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Lauri Forsman and Markku J. Penttinen

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Lauri Forsman and Markku J. Penttinen

University of Tampere
Department of Computer Science
P.O. Box 607
FIN-33101 Tampere, Finland

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Lauri Forsman
Nokia Telekommunications
P.O. Box 311
FIN-00045 Nokia Group
Lauri.Forsman@ntc.nokia.com

Markku J. Penttinen
Finnish Forest Research Institute
Unioninkatu 40 A
FIN-00170 Helsinki
Markku.Penttinen@metla.fi

Abstract

This study analyses the factors affecting investment decisions concerning end-user support (EUS), which is even more complex than that of centralised data processing (DP). The alternatives of proactive and reactive end-user support (EUS) in a modern LAN environment are compared by analysing the failure risk of one specific component (HUB) of the LAN. The additional preventive actions and management costs are considered as well. Both proactive and reactive EUS are analysed in terms of investment and risk management. Arguments for and against enhanced support capability and a fault tolerant system structure are sought for optimising risk/spending levels. The reliability theory with its demand patterns demonstrated by electronic components has been used in the spirit of inventory-production theory in order to quantify the risk both with deterministic and random failure intensity parameters.

Exact Bayesian tests have been developed in order to evaluate the two vendor MTBF figures, only the first of which turns out to match the observation. Bayesian posterior failure distributions have been estimated both in the deterministic and random failure intensity cases, the last of which results in a binomial distribution with an annual mean of 16 HUBs and a standard deviation of 4 HUBs. The cost parameters estimated by NOKIA from the field have been used, and the costs of alternative policies have been assessed.

The annual expected reactive cost, with a lower hourly developer cost option of kFIM 563, exceeds the annual proactive cost of kFIM 552. An additional investment, i.e. systems for network monitoring equipment of kFIM 210 with a three-year pay-back period can be recommended. However, the expected reactive cost would not carry the investment where proactive policy would require an additional management effort compared with the reactive one. The additional preventive actions, costing kFIM 672 annually, could be covered only by assuming that developer capacity is a sales-limiting facxtor.

Recommendations and sensitivity considerations can easily be provided for the day-to-day decision-making of IT and SBU management, using the developed calculation models with updated cost and failure statistics data. A key notion of the study is to develop a management tool for NOKIA's DP management.

Keywords: Investment planning, reliability, fault tolerance, DP management, management policy.

1 Introduction

Investments in business oriented-information technology (IT) have in principle been justified by business benefits exceeding costs. However, limited opportunities to quantify the real benefits restrict the use of investment planning and control. The contradiction between urgent need of economic evaluation of IT and the lack of relevant research findings has emphasised research into IT investments as an essential part of IT management. Both the business value of computers and IT investments as a whole have been studied systematically (Strassmann 1990 and 1997). The expenditure of firms for End User Computing (EUC),[1] an expanding part of IT, was expected to grow from 30% to an average of over 40% of total allocation in three years, as already noted by Kwan and Curley (1989). Actually, the share increase of PC/workstations, comparing the percentage of processing by hardware (HW) category, is projected to increase by 75% by the end of the decade according to IS researchers (McLean et al. 1993). The most critical change might be that the support cost of 28% is in the data centre environment, but 77% in a distributed computing environment (Kirwin et al. 1995). This challenge justifies the investment and cost minimisation approach in this study. This exponential growth of distributed computing has been managed by organising End-user Support, (EUS) typically in the form of a Help or Service Desk (HD/SD).

