, if the consumption estimate has a systematic error, the production will always be too high or too low compared to the real consumption. Consequently, this leads to infinite or zero inventory level at the manufacturer inventory. Secondly, Level 2 and Level 3 inventories order items according to their own policies causing oscillation in the demand even though the manufacturer knows that the real consumption is not oscillating. Therefore, the manufacturer must supply the ordered items and produce a different number of items than the actual consumption would require.

In an informed mode the demand from Level 2 inventories to Level 1 manufacturer inventory remains the same, but the manufacturer production is controlled through the inventory target equation

$$I_t = K \cdot C_a \cdot T_d \qquad (22)$$

where C_a is the actual daily consumption received via remote condition monitoring, and T_d is the delay of the production process for the manufacturer inventory. Safety factor K compensates the random fluctuation and systematic errors in the actual consumption measurement.

Table 10 summarises the effect of connecting the consumption information to Level 3 inventory target calculation. The peak production rate of 33.594 items /day on day 210 is 6.65 % higher than the actual consumption. The undershooting is only -0.67 %.

Day	Demand	Production	Difference
0	30.0	30.000	0 %
100	31.5	30.000	0 %
210	31.5	33.594	6.65 %
298	31.5	31.290	-0.67 %

Table 10 Step response of the production rates in an informed mode.

In Table 11, the manufacturer shares the consumption information with Level 2 inventories in order to reduce the oscillation in the demand from Level 2. Level 2 inventories use the available consumption information in their inventory target calculations similarly to the manufacturer inventory. Because Level 3 inventories see the consumption directly, the whole supply chain is fully informed about the real consumption. The overshooting of the production is further reduced from 6.65 % to 5.82 % on day 210 and the undershooting reduces to -0.33 %.

Day	Demand	Production	Difference
0	30.0	30.000	0 %
100	31.5	30.000	0 %
210	31.5	33.332	5.82 %
310	31.5	31.395	-0.33 %

Table 11 Step response of the production rates in a fully informed mode.

As Figure 36 shows, the main reduction in the oscillation is achieved by connecting the consumption to the manufacturer inventory. Information sharing with Level 2 inventories reduces the oscillation slightly further.

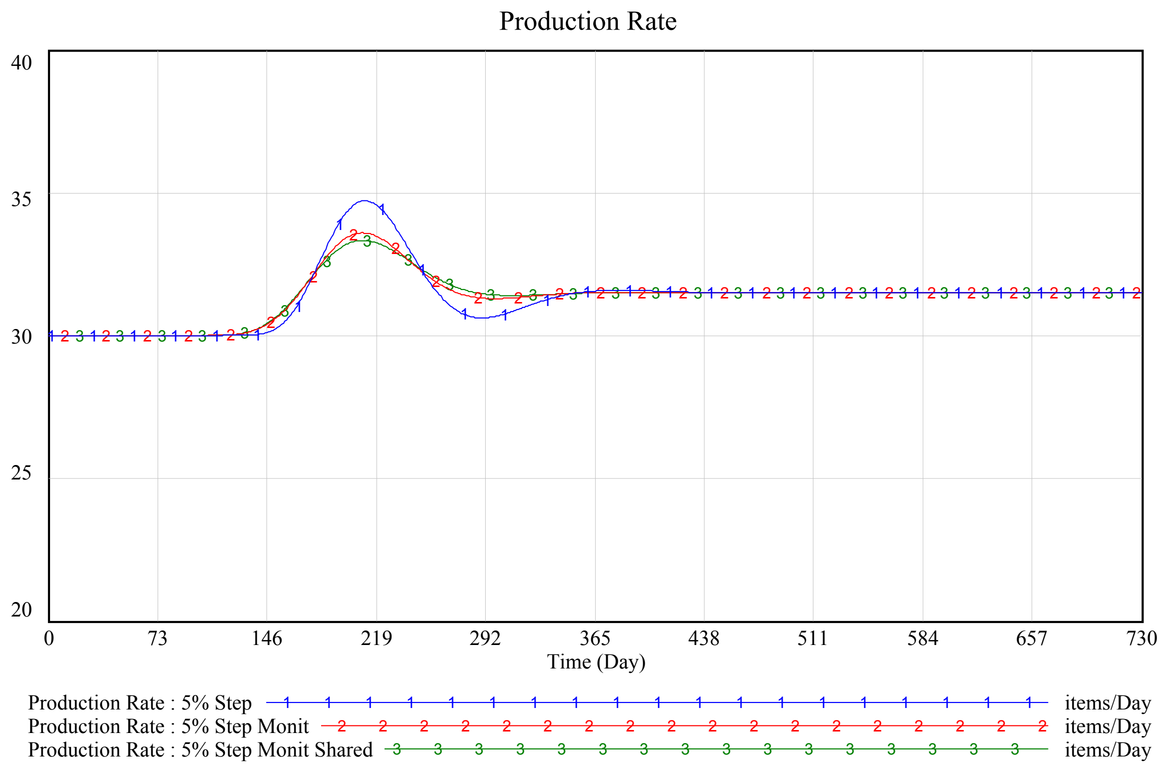


Figure 36 Step response of the production rate in the normal (Line 1), informed (Line 2) and fully informed (Line 3) modes.

6.6.8 Random data responses in the informed and fully informed modes

A step test does not reveal all the system dynamics, however. To study the real effect of condition monitoring and information sharing a random consumption with a mean value and variance of 30 items/day is applied to the three system modes. The consumption data is white noise as shown in Figure 37.

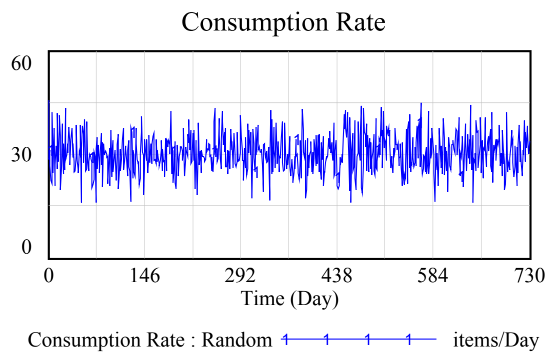


Figure 37 Random consumption with 30 items / day as the mean value and variance.

The production rates and inventory levels of each system mode are shown in
Figure 38 and Figure 39. As indicated by the step tests, the fully informed mode is the most stable in respect to the production rates and the manufacturer inventory levels.

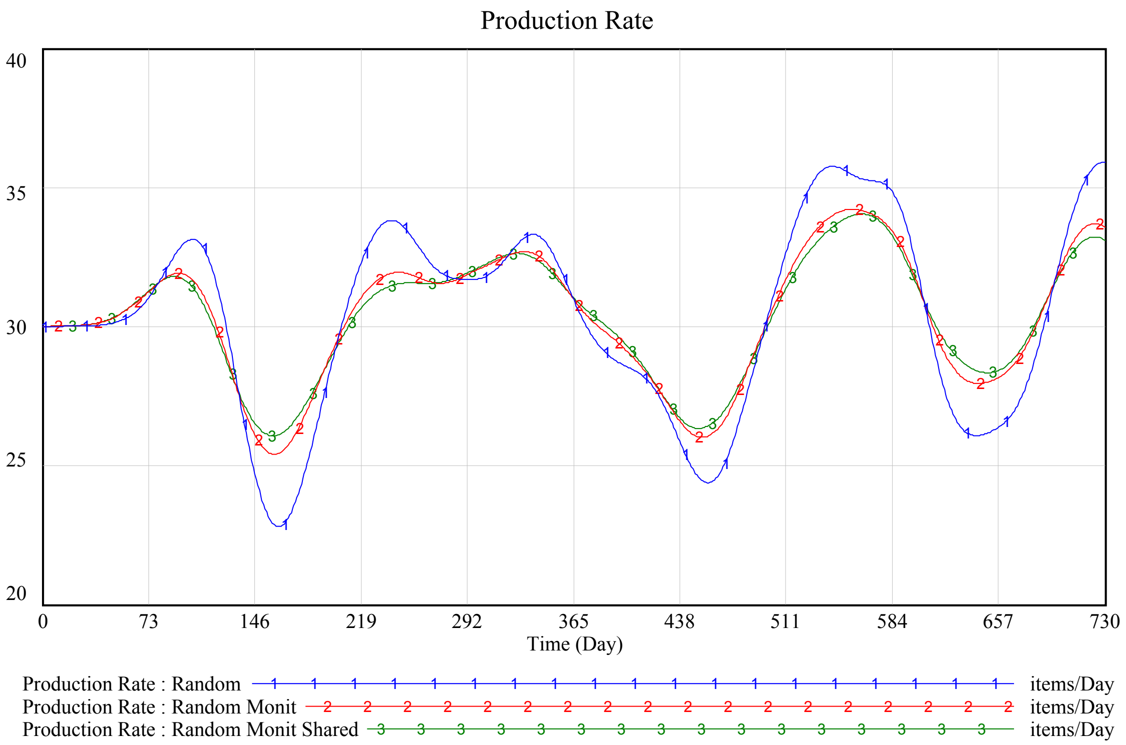


Figure 38 Production rates in the normal (Line 1), informed (Line 2) and fully informed (Line 3) mode with the random consumption data.