An HW reliability and maintainability problem which emerged while using EUC technology is analysed in this study. From the end users' point of view as a whole, by definition the EUC context seems in practice to be the stand alone software (SW) products, such as word processing and spreadsheets, as well as modern client/server applications, the last of which typically require more support manpower and expertise than the traditional on-line applications (Keyes 1996). The organisational part of EUC management consists of strategy, technology and management action, the last of which consists of support services and control policies/procedures according to Brancheau and Brown (1993) among others. They found that the EUC literature provides a wealth of descriptive data, but only a small number of theoretical frameworks. They suggest quantitative **variables** associated with outcome components such as **reliability** and **maintainability, which are discussed and analysed in this study.**

Where a user has difficulties with some computer-based task, the loss of work time may be excessive. Difficulties are often solved by trial and error and by learning or asking for unofficial peer support. These productivity losses of personnel capacity are referred to as hidden costs (Heikkilä 1995). Moreover, if the computer technology does not perform properly, it leads to similar, but potentially more serious losses. For example, if a server for some work group breaks down, the productivity of the whole group is compromised. Further, if a Local Area Network (LAN) fails to work, it could affect the work of hundreds of people. In some business areas, the systems may be directly linked to the customer interface, and thus demand high quality, professional computing technology.

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[1] In this paper we apply the concept of "EUC" in the same sense as Panko (1988). Panko's main interest has been in phenomena like *Post-DP revolution*, *Managerial and Professional Computing.* He emphasised the departmental aspect of EUC and the coverage of a large part of the staff.

The risk of lost capacity can be compensated for by investing in technology and service, thereby decreasing the probability of failure. However, some risks remain no matter how proactive the investment approach is. To cover these remaining risks, reactive EUS is required.

As against the verbal descriptions such as Brancheau and Brown (1993), empirical observations, failure risk modelling and quantitative planning are focused on in this study, the crux of which is balancing between the proactive and reactive approaches.

Proactive and reactive management

The rapid development of IT has emphasised new HW and SW solutions, such as distributed data processing (DDP) herein called distributed organisational computing (D-OC). Distributed PCs are networked and linked to the common services through Local Area Networks (LANs). Physical connection between the LAN and the PC is channelled through local communication concentrators (HUB). Their job is to link the LAN backbone network and the user cabling. Each HUB in the NOKIA HW configuration acts as a gate to the corporate network for 22–24 users. The corporate network provides most of the daily computing services needed by the strategic business unit (C-SBU) in NOKIA Telecommunications Ltd. The HUBs link the users to the centralised corporate databases and processing, external networks, Internet, etc. (Figure 1).

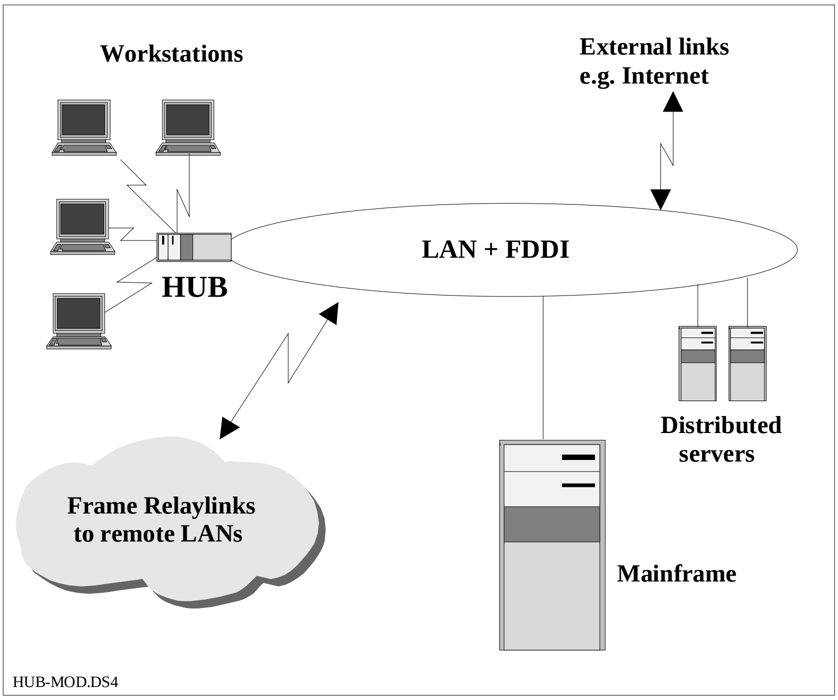

Figure 1. The local communication concentrator (HUB) in the NOKIA local area network (LAN)

Each HUB provides the physical gateway for a cluster of workstations to the corporate network and common services. The number of such HUBs and clusters is in the order of a hundred. The purpose of the HUB is to provide “media flexibility, increased port density, integrated network security and bridging/switching options in departmental and remote Ethernet LANs” (3Com 1995).

Applications have been re-designed to conform with the modern HW/SW frames, using client/server techniques. Some researchers emphasise the end-users’ role in the development, especially the acceptance of microcomputer technology (Igbaria 1993) or the learning and diffusion processes of ‘learning-intensive technologies such as IT in general and PCs in particular (Heikkilä 1995). Some studies focus on special features, such as the role of antecedents in the process (Brown and Magill 1994).

In risk management one typically has conflicting goals and costs. The less preparations are made in advance, the higher the “reactive” failure costs are, while reducing failure risk means higher “proactive” preparation costs. This balancing follows the logic of insurance. A simplified view of this trade-off between proactive and reactive costs has been published by Grose (1987), and by Suominen (1994) and Berg (1994) (Figure 2).

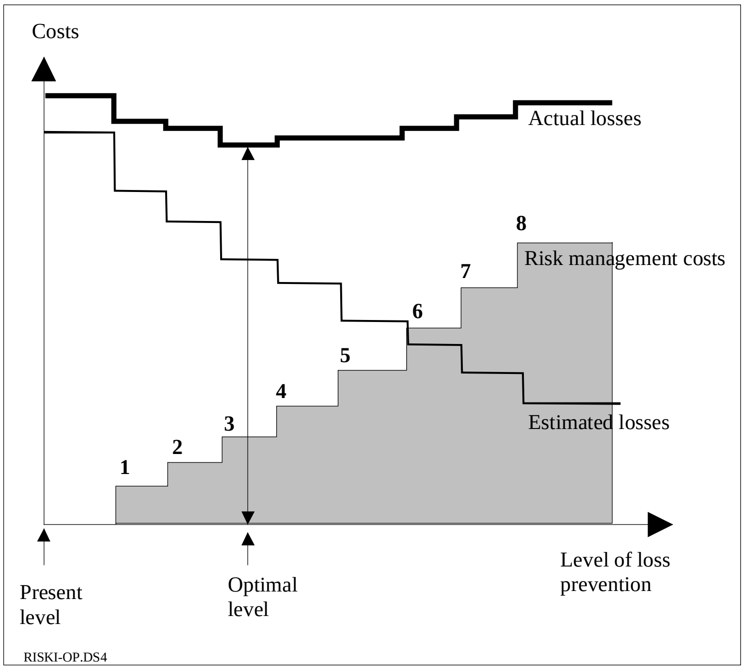

Figure 2. The optimum level of total costs compromises the estimated accident losses (reactive) and the risk management costs of their prevention (proactive)

The downtime cost analysis focuses on cumulative potential savings rather than costs. The cumulative **potential saving** S consists of four components

$$S = \Delta P - C_p - C_a - C_r - C_m \ . \qquad (1)$$

The productivity increase, ΔP, stands for the benefits and actual savings. The **proactive costs**, C_p, of system robustness (e.g. redundancy) and administration (holding costs in the inventory-production theory) represent the applied maintenance level in the spirit of a stationary management policy and of the steady state economy. Conversely, the **cost of actions**, C_a, **before potential failure** (ordering costs) means exceptional operations such as orders, emergency orders or replacement of critical parts before a potential failure. The reactive costs, C_r, are caused by a realised failure (shortage costs in the inventory-production theory)[2]. The management costs, C_m, refer to those of EUS, IT, and strategic business unit (SBU) management. An overview of the IS-managerial dimensions is shown in Figure 3. The main risk shown in the diagram is the risk of losing business because IT fails to fulfil the requirements of the business process. If requirements are met only partially, the IT problems cause a risk of capacity losses. The **reactive costs** are incurred when these two risks materialise. Proactive costs cover all those stationary cost items which reduce these risks. Action costs are due to specific actions needed to cope with an alert, proactive or reactive (immediate risk or acute problem). The productivity increase has not been measured here, because a pure cost minimisation approach captures the essential features of the real problem.