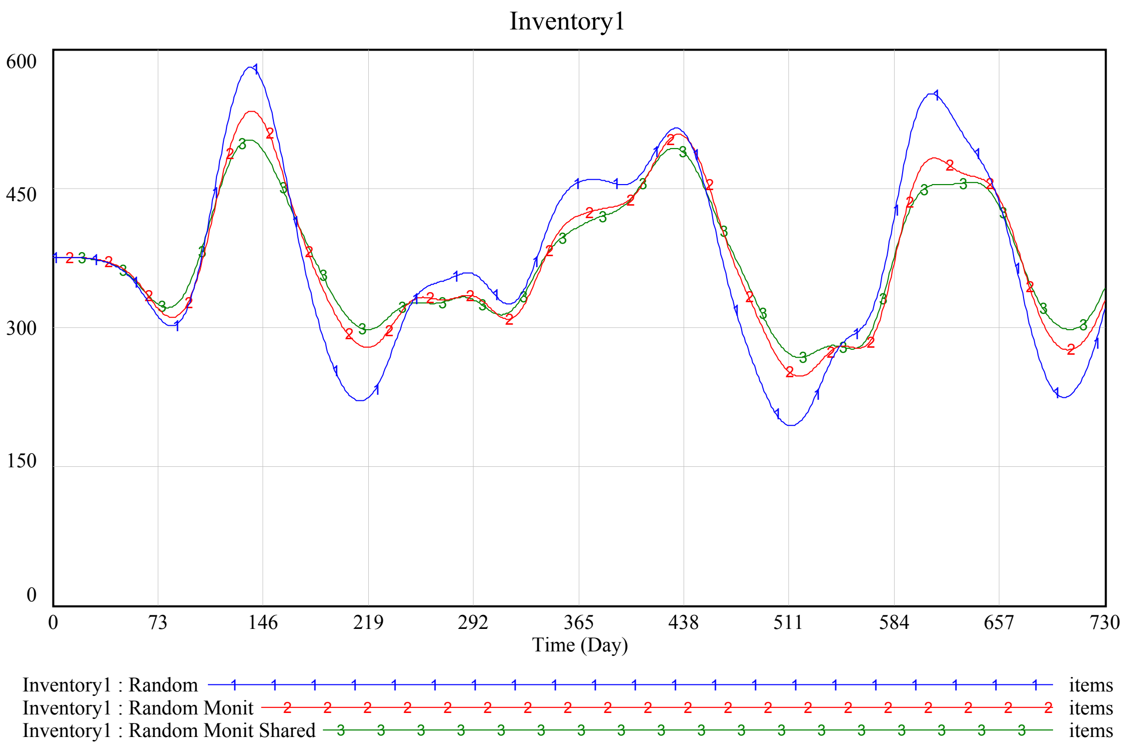


Figure 39 Manufacturer inventory levels in the normal (Line 1), informed (Line 2) and fully informed (Line 3) modes with the random consumption data.

The numerical comparisons are presented in Table 12 and Table 13. Because the sample size is limited, the average production rates and inventory levels differ from the long-time average values 30.0 and 375.0.

	Average production rate (items/day)	Standard deviation
Normal mode	30.328	3.402
Informed mode	30.332	2.316
Fully informed mode	30.329	2.113

Table 12 Average production rates and standard deviations in the normal, informed and fully informed modes with the random consumption data for 730 days.

	Average inventory level (items)	Standard Deviation
Normal mode	370.490	101.130
Informed mode	370.940	75.989
Fully informed mode	371.557	65.182

Table 13 Average manufacturer inventory levels and standard deviations in the normal, informed and fully informed modes with the random consumption data for 730 days.

The average level of manufacturer inventory in all three modes seems to be too high. The optimal average inventory level calculated with 99.5 % availability (stdev·2.58), and average capital value calculated with a fictive item value of Eur 25,000 are presented in Table 14. The results that cannot be seen from the step test are very interesting: the optimal average inventory level drops to 75.1 % and further to 64.5 % of the optimal values of the normal mode releasing a maximum capital of Eur 2,318,639 from the inventory. With 15 % own capital cost this would yield yearly additional savings of Eur 347,795.

	Optimal average inventory level (items)	Average capital value (Eur)	Proportion of normal mode
Normal mode	260.916	6,522,909	0 %
Informed mode	196.051	4,901,267	75.1 %
Fully informed mode	168.171	4,204,269	64.5 %

Table 14 Optimal manufacturer inventory levels and capital value in the normal, informed and fully informed modes

In practice, the reduction of the inventory levels takes place through the reduction of safety factors K (21) (22) that partly define the variability of the system. Therefore, the reduction of K reduces the deviations even more than in the presented Table 12 and Table 13. However, Table 14 can be considered as a good approximation of a minimum inventory level reduction.

In summary, the simulation results allow to state that using the real-time material consumption information received via remote condition monitoring as a demand estimate reduces the upstream supply chain variability of the maintenance materials.

6.6.9 Further considerations

In the normal mode, reduction of smoothing delays of all the inventories to 21 days from the original 56, 35 and 21 days reduces the manufacturer inventory standard deviation to 75.090. If comparing this value to Table 14, it can be seen that the value is less than in the normal and informed mode with the original smoothing delays. This indicates that too long a delay in demand averaging may increase the supply chain variability, which is an observation made by Chen et. al (2000b). In the fully informed mode, the 21 days data smoothing results in a standard deviation of 40.507 which represents a 53.9 % proportion of the normal mode. The proportional reduction is higher than in Table 14 with the original smoothing delays. The reason for this is that the use of real-time consumption information at 1st (manufacturer) and 2nd level inventories makes it feasible to use shorter smoothing delays, which decreases the supply chain variability.

In other words, the use of real-time consumption also enables the reduction of the demand averaging delays, which in turn reduces the variability even more.

If the inventory correction delays are halved, the respective standard deviations for the manufacturer inventory in the normal mode and the fully informed mode are increased to 206.450 and 104.902. That is, if controlling a slow system too quickly, the system disturbances will be amplified, which supports the observations of Forrester (1961).

6.6.10 Summary and comparison to the results of other similar studies

Remote condition monitoring can be used for reducing the variability of the spare parts supply chain. The possible reduction in the inventory levels can be significant, especially if the actual consumption information is shared with all the inventory levels. Furthermore, the use of real-time consumption enables the reduction of the demand averaging delays, which also reduces the supply chain variability. The model results support the findings of Lee et al. (1997), Chen et al. (2000a, 2000b) and Forrester (1961) specified in chapters 6.6.3 and 6.6.9. The main contribution of the model is to study the practical idea that remote information acquisition of the spare parts can be used also for a direct benefit to the machine manufacturer without any maintenance-related service business between the manufacturer and the machine user. Furthermore, supply chain optimisation does not require changes in the business strategy of the machine manufacturer.

7 DISCUSSION AND CONCLUSIONS

The viewpoint of this research was that of maintenance systems and system control. The effect of condition monitoring on the maintenance systems was studied by reviewing maintenance and systems literature, as well as by using conceptual and mathematical models.

Most of the research papers and literature related to this research have been written from the reliability point of view. That is, the objective has been in modelling and improvement of machine or production line reliability. Although it is necessary to understand the use of reliability engineering techniques in order to control the reliability of machines, it is at least equally important to understand the maintenance systems and their control to efficiently reach and maintain the required reliability.

Preventive maintenance is feed-forward control and reactive maintenance is feed-back control. Condition-based maintenance represents neither pure feed-forward nor pure feed-back control. If the preventive maintenance schedule is changed according to the occurred failures as in model IV, the maintenance system can be considered an adaptive system with a high-level feed-back control. Information systems and automatic condition monitoring cannot be applied efficiently if these fundamental control activities and the information flows of the maintenance systems are not understood.

The resulting models (I-V) help in understanding what is the effect of information to the maintenance systems i) by identifying and defining the logical and ordinal relations between maintenance system objects, ii) by identifying the applicable control methods, iii) by simulating the detection of failure events of single components and i-iv) by simulating flows of information and materials in systems consisting of large populations of components.

7.1 SUMMARY OF MAINTENANCE SYSTEMS CONTROL

Feed-forward control with preventive maintenance assumes that after some usage the risk for machine failures is high and the machine should be therefore maintained. However, the actual effectiveness of the maintenance systems can be measured only with the help of the occurred failures. Paradoxically, not many failures can be observed in an effective maintenance system. Consequently, the maintenance system efficiency becomes known only in the long run, making quick control difficult and slow control too slow. Additionally, the uncertainty in the failure and maintenance system dynamics, and the possible variances in repeatability of the maintenance actions make the effect of control actions vary and thus reduces reliability. Often, the effects of preventive maintenance can be seen several years after that maintenance action. Long delays of failure processes make failure feedback-based adjustments to the preventive maintenance program uncertain.