The failure process and the reliability technique

The focus of the management model is the behaviour of the distributed HUBs (3COM LInkBuilder FMS II of the LAN) (Figure 1). Where the HUB fails, most of the productive work of all experts linked through it is impossible. The traditional reliability technique concepts, such as mean time between failures (MTBF) and mean time to repair (MTTR), are key concepts of the analysis. The MTBF is based on the properties of the HUB. It is (i) stated beforehand by the vendor, termed the prior MTBF, and (ii) demonstrated by the empirical evidence of the products in operational use in practice, termed the posterior MTBF.

The methodological approach of this study is that of inventory-service and risk modelling based on the evaluation of stochastic failure processes, which in the end is founded on observations in the field. The failure process model building relies on the discipline of reliability systems, more precisely on the compound Poisson process, which assumes an exponential failure law for each individual component. In fact, the exponential failure law has already traditionally been a common planning assumption (Ross 1976). Moreover, empirical studies have demonstrated that the exponential failure assumption fits the behaviour of electronic components (Kaylan 1983).

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[2] The capacity losses of personnel in the case of failure of the network cause hidden costs (Heikkilä 1995) in the sense that end users cannot work, which implies the cost impact remaining invisible and outside all cost accounting procedures.

The impact of proactive efforts on the failure process is difficult to estimate. For example, statistics on traffic accidents occurring on old, dangerous railways are known in detail, but the number of lives saved following the construction of new safety systems is nearly impossible to assess. This dilemma of the proactive approach with respect to costs, risks and measurement in the society has been rigorously analysed by Keeney (1995).

The benefits and costs in the evaluation of the failure process

Loosely speaking, the problem definition of the management task in question consists of two parts: failure process analysis without any economic evaluation, and the management model formulation based on the evaluation of the process with the help of benefit and cost parameters. The evaluation links the risk and the benefit/cost parameters.

The concepts used for the DP management task (Formula (1)) are of the traditional production-inventory theory type, which recognises holding (proactive), shortage (reactive), replenishment/production costs (action) and management costs (Naddor 1966).

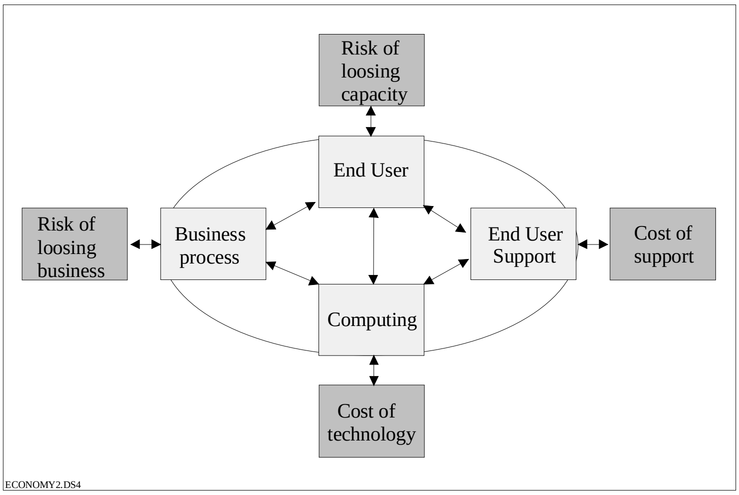

Figure 3. Risks and budget can be balanced by investing in the technology and enhancing the support service

The benefits are available only whenever the HUB is working properly. The potential increase in productivity, ΔP, however, is not included. The reactive costs, C_r, are considered in the case of failure of the HUB. The costs of proactive measures C_p, such as change of parts before they fail, additional maintenance, etc. are estimated in detail. The cost of actions, C_a, before potential failure are caused by exceptional operations, primarily sporadic non-systematic, such as replacement of critical parts before potential failure.

The notion of the study

This study relies on earlier contributions and a comprehensive case study using empirical data from NOKIA Corporation, in order to develop a novel model for managerial decision-making.

The problem of this study is to determine a balance between the proactive and reactive approaches, based on the following steps: the reliability theory model for the risk quantification will be constructed and estimated. The cost parameters will be estimated. The management model will be constructed in order to combine the risk and costs and results and recommendations for IT and SBU management are provided.

2 Previous work

Reliability theory offers concepts such as the Mean Time Between Failures (MTBF) and techniques for quantitative analysis needed for planning, e.g. the preventive server maintenance above (Welch 1997). Empirical studies have shown that the MTBF of electronic components typically follows an exponential law as demonstrated by Kaylan (1983). The demand of, say, electronic spare parts over a period of time then follows the Poisson distribution.

This study belongs to the area of Multi-Echelon Repairable Inventory Control (METRIC) (Abboud 1996), but the model is less complex. A similar management problem to that in this study has been analysed by Koskela (1993), who studied the spare parts of NOKIA assuming a constant failure intensity λ = 1/MTBF. If the failure intensity λ of a technical component varies according to the gamma distribution among components of the same type, the demand follows a negative binomial distribution (Kendall and Stuart 1977). The existence of probability laws for the risk behaviour itself allows the application of Bayesian methodology instead of standard statistical methods. In this case both the tests and estimates are based on the so-called posterior distributions as described by Box and Tiao (1992).

Note that even non-homogenous Poisson processes with a time-varying failure intensity $\lambda = \lambda(t)$ can be estimated as shown by Lenk and Rao (1995). However, the empirical data here is sufficient only for homogenous models. A technique called parameter maps for combining sequential estimations, and even a prior parameter, with the Bayesian Poisson demand has been suggested by Buck et al. (1995) and applied here. Moreover, if the prior distribution of the failure intensity λ, or at least its mean and standard deviation, could be provided by the vendor, the two stages of Bayesian reliability tests with empirical technology observations and the corresponding posterior distributions based on the use of both prior and posterior data, could be estimated together (Whitmore et al. 1994), which has been done in this study.

Basic features of end-user computing (EUC) have been described by Brancheau and Brown (1993), and studied in the Finnish context by Heikkilä (1995). The concept of proactivity is often used in the context of EUS. However, there seem to be only a few previous research findings available. General risk management (Berg 1994; Suominen 1994) is one framework within which to study proactivity from the economic perspective. Keeney (1995) has analysed the consequences of proactive and reactive policies respectively. He emphasises the difficulty in estimating profits, even a saved life, as the consequence of proactive investments. Risk management is defined as:

“Risk management is a holistic view of the existing risks and a systematic study of the options how to minimise their effects followed by the selection and implementation of the most efficient actions identified in that study” (Berg 1994).

Bruton (1995) describes proactivity as “regular study of user problems encountered with a view to preventing them in future”. This may also be achieved by “creation of an inventory of user equipment to help with diagnosing and solving problems the users may have”.

Bruton gives a list of specific services to maintain proactivity:
- formalised analysis of the previous fortnight’s Help Desk queries and focusing on the most frequent problems
- producing and delivering reports on changes made to the computer network
- compiling and maintaining a directory and regular report on computer usage and investment feasibility
- maintaining a register of equipment
- keeping a central catalogue of technical objects
- producing monthly newsletters
- monitoring the learning of new company employees
- analysing new technologies and preparing their deployment.