Unexpected number of failures causes challenges to maintain the proactive maintenance program. Fire-fighting breakdowns reduce the possibility to do condition-based and preventive maintenance. This may cause more failures later. Insufficient worker resources make the maintenance systems respond more slowly to the needs to increase the proportion of proactive maintenance.

Also, correct selection of maintenance system efficiency measurement metrics is critical. If not using total cost of maintenance and failures as the controlled variable the control may become irrational and favours some maintenance policies more than others.

In summary, slow system dynamics make optimal maintenance system control very difficult.

7.2 THE EFFECT OF CONDITION MONITORING ON MAINTENANCE SYSTEMS

Observability defines the key relationship between a machine and a maintenance system. Without observations it is impossible to say anything about reliability, repeatability, efficiency or controllability. Therefore, in addition to human perceptions, condition monitoring is the only way to measure how a maintenance system performs.

Condition-based and preventive maintenance are not mutually exclusive maintenance policies. Compared to preventive maintenance only, condition-based maintenance may yield much more efficient maintenance systems. However, condition monitoring is not likely to be fully accurate or it is too slow compared to all the failure types. Thus, condition-based maintenance should not always be considered as a replacing, but a complementing policy to preventive maintenance. Mixing preventive maintenance and condition-based maintenance may yield the most optimal results.

More speedy reaction to a possible failure increases the proportion of the failures that a maintenance system can prevent. Therefore, a CMMS and a condition monitoring system may support each other. However, in reality, a formal maintenance process workflow may be bypassed in order to execute the condition-based maintenance action in time.

Repairing in a hurry is quite likely more error-prone than well-planned proactive maintenance. Condition-based maintenance reduces failures and increases the proportion of proactive maintenance. In theory, this would lead consequently to more sufficient worker resources and therefore would also increase the controllability of the maintenance system.

The research supported the other studies about the reduction of supply chain variability if sharing consumption information by using condition monitoring. This represents a novel and practical idea of linking the component replacement information directly from the machines to the manufacturer-end of the supply chain. Compared to the other results of the research, this may turn out as the most valuable short-term application area of the research.

In summary, condition monitoring can be seen as a method for increasing system observability and therefore an enabler for more effective maintenance systems. However, the effect of condition monitoring depends on the accuracy of the monitoring and the failure diagnosis, and is also affected by the failure patterns, the repeatability of maintenance actions and the delay to arrange the maintenance actions. In spare parts supply chains, remote condition monitoring can be used to stabilise the supply chain variability and to reduce the supply chain sensitivity to random noise and sudden changes in the consumption.

7.3 THE ABILITY OF THE SIMULATION MODELS TO PREDICT MAINTENANCE SYSTEMS BEHAVIOUR

The presented models are based on rough assumptions of the maintenance and failure processes. Parameterisation of the models with actual data should be done cautiously because the purpose of the models is not to predict future states of real systems but to describe the behaviour of such systems. Also, the observability of delays, failure types and frequencies, and the cost data for the models is in general terms weak.

However, the models should be accurate enough to predict the relative magnitudes and directions of the maintenance system outputs in regard to the inputs.

7.4 FUTURE DIRECTIONS AND ISSUES

The developed models form together a foundation for future maintenance information system development projects. The maintenance system model developed with the knowledge modelling tool indicate that the logical and ordinal structures of maintenance systems can be captured in the real life. The quantitative simulation models should be developed further to take into account the incompleteness of the source data and verified against real observations before applying them in practice. The quantitative models could be implemented in the knowledge modelling tool to be used in analysing existing systems or in considering modifications for them. Combination of real-time condition monitoring and computerised maintenance management system to the tool would enable model-based real-time control of maintenance systems.

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APPENDIX A: INTERVIEWS

INT VW	ORGANISATION	TITLE	DATE	SUBJECT
1.1	Metso Paper	VP, Research and Technology Development	12.3.2002	Maintenance and reliability of paper machines
1.2	Metso Paper	Development Manager	12.3.2002	Maintenance of paper machines
2	Metso Automation	Senior VP, Strategy and Marketing	13.3.2002	Service technologies of an automation company
3	Metso Minerals	VP, Business Development	18.3.2002	Maintenance and reliability in mineral processing machines
4	Metso Field Systems	Product Manager, Loop Performance Solutions	3.4. 2002	Performance tuning services
5.1	Metso Automation	Director, Asset Management Solutions	11.4.2002	Service and automation technologies in paper machines
5.2	Metso Automation	Product Manager, R&D	11.4.2002	Service and automation technologies in paper machines, RCM
6	Metso Paper	VP, Partner Services	10.5.2002	Computerised maintenance management and paper machine maintenance
7	Metso Field Systems	Product Manager, Maintenance Logistics Solutions	3.6.2002	Spare parts services of industrial valves
8	TietoEnator	Product Manager, PowerMaint	5.6.2002	PowerMaint CMMS functionality
9	Maxiflex Oy	Managing Director, MRO Software	5.6.2002	Maximo CMMS functionality
10	Cap Gemini Ernst & Young	Key Account Manager, Manufacturing & Energy	10.6.2002	Service technologies and business processes
11	Metso Field Systems	Director, Field System Solutions	6.8.2002	Computerized maintenance systems and failure requirements management
12	Artekus Oy	Marketing Director	7.8.2002	Arttu CMMS functionality
13	Metso Field Systems	Product Specialist	16.8.2002	Valve factory and site service
14	Metso Field Systems	Manager, Maintenance	16.8.2002	Valve factory service computerised maintenance management system
15.1	Metso Field Systems	Senior Research Engineer	22.8.2002	Automatic diagnostics and operating state identification

INT VW	ORGANISATION	TITLE	DATE	SUBJECT
15.2	Metso Field Systems	Project Engineer	22.8.2002	Automatic diagnostics and operating state identification
16	Rissa Consulting Oy	Principal Consultant	4.10.2002	Remote monitoring and service platforms
17	StoraEnso Oyj	Mill Maintenance Manager	30.10.2002	Bearing failure modelling
18.1	Jaakko Pöyry Oy	Product Manager, Automation and Information technology	22.11.2002	Plant design model and structured design information in diagnostics
18.2	Jaakko Pöyry Oy	Design Manager, Information technology	22.11.2002	Plant design model and structured design information in diagnostics
19	MRO Software	Sales Operations Manager	27.11.2002	CMMS & PDA productivity improvements
20	Nero Research Oy	Managing Director	13.12.2002	Automatic failure identification and diagnostics with neural networks
21.1	Safematic Oy	Control and Monitoring Systems, Bearing Lubrication Systems	7.1.2003	Reasons to implement remote diagnostics and monitoring in industrial lubrication systems
21.2	Safematic Oy	Technical Director, Lubrication And Sealing Systems	7.1.2003	Reasons to implement remote diagnostics and monitoring in industrial lubrication systems
21.3	Safematic Oy	R & D Co-ordinator, Bearing Lubrication Systems	7.1.2003	Reasons to implement remote diagnostics and monitoring in industrial lubrication systems
21.4	Safematic Oy	Product Manager, Bearing Lubrication Systems	7.1.2003	Reasons to implement remote diagnostics and monitoring in industrial lubrication systems

APPENDIX B: MODEL III IN MATHCAD 2001I FORMAT

The effect of diagnostics and maintenance on reliability - one failure event type of a replaceable component (or 100% restoration)

$$f\_weibull_{rate}(x,\beta,\eta) := \frac{\beta}{\eta}\cdot\left(\frac{x}{\eta}\right)^{\beta-1}$$

$$f\_weibull_{cumrate}(x,\beta,\eta) := \left(\frac{x}{\eta}\right)^{\beta}$$

$$f\_weibull_{pdf}(x,\beta,\eta) := \frac{\beta}{\eta}\cdot\left(\frac{x}{\eta}\right)^{\beta-1}\cdot e^{-\left(\frac{x}{\eta}\right)^{\beta}}$$

$$f\_weibull_{cdf}(x,\beta,\eta) := 1 - e^{-\left(\frac{x}{\eta}\right)^{\beta}}$$

$$CDF(x,\beta,\eta) := f\_weibull_{cdf}(x,\beta,\eta)$$

$$f\_weibull_{icdf}(pr,\beta,\eta) := qweibull(pr,\beta)\cdot\eta$$

$$f\_weibull_{\mu}(\beta,\eta) := \eta\cdot\Gamma\left(1+\frac{1}{\beta}\right)$$

$$f\_\eta(\mu,\beta) := \frac{\mu}{\Gamma\left(1+\frac{1}{\beta}\right)}$$

$$f\_weibull_{\sigma}(\beta,\eta) := \sqrt{\eta^{2}\cdot\Gamma\left(1+\frac{2}{\beta}\right)-\left(\eta\cdot\Gamma\left(1+\frac{1}{\beta}\right)\right)^{2}}$$

$$f\_weibull_{median}(\beta,\eta) := \eta\cdot\ln(2)^{\frac{1}{\beta}}$$

*Start with some component (*http://www.barringer1.com/wdbase.htm)