Proactivity is analysed by Welch (1997) in the context of network management. He concludes that “solving problems under pressure is never a good idea and doing so can lead to more serious problems down the road. Finding and solving problems before users notice them should be paramount to any network manager. Proactive management can dramatically reduce your support loads because you deal with a problem once rather than for each user”.

The main steps for proactivity in a network management context include (Welch 1997):
- educating users
- preventive server maintenance
- separating test and production environments (servers and network components)
- standardising device names
- carefully planning and testing all system changes.

The definition of Distributed Organisational Computing (D-OC) is refined from Forsman (1997): **D-OC is organization-wide, task-related computing, which is based on cooperatively managed distributed services and resources**. This study as well as Forsman (1997) has connections with the action research tradition (Kerola and Reponen 1996; Stringer 1996). There is a strong tradition of basic IT investment guides (Karvinen et al. 1994), which use some concepts of this study, typically without any systematic observation and quantitative analysis. However, observations, failure process and management modelling form quantitative cornerstones here.

3 Material and Methods

3.1 The demand process of one ventilator

Some studies make the straightforward assumption that the demand for electronic components follows a Poisson distribution. Koskela (1993), for example, studied the demand for spare parts in the Nokia Telecommunications Customer Support Centre. Actually, the fundamental empirical finding, shown already by Drenick (1960), is that **one** electronic component has not failed after time t with a probability of $F(t) = \exp(-\lambda t)$ called the survivor function of the exponential distribution. The parameter λ is the mean failure rate $\lambda = 1/MTBF$ and MTBF is the mean time between failures of the component. Note that the MTBF of the HUB ventilator was, according to the vendor, roughly 2 years and two months.

If the failure rate is exponential with intensity λ, which is assumed to be both constant over time and the same among different ventilators, the demand during a time period t forms a Poisson process. The probability $\Pr\{n\}$ that exactly n replacement units will be needed during t for **one ventilator place in one HUB** is then

$$\Pr\{n\} = \exp(-\lambda t)\,(\lambda t)^n / n!\ . \qquad (2)$$

Note that both the mean μ and the variance σ^2 of the Poisson distribution above is λt, $\mu = \sigma^2 = \lambda t$. When assuming a Poisson distribution, only one figure, MTBF, is sufficient information because the shape of the distribution, including the variance, is frozen by the one parameter μ independently of the empirical data. Recall that the amount n can be interpreted as the number of arrivals (replacements) of a renewal process with exponential inter-arrival (replacement) times (Feller 1971).

The ventilator is assumed here to have a **constant** failure rate over time λ, and this has been found to be sufficient in practice, especially when analysing the need for many electronic devices. The process is then called **homogeneous**. However, the analysis and application of even heterogeneous Poisson processes with $\lambda = \lambda(t)$ can be performed and parameters estimated (Lenk and Rao 1995). Unfortunately, the estimation of heterogeneous Poisson processes requires amounts of data obtained, e.g. from traffic control. When IT management problems are investigated the limited number of observations typically forces the homogeneity assumption. In this study, the failure rate does not vary in time, but both the deterministic rate case with the same λ in the ventilator population and the stochastic rate case of the random $\underline{\lambda}$ over the population are analysed.

3.2 The prior vendor MTBFs and the observed failures

The calculations use both the vendor announced prior MTBF and the posterior empirical evidence of the NOKIA corporation, in order to obtain failure distributions. The vendor was not able to provide distribution information other than the **two MTBFs** (mean time between failures), one at the beginning **19,272 hours**, roughly 2 years 2 months, and subsequently an improved version, 63,265 hours, roughly 7 years 2 months. The corresponding failure rates are λ_1 = 1/26.3 month^{-1} and λ_2 = 1/86.4 month^{-1}. Unfortunately, no information on the shape of the prior distribution of the parameter λ was given by the vendor. This limitation in the information supports the assumption that λ does not vary from box to box among the 280 ventilators in the field.