$\beta := 2.5$

$\eta := 100000$

$$MTTF_{comp} := \frac{f\_weibull_{\mu}(\beta,\eta)}{24}$$

$\eta := f\_\eta\left(MTTF_{comp},\beta\right)$

$\eta = 4166.667$

$f\_weibull_{\sigma}(\beta,\eta) = 1581.944$

Machine utilization (operating time / calendar time)

$Ut := 0.8$

Mean calendar times to repair and maintain, and obtain a machine

$MTTR := 5$

$MTTM := 5$

$MDT := 15$ Mean delivery time

Maintenance and repair costs

$CCOMPONENTPRICE := 10000$

$CREPAIRWORK := 2000$

$CMAINTWORK := 1000$

$CMDAILYLOSTCAPACITY := 0$

$CDAILYINCOP := 0$

$CDAILYINCQUALITY := 0$

$CDAILYLOSTCAPACITY := 10000$

$CMAINT := CCOMPONENTPRICE + CMAINTWORK + CMDAILYLOSTCAPACITY \cdot MTTM$

$CDDAILYINC := CDAILYINCOP + CDAILYINCQUALITY + CDAILYLOSTCAPACIT\text{Y}$

$CREPAIR := CCOMPONENTPRICE + CREPAIRWORK + MTTR \cdot CDDAILYIN\text{C}$

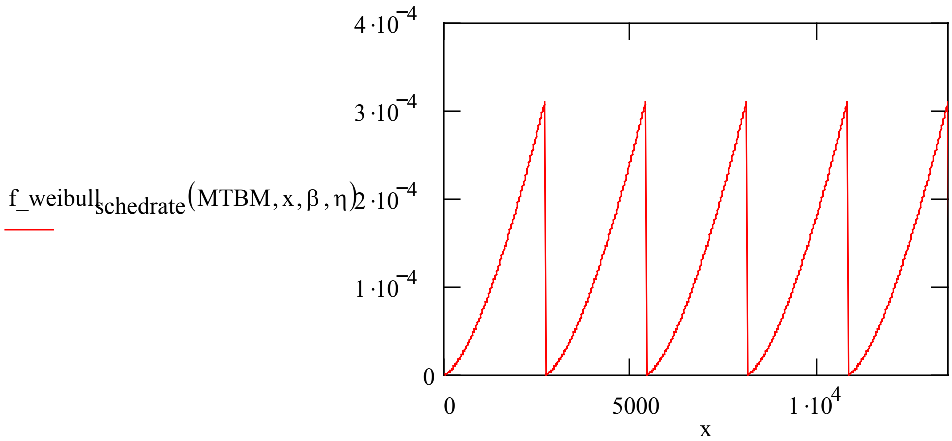
The cost function of maintenance and repair is

$f\_cost(nmaint, nrep) := CMAINT \cdot nmaint + CREPAIR \cdot nrep$

The effect of scheduled maintenance on failures

$MTBM := 2700$ Current maintenance interval (operating time) - Does not include the repairs of failures!

$$f\_weibull_{schedrate}(MTBM, x, \beta, \eta) := \frac{\beta}{\eta} \cdot \left(\frac{mod(x, MTBM)}{\eta}\right)^{\beta-1}$$



$$f\_weibull_{schedcumrate}(MTBM, x, \beta, \eta) := \int_0^x f\_weibull_{schedrate}(MTBM, x, \beta, \eta)\, dx$$

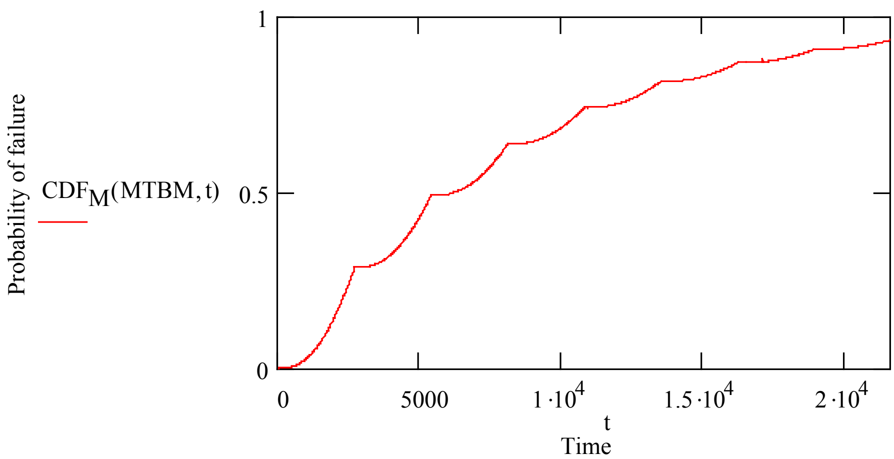
$$f\_weibull_{schedcdf}(MTBM, x, \beta, \eta) := 1 - e^{-f\_weibull_{schedcumrate}(MTBM, x, \beta, \eta)}$$

$$f\_weibull_{schedpdf}(MTBM, x, \beta, \eta) := \frac{d}{dx} f\_weibull_{schedcdf}(MTBM, x, \beta, \eta)$$

$$CDF_M(MTBM, x) := f\_weibull_{schedcdf}(MTBM, x, \beta, \eta)$$

$\beta = 2.5$

$\eta = 4166.667$



The mean operating time to failure (MTTF) of the function from last failure

$$\text{MTTF} := \int_0^{15\text{MTTF}_{comp}} \left(1 - \text{CDF}_M(\text{MTBM}, x)\right) dx$$ Set the upper limit to "infinity"

$\text{MTTF} = 8579.109$

$\text{MTBM} = 2700$

$\frac{\text{MTTF}}{\text{MTBM}} = 3.177$

The number of maintenances for each failure is given by adding the probabilities that there is 0 maintenances, 1 maintenance 2, maintenances, etc...

$$\text{NMAINTPERF} := \sum_{i=0}^{99} \left[\text{CDF}_M[\text{MTBM}, \text{MTBM}\cdot(i+1)] - \text{CDF}_M(\text{MTBM}, \text{MTBM}\cdot i)\right]\cdot i$$

$\text{NMAINTPERF} = 2.487$

The total calendar time to reach the first repaired failure is given by the number of maintenances *MTTM+MTTF/Ut+MTTR

1 $\text{MTTFR} = \text{NMAINTMTTM} + \frac{\text{MTTF}}{\text{Ut}} + \text{MTTR}$

2 $\text{NMAINT} = \text{NREP}\cdot\text{NMAINTPERF}$

These intervals, meaning failures, are 365/MTTFR in a year

3 $\text{NREP} = \frac{365}{\text{MTTFR}}$

Solving the system 1,2,3 gives

$$\text{NMAINTPERF}\cdot\text{MTTM}\cdot\text{NREP}^2 + \left(\frac{\text{MTTF}}{\text{Ut}} + \text{MTTR}\right)\cdot\text{NREP} - 365 = 0$$

$$\text{NREP} := \frac{-\left(\frac{\text{MTTF}}{\text{Ut}} + \text{MTTR}\right) + \sqrt{\left(\frac{\text{MTTF}}{\text{Ut}} + \text{MTTR}\right)^2 + 4\cdot\text{NMAINTPERF}\cdot\text{MTTM}\cdot 365}}{2\cdot\text{NMAINTPERF}\cdot\text{MTTM}}$$

$\text{NMAINT} := \text{NMAINTPERF}\cdot\text{NREP}$

$\text{NREP} = 0.034$

$\text{NMAINT} = 0.085$

So the operational availability is

$$A_o := \frac{365 - (\text{NREP}\cdot\text{MTTR} + \text{NMAINT}\cdot\text{MTTM})}{365}$$

$A_o = 0.998$

The total costs of maintenance and downtime in a year is therefore:

$\text{f\_cost}(\text{NMAINT}, \text{NREP}) = 3039.845$

Note that this system is such that the maintenance is executed in intervals MTBM after each failure or maintenance. That is, the maintenance schedule is not fixed to certain days but to the MTBM interval.

Simulation

$\text{MTBM} := 2700$

$\text{MTBI} := 0.1$ Mean operating time between condition monitoring inspections in days

$DT_{median} := 40$ Median detection time in operation days before failure if the condition monitoring is continuous. This is defined by the failure type and CM method.

$DT_{mode} := 20$ Most often encountered detection time

$DT_{min} := 1$ The 10% fractile of all detection times (counting from infinity to zero!)

$DT_{max} := 50$ — The 90% fractile of all detection times (counting from infinity to zero!)

$CINSP := 0$ — Cost of one inspection

$DC := 0.75$ — Diagnostics coverage % of failures detected

$MTTAM := 15$ — Mean operating time to arrange a maintenance break when a failure has been diagnosed. This is in fact function of current machine reliability, the scheduled opportunity as well as availability of resources.

$$t := \begin{pmatrix} DT_{min} \\ DT_{median} \\ DT_{max} \end{pmatrix} \qquad F := \begin{pmatrix} 0.10 \\ 0.50 \\ 0.90 \end{pmatrix}$$

$$f\_detection_{pdf}(x,\alpha,\lambda) := dgamma(x\cdot\lambda,\alpha)$$

$$f\_detection_{cdf}(x,\alpha,\lambda) := pgamma(x\cdot\lambda,\alpha)$$

$$f\_detection_{icdf}(p,\alpha,\lambda) := \frac{qgamma(p,\alpha)}{\lambda}$$

$$LSQ(\alpha,\lambda) := \sum_{i=0}^{rows(t)-1} \left(f\_detection_{cdf}(t_i,\alpha,\lambda) - F_i\right)^2$$

Least Square Method for Curve Fitting

$\alpha := 1.1$

$$\lambda := \frac{\alpha - 1}{DT_{mode}}$$

Given

$\alpha > 0$

$\lambda > 0$

$DT_{mode}\cdot\lambda > 1$

$\alpha - 1 = DT_{mode}\cdot\lambda$

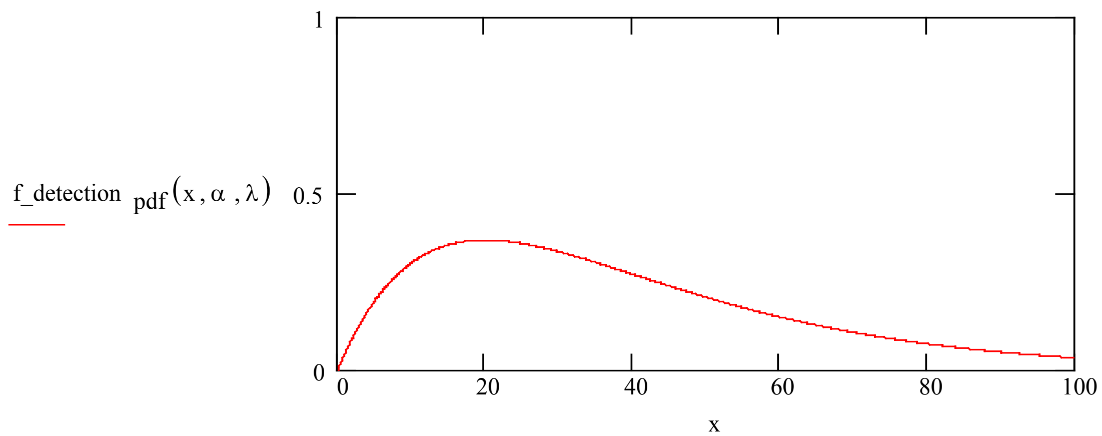
Fix the mode value

$$\begin{pmatrix} \lambda \\ \alpha \end{pmatrix} := Minimize(LSQ,\lambda,\alpha)$$

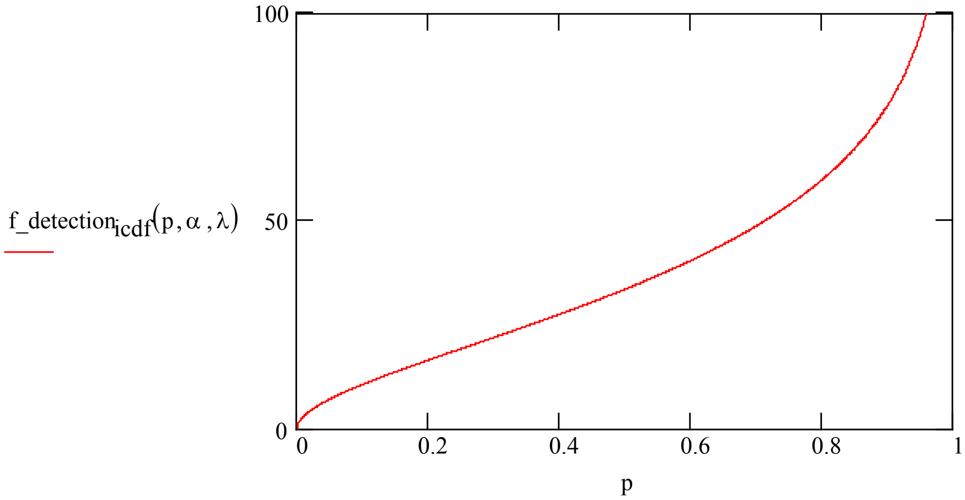
$\lambda = 0.05$

$\alpha = 2$

Detection density function



Detection icdf function - the failure prediction time as a function of probability, if the failure is predicted at all.



The effect of MTTAM to diagnostics coverage

$\left(1 - f\_detection_{cdf}(MTTAM, \alpha, \lambda)\right) \cdot DC = 0.620$

$f\_detection_{cdf}(MTTAM, \alpha, \lambda) = 0.173$

Simulation algorithm

- Simulates events of failures and maintenance actions, st is the maximum simulation time

```
f_events(st) := | levent_ot ← 0
                | event_ot ← 0
                | events[0,2] ← 0
                | i ← 0
                | while (0 < 1)
                |   | fail_t ← f_weibull_icdf(rnd(1), β, η) + levent_ot
                |   | maint_t ← levent_ot + MTBM
                |   | if fail_t < maint_t
                |   |   | if rnd(1) < DC
                |   |   |   | d ← f_detection_icdf(rnd(1), α, λ)
                |   |   |   | d_t ← levent_ot  if ceil((fail_t − d − levent_ot)/MTBI)·MTBI + levent_ot < levent_ot
                |   |   |   | d_t ← ceil((fail_t − d − levent_ot)/MTBI)·MTBI + levent_ot  otherwise
                |   |   |   | if (d_t + MTTAM ≥ fail_t)
                |   |   |   |   | maintain ← 0
                |   |   |   |   | event_ot ← fail_t
                |   |   |   | otherwise
                |   |   |   |   | maintain ← 1
                |   |   |   |   | event_ot ← d_t + MTTAM
                |   |   | otherwise
                |   |   |   | maintain ← 0
                |   |   |   | event_ot ← fail_t
                |   | otherwise
                |   |   | maintain ← 1
                |   |   | event_ot ← maint_t
                |   | while event_ot − levent_ot ≥ MTBI  if MTBI ≥ 1
                |   |   | events[i,2] ← levent_ot + MTBI
                |   |   | break  if events[i,2] > st
                |   |   | levent_ot ← levent_ot + MTBI
                |   |   | i ← i + 1
                |   | break  if event_ot > st
                |   | events[i,1−maintain] ← event_ot
                |   | levent_ot ← event_ot
                |   | i ← i + 1
                | events
```

```
f_removenulls(invector) := | outvector_0 ← 0
                           | j ← 0
                           | for i ∈ 0 .. rows(invector) − 1
                           |   if invector_i > 0
                           |      | outvector_j ← invector_i
                           |      | j ← j + 1
                           | outvector
f_intervals(eventlist) := | j ← 0
                          | intervals_0 ← 0
                          | for i ∈ 0 .. rows(eventlist) − 1
                          |    | intervals_j ← eventlist_i − eventlist_(i−1)  if j > 0
                          |    | intervals_0 ← eventlist_0  otherwise
                          |    | j ← j + 1
                          | intervals
```

Simulate 1000000 years of operation time

```
n := 1000000
events := f_events(365 ·n)
```

Failures on the first column, maintenance on 2nd, and inspections on 3rd

$events^T$ =

	0	1	2	3	4	5	6
0	2700	5400	8100	10800	12101.3	14345.9	17045.9
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0

```
allevents := events^⟨0⟩ + events^⟨1⟩
total_ot := max(events)
allintervals := sort(f_intervals(allevents))
```

Take the intervals between failure and maintenance events

```
calendarevents := | calendarevents_(0,0) ← 0
                  | calendarevents_(0,1) ← 0
                  | lastDelay ← MTTM
                  | tmpEvents ← events / Ut
                  | for i ∈ 0 .. rows(events) − 1
                  |    | if tmpEvents_(i,0) > 0
                  |    |    | calendarevents_(i,0) ← tmpEvents_(i,0) + lastDelay
                  |    |    | lastDelay ← MTTM
                  |    | otherwise
                  |    |    | calendarevents_(i,1) ← tmpEvents_(i,1) + lastDelay
                  |    |    | lastDelay ← MTTR
                  | calendarevents
allcalendarevents := calendarevents^⟨0⟩ + calendarevents^⟨1⟩
allcalendarintervals := sort(f_intervals(allcalendarevents))
repairtimes := f_removenulls(events^⟨1⟩)
repairintervals := f_intervals(repairtimes)
mainttimes := f_removenulls(events^⟨0⟩)
```

$maintintervals := f\_intervals(mainttimes)$

All the event intervals, repair intervals and maintenance intervals

$allintervals^T =$

	0	1	2	3	4	5	6	7	8	9
0	14.529	15	15	15	34.2	39.6	42.3	50.2	54.1	54.3

$repairintervals^T =$

	0	1	2	3	4	5
0	22208.41	69259.229	24982.227	7982.06	30702.323	516.616

$maintintervals^T =$

	0	1	2	3	4	5	6	7
0	2700	2700	2700	2700	1301.3	2244.6	2700	2700

$insptimes := f\_removenulls\left(events^{\langle 2 \rangle}\right)$

The need for materials is defined by either maintenance or failures

$\mu_{all} := mean(allintervals)$

$\sigma_{all} := Stdev(allintervals)$

$\mu_{all} = 2457.378$

$\sigma_{all} = 493.992$

Confidence level 99%

$allintervals_{round[(rows(allintervals)-1)\cdot 0.99]} = 2700$

The values of repair and maintenance intervals are as follows

The mean operating time to failure of the function from last failure

$\mu_r := mean(repairintervals)$

$\sigma_r := Stdev(repairintervals)$

$medrep := median(repairintervals)$

$\mu_r = 22738.489$

$\sigma_r = 22284.381$

$medrep = 15796.737$

The mean operating time to maintenance of the function from last maintenance

$\mu_m := mean(maintintervals)$

$\sigma_m := Stdev(maintintervals)$

$medmaint := median(maintintervals)$

$\mu_m = 2755.106$

$\sigma_m = 836.778$

$medmaint = 2700$

Number of repairs and maintenances

$NREP := rows(repairtimes)$

$NREP = 16051$

$NMAINT := rows(mainttimes)$

$NMAINT = 1.325 \times 10^5$

$NREP + NMAINT = 1.485 \times 10^5$

$\frac{NMAINT}{NREP} = 8.254$

$$NINSP := \begin{array}{|l} 0 \text{ if } MTBI < 1 \\ rows(insptimes) \text{ otherwise} \end{array}$$

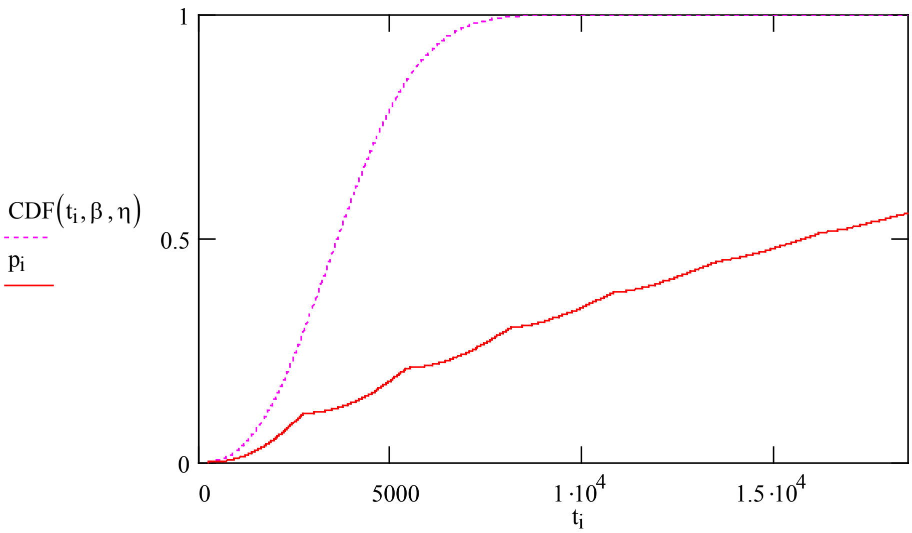
$NINSP = 0$

$i := 0 .. rows(repairintervals) - 1$

$t := sort(repairintervals)$

$p_i := \frac{i}{rows(repairintervals)}$

Failure probability function under condition monitoring and maintenance



The total maintenance costs

$TCT := \frac{total\_ot}{Ut} + NMAINT \cdot MTTM + NREP \cdot MTTR$

Total simulated calendar time

$TCT = 4.57 \times 10^{8}$

$NMAINT := \frac{NMAINT}{TCT} \cdot 365$

Number of maintenances in a year

$NREP := \frac{NREP}{TCT} \cdot 365$

Number of repairs in a year

$NINSP := \frac{NINSP}{TCT} \cdot 365$

$NREP = 0.013$

$NMAINT = 0.106$

$NINSP = 0$

$f\_cost(nmaint, nrep, ninsp) := f\_cost(nmaint, nrep) + ninsp \cdot CINSP$

Simulated costs of maintenance

$f\_cost(NMAINT, NREP, NINSP) = 1958.778$

Operational availability

$A_o := \frac{365 - (NREP \cdot MTTR + NMAINT \cdot MTTM)}{365}$

$A_o = 0.99837$

APPENDIX C: MODEL IV IN VENSIM 5.0 TEXT FORMAT

```
Idle Workers=                   INTEG (Repair Worker Deallocation
                                Rate+Maintenance Worker Deallocation
                                Rate-Repair Worker Allocation Rate-CB
                                Maintenance Worker Allocation Rate-PM
                                Worker Allocation Rate, Number Of
                                Workers)
Number Of Workers=              30
Total Lifetime of Components=   INTEG (Components In Operation-
                                (Necessary CBM Work Start
                                Rate+Components Failing During Waiting
                                Rate+PM Work Start Rate+Undetected
                                Failure Rate+Unnecessary CBM Work
                                Start Rate)*Average Lifetime of
                                Components,1)
Failure Rate2=                  MAX(Working Components To Be CB
                                Maintained/1000*Statistical Failure
                                Distribution(Average Lifetime of
                                Components/Component MTTF),0)
Components In Operation=        Components That Fail Soon+Components
                                that Fail in their Infant Life+Working
                                Components+Working Components To Be CB
                                Maintained
Working Components To Be CB Maintained= INTEG (False Diagnostics alarm
                                Rate-Unnecessary CBM Work Start Rate-
                                Failure Rate2,0)
Components That Fail Soon=      INTEG (Failure Rate+Failure Rate2-
                                Detected Failure Rate-Undetected
                                Failure Rate,0)
Difference=                     Y-Min Percentage of Operating and
                                Maintained Components*1000
Y=                              1000-Components Under Repair-Failed
                                Components Due to Aging-Failed
                                Components Due To Infant Failures
Total Failed Components=        Failed Components Due To Infant
                                Failures+Failed Components Due to
                                Aging
Integral Gain=                  5
Integral of Difference=         INTEG (Difference,0)
Failures=                       MAX(Working
                                Components/1000*Statistical Failure
                                Distribution(Average Lifetime of
                                Components/Component
                                MTTF),0)*(1+STEP(0,2340))
Component MTTF=                 520
Repair Quality=                 Average Repair Quality
Repair Work Start Rate 1=       ZIDZ(Failed Components Due to
                                Aging,Total Failed Components)*Repair
                                Work Start Rate
Renewal Delay=                  MAX(MIN(0.7*520+Integral Gain*Integral
                                of Difference+Difference*Correction
                                Gain,520),208)
Failed Components Due To Infant Failures= INTEG (Infant Failure Rate-
                                Repair Work Start Rate 2,0)
Components Under Repair=        INTEG (Repair Work Start Rate 1+Repair
                                Work Start Rate 2-Errorneus Repair
                                Rate-Quality Repair Rate, 0)
Required PM Start Rate=         Working Components/Renewal Delay
```

```
Required Repair Start Rate=      Total Failed Components/Administration
                                 Delay of A Worker
Repair Work Start Rate 2=        ZIDZ(Failed Components Due To Infant
                                 Failures,Total Failed
                                 Components)*Repair Work Start Rate
Failed Components Due to Aging=  INTEG (Undetected Failure
                                 Rate+Components Failing During Waiting
                                 Rate-Repair Work Start Rate 1,0)
False Diagnostics Proportion=    0
Components Under Maintenance=    INTEG (Necessary CBM Work Start
                                 Rate+Unnecessary CBM Work Start
                                 Rate+PM Work Start Rate-Quality
                                 Maintenance Rate-Errorneous
                                 Maintenance Rate, 0)
Maintenance Quality=             Average Maintenance Quality+Average
                                 Maintenance Quality*Noise
Average Repair Quality=          0.9
Components Failing During Waiting Rate= Failing Components To Be CB
                                 Maintained/(Failure Detection Time-
                                 Average Waiting of CB Components To
                                 Maintenance)
Average Maintenance Quality=     0.95
Noise=                           0*0.025* SIN(Time*2*3.14159/Period)+
                                 0*STEP(-0.05, 1560)+0*RANDOM NORMAL(-
                                 0.05, 0.05 , 0, 0.01, 0)
False Diagnostics alarm Rate=    False Diagnostics Proportion*Detected
                                 Failure Rate
Average Waiting of CB Components To Maintenance= ZIDZ(Total Waiting
                                 Time of Failing CB Components, Failing
                                 Components To Be CB Maintained)
Failing Components To Be CB Maintained= INTEG (Detected Failure Rate-
                                 Necessary CBM Work Start Rate-
                                 Components Failing During Waiting
                                 Rate, 0)
Total Components To Be CBM=      Failing Components To Be CB
                                 Maintained+Working Components To Be CB
                                 Maintained
Unnecessary CBM Work Start Rate= ZIDZ(Working Components To Be CB
                                 Maintained,Total Components To Be
                                 CBM)*CBM Work Start Rate
Working Components=              INTEG (Quality Repair Rate+Quality
                                 Maintenance Rate-Failure Rate-PM Work
                                 Start Rate-False Diagnostics alarm
                                 Rate,1000)
Required CB Maintenance Start Rate=Total Components To Be
                                 CBM/Administration Delay of A Worker
Total Waiting Time of Failing CB Components= INTEG (Failing Components
                                 To Be CB Maintained-(Components
                                 Failing During Waiting Rate+Necessary
                                 CBM Work Start Rate)*Average Waiting
                                 of CB Components To Maintenance, 1)
Necessary CBM Work Start Rate= ZIDZ(Failing Components To Be CB
                                 Maintained,Total Components To Be
                                 CBM)* CBM Work Start Rate
Period=                          52
Correction Gain=                 50
Average Maintenance Time=        4
Min Percentage of Operating and Maintained Components= 0.997
Failure Rate=                    Failures
Administration Delay of A Worker=1
Available CB Maintenance Start Rate= MAX(Available Repair Start Rate-
                                 Repair Work Start Rate,0)
```

```
Available PM Start Rate=        MAX(Available CB Maintenance Start
                                Rate-CBM Work Start Rate,0)
Available Repair Start Rate=    Idle Workers/Worker Allocation Per
                                Component Failure/Administration Delay
                                of A Worker
Maintenance Worker Deallocation Rate= Maintenance Workers/Average
                                Maintenance Time
Average Lifetime of Components=  Total Lifetime of
                                Components/Components In Operation
PM Worker Allocation Rate=      PM Work Start Rate*Worker Allocation
                                Per Maintenance
CBM Work Start Rate=            MIN(Available CB Maintenance Start
                                Rate,Required CB Maintenance Start
                                Rate)
CB Maintenance Worker Allocation Rate= CBM Work Start Rate*Worker
                                Allocation Per Maintenance
PM Work Start Rate=             MIN(Available PM Start Rate,Required
                                PM Start Rate)
Repair Workers=                 INTEG (Repair Worker Allocation Rate-
                                Repair Worker Deallocation Rate, 0)
Undetected Failure Rate=        MAX(Components That Fail Soon*(1-
                                Diagnostics Coverage)/Failure Time4,0)
Worker Allocation Per Maintenance= 1
Repair Worker Deallocation Rate= Repair Workers/Average Repair Time
Maintenance Workers=            INTEG (CB Maintenance Worker
                                Allocation Rate+PM Worker Allocation
                                Rate-Maintenance Worker Deallocation
                                Rate,0)
Repair Work Start Rate=         MIN(Available Repair Start
                                Rate,Required Repair Start Rate)
Repair Worker Allocation Rate=  Repair Work Start Rate*Worker
                                Allocation Per Component Failure
Worker Allocation Per Component Failure= 2
Statistical Failure Distribution ([(0,0)-
                                (2,40)],(0,0),(0.1,0.001),(0.2,0.01),(
                                0.3,0.051),(0.4,0.161),(0.5,0.392),
                                (0.6,0.813),(0.7,1.507),(0.8,2.57),(0.
                                9,4.117),(0.95,5.111),(1,6.274),(1.1,9
                                .186),(1.3,17.921),(1.5,31.765))
Failure Detection Time=         8
Average Infant Failure Time=    5
Failure Time4=                  12
Average Repair Time=            3
Quality Maintenance Rate=       Components Under
Maintenance*Maintenance Quality/Average Maintenance   Time
Detected Failure Rate=          MAX(Components That Fail
                                Soon*Diagnostics Coverage/(Failure
                                Time4-Failure Detection Time    ),0)
Diagnostics Coverage=           0
Errorneous Maintenance Rate=    Components Under Maintenance*(1-
                                Maintenance Quality)/Average
                                Maintenance Time
Errorneus Repair Rate=          Components Under Repair*(1-Repair
                                Quality)/Average Repair Time
Infant Failure Rate=            Components that Fail in their Infant
                                Life/Average Infant Failure Time
Quality Repair Rate=            Components Under Repair*Repair
                                Quality/Average Repair Time
Components that Fail in their Infant Life= INTEG (Errorneous
                                Maintenance Rate+Errorneus Repair
                                Rate-Infant Failure Rate, 0)
```

APPENDIX D: MODEL V CONSUMPTION ANALYSIS IN MATHCAD 2001I FORMAT

Materials consumption

$\text{mean}(\text{allcalendarintervals}) = 3071.722$

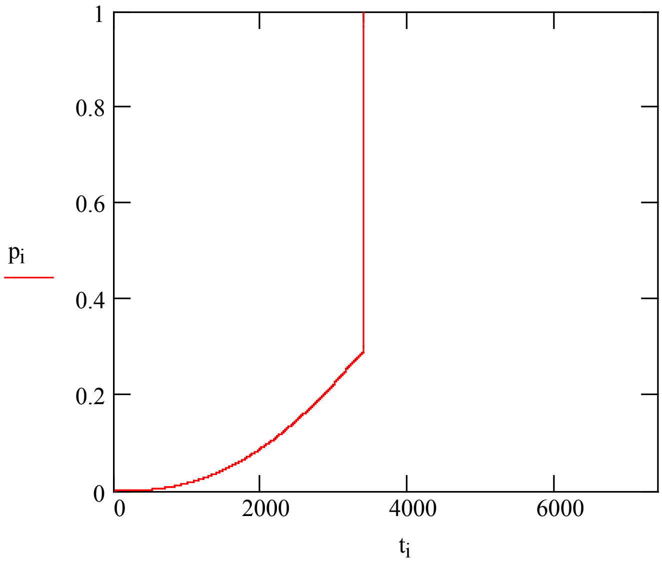
$i := 0 .. \text{rows}(\text{allcalendarintervals}) - 1$

$t := \text{sort}(\text{allcalendarintervals})$

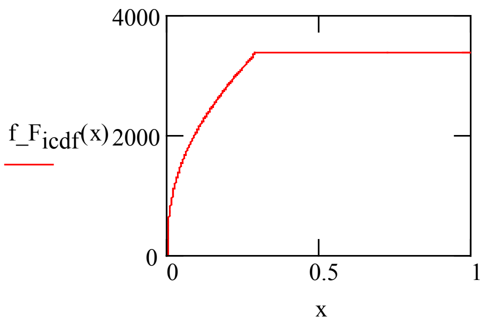
$$p_i := \frac{i}{\text{rows}(\text{allintervals})}$$

Component need probability as a function of calendar time

Note that periodic maintenance reduces variance and defines a clear boundary to confidence levels.



$f\_F_{icdf}(pr) := \text{linterp}(p, t, pr)$ Inverse function for further simulations



Set number of simulated years and number of machines

$n := 1000$

$nmach := 100$

$$f\_simt(max\_t, nmach, f\_F_{icdf}) := \left| \begin{array}{l} prev\_t \leftarrow 0 \\ i \leftarrow 0 \\ event\_t \leftarrow 0 \\ \text{for } k \in 0 .. nmach - 1 \\ \quad \left| \begin{array}{l} \text{while } (0 < 1) \\ \quad \left| \begin{array}{l} event\_t \leftarrow prev\_t + f\_F_{icdf}(rnd(1)) \\ \text{break if } max\_t \le event\_t \\ retA_i \leftarrow event\_t \\ prev\_t \leftarrow event\_t \\ i \leftarrow i + 1 \end{array} \right. \\ prev\_t \leftarrow 0 \\ event\_t \leftarrow 0 \end{array} \right. \\ sort(retA) \end{array} \right.$$

$machgroupintervals := f\_intervals(f\_simt(365 \cdot n, nmach, f\_F_{icdf}))$

$machgroupintervals^T =$

	0	1	2	3	4	5	6	7	8
0	339.367	119.386	512.221	28.059	6.716	37.593	419.122	11.186	31.426

$\mu_{group} := mean(machgroupintervals)$

$\sigma_{group} := stdev(machgroupintervals)$

$\mu_{group} = 30.827$

$\sigma_{group} = 32.14$

$i := 0 .. rows(machgroupintervals) - 1$

$t := sort(machgroupintervals)$

$t^T =$

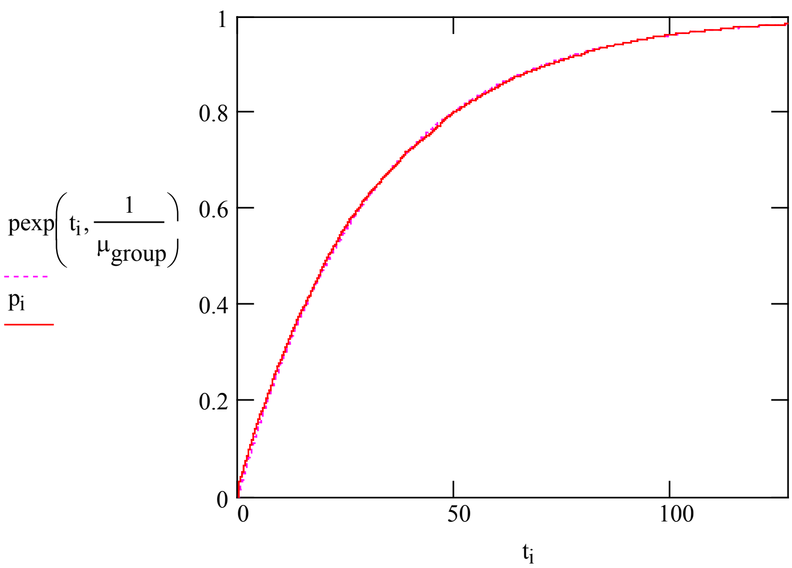
	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0

$$p_i := \frac{i}{rows(machgroupintervals)}$$

$p^T =$

	0	1	2	3	4	5	6
0	0	$8.446 \cdot 10^{-5}$	0	0	0	0	0.001

Spare parts consumption interval cdf of a machine group



$\mu_{group} = 30.827$

With many machines operating, failing and maintained independently the consumption distribution converges to an exponential distribution with a mean value that equals mean life time of single machine divided by the number of machines. Number of arrivals with 95% condifdence level during the delivery time is given by inverse cdf of a poisson distribution. (Homogeneous Poisson process, HPP) This is the reorder point of the inventory. (NIST/SEMATECH e-Handbook of Statistical Methods, http://www.itl.nist.gov/div898/handbook/)

$MDT = 15$

$$ROP := qpois\left(0.95, \frac{MDT}{\mu_{group}}\right)$$

$ROP = 2$

$$f\_EOQ(ausage, corder, acunit) := \sqrt{\frac{2 \cdot ausage \cdot corder}{acunit}}$$

$$EOQ := f\_EOQ\left(\frac{365}{\mu_{group}}, 1000, CCOMPONENTPRICE \cdot 0.20\right)$$

$EOQ = 3.441$

Buffering the consumption in an inventory, results in a following distribution for the upstream demand from this inventory:

$EOQ := 14$

```
buff_cons := | k ← 0
             | buffA_0 ← 0
             | i ← 0
             | while 1 > 0
             |   | sum ← 0
             |   | for j ∈ 0 .. EOQ − 1
             |   |   | sum ← sum + machgroupintervals_i
             |   |   | i ← i + 1
             |   |   | return buffA if i = rows(machgroupintervals)
             |   | buffA_k ← sum
             |   | k ← k + 1
```

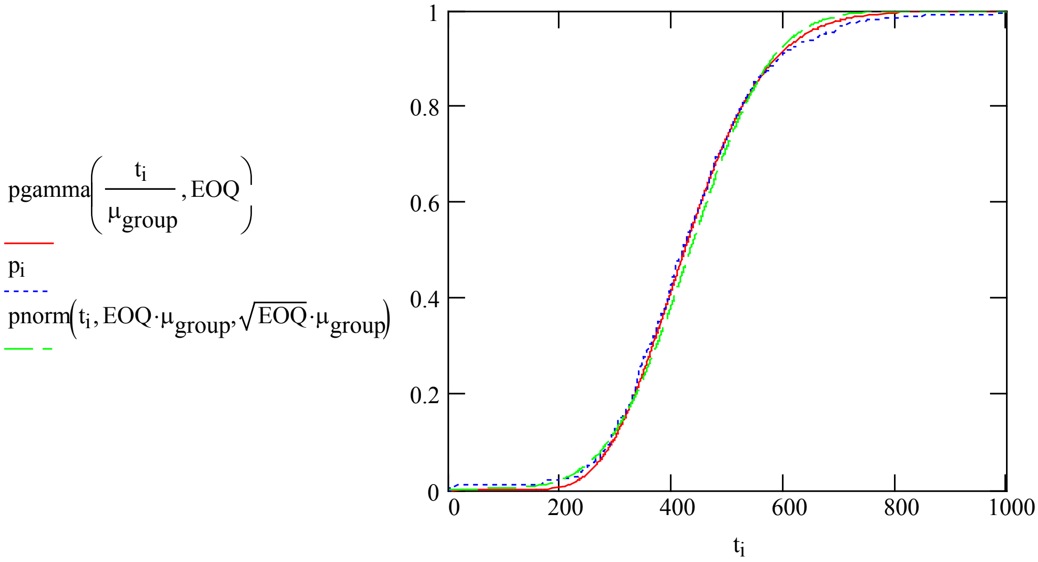
$buff\_cons^T =$

	0	1	2	3	4	5	6	7
0	2048.875	986.375	339.75	0	0	0	0	1473.651

$i := 0 .. rows(buff\_cons) - 1$

$t := sort(buff\_cons)$

$$p_i := \frac{i}{rows(buff\_cons)}$$



Spare parts orders distribution when the real consumption is buffered by EOQ. With EOQ=1, the consumption follows exponential distribution, with EOQ>=1 the consumpiton follows Gamma distribution. With EOQ >> 1 the consumption can approximated with normal distribution (according to the central limit theorem) where mean is EOQ*mean of the exponential distribution and std. deviation is sqrt(EOQ)*mean of the exponential distribution.

APPENDIX E: MODEL V IN VENSIM 5.0 TEXT FORMAT

```
Expected Demand2=                SMOOTH3I( IF THEN ELSE(Shared
                                 Information Status=0 :OR:Remote
                                 Monitoring Status=0,Purhasing Plan3,
                                 Remote Monitoring),Averaging
                                 Timeframe2, Average Consumption)
Expected Demand3=                SMOOTH3I( Consumption Rate, Averaging
                                 Timeframe3,Average Consumption )
Averaging Timeframe2=            35
Averaging Timeframe3=            21
Consumption Rate=                RANDOM NORMAL(0, Average Consumption*6
                                 , Average Consumption, 1*SQRT(Average
                                 Consumption), 0)
Production Rate=                 DELAY3I(MIN(Production Plan,Max
                                 Capacity),Production Delay, Average
                                 Consumption)
Expected Demand1=                SMOOTH3I(IF THEN ELSE(Remote
                                 Monitoring Status=1, Remote
                                 Monitoring, Purhasing Plan2),
                                 Averaging Timeframe1, Average
                                 Consumption)
ShippingRate2to3=                DELAY3I(IF THEN ELSE( Inventory2>0
                                 ,Purhasing Plan3, 0), Shipping
                                 Delay2to3, Average Consumption)
Shipping Rate1to2=               DELAY3I(IF THEN ELSE( Inventory1>0,
                                 Purhasing Plan2, 0), Shipping
                                 Delay1to2, Average Consumption)
Inventory Target1=               Expected Demand1*(K*Production Delay)
Average Consumption=             30+0*STEP(1.5,100)
Inventory Correction Delay3=     14
Demand Rate 3=                   IF THEN ELSE(Inventory3>0,Consumption
Rate,0)
Inventory Correction Delay2=     28
K=                               2.5
Inventory Target2=               Expected Demand2*(Shipping
Delay1to2*K)
Inventory Target3=               Expected Demand3*(Shipping
Delay2to3*K)
Shipping Delay2to3=              7
Inventory3=                      INTEG (+ShippingRate2to3-Demand Rate
                                 3,Average Consumption*(K*Shipping
                                 Delay2to3-Inventory Correction
                                 Delay3))
Purhasing Plan3=                 MAX((Inventory Target3-
                                 Inventory3)/Inventory Correction
                                 Delay3,0)
Remote Monitoring=               Consumption Rate
Remote Monitoring Status=        0
Production Delay=                21
Production Plan=                 MAX(Inventory Target1-
                                 Inventory1,0)/Production Correction
                                 Delay1
Purhasing Plan2=                 MAX((Inventory Target2-
                                 Inventory2)/Inventory Correction
                                 Delay2,0)
Shared Information Status=       0
Shipping Delay1to2=              14
Production Correction Delay1=    40
```

Inventory2=	INTEG(+Shipping Rate1to2-ShippingRate2to3, Average Consumption*(K*Shipping Delay1to2-Inventory Correction Delay2))
Max Capacity=	37.5
Inventory1=	INTEG (Production Rate-Shipping Rate1to2, Average Consumption*(K*Production Delay-Production Correction Delay1))
Averaging Timeframe1=	56

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