The observation period was from 5/1995 to 9/1996 on Campus B and Campus C, on average 9 months, and from 11/1995 to 8/1996 on Campus A 5/1995, but on average from 3/1996 to 10/1996 i.e. 7 months on Campus A. Thus the average duration of the observation time was **8 months.**

The failures of the HUB ventilators, two in each HUB, were as follows:

Table 1. The ventilator failures on NOKIA campuses

	Campus B	Campus C	Campus A	All
HUBs with one ventilator broken	20	26	3	49
HUBs with both ventilators broken	3	8	3	14
Number of ventilators broken in all	26	42	9	77
Number of ventilators installed	160	74	46	280
Failure rate in percentages	16.3	56.8	19.6	27.5

In all, there were 140 HUBs, with altogether 280 ventilators, of which 77 or 27.5% were broken during the observation period of 8 months.[3] On the assumption of a constant failure rate, parameter λ would provide the mean of μ_1 = 1/3.29, which equals the failure probability of 30.4%, and μ_2 = 1/10.8, which equals the failure probability of 9.3%, during the 8 months corresponding to MTBFs of 19,272 hours and 63,265 hours respectively.

Surprisingly, the original (first) vendor rate is even higher than the observed failure (hit) rate of 27.5%. By contrast, the revised (second) vendor rate differs essentially from the empirical evidence.

3.3 The Bayesian posterior failure rate distribution and its fit with the prior vendor MTBFs

First, it is assumed that the failure rate does not vary from ventilator to ventilator, so that the prior demand of each ventilator follows the Poisson distribution. Consider a set of 280 independent test benches of ventilators. On each test bench there is a Poisson (renewal)

[3] On Campus B 160 units in 80 HUBs have been changed, of which 20 had one broken ventilator. Three HUBs had both ventilators broken. On Campus C 74 units of 37 HUBs were changed of which 26 had one broken unit and 8 both units broken. On Campus A 46 units of 23 HUBS were changed of which 3 had one and 3 both ventilators broken.

process (Formula (2)), which requires 0, 1, 2, .. replacements. The empirical frequencies F = $(f_1, f_2, ..., f_{280})$ are either zero, one or two or… as noted in Table 1 above.

The random number of failures $\underline{\mu}$ then has **the Bayesian posterior distribution**, given by the failure frequency observations vector F (Box and Tiao 1992, p. 40)

$$p(\mu|F) = \mu^{(f.-1/2)} \exp(-v\mu) \; v^{[-(f.+1/2)]} \left[\Gamma(f.+1/2\right]^{-1}, \qquad (3)$$

where the number v of independent frequencies is 280, the sum f. of the failure frequencies is 77, $\Gamma(\cdot)$ is the gamma function and $\mu > 0$. Note that the confidence intervals of μ can be calculated directly from the distribution (3). The posterior distribution (3) above is that of $\underline{\mu}$. Actually, $v\underline{\mu}$ is distributed as 0.5 $\aleph^2$ (chi-square/2) with 2f.+1 = 155 degrees of freedom where f. = 77 is the number of failures. Thus the maximum likely estimate of the posterior distribution mean $\underline{\mu}$ of (3) equals the number of failures modified by 0.5 and then divided by the number of ventilators (f. + 1/2)/v = (77+0.5)/280 = 27.7% (Box and Tiao 1992).

The fitness of the vendor information against the empirical evidence is tested by applying the derived Bayesian posterior distribution (3). The vendor MTBF of 19,272 hours over 8 months refers to μ = 0.304 and to 85 failures on average, and their MTBF of 63,265 hours to μ = 0.0926 and to 26 failures on average. The posterior distribution of $v\mu$ above can also be used to test the fitness of the first and the second vendor MTBFs with the empirical observations. For the first MTBF, the probability Pr $\{0.5\ \aleph^2_{155} < 85\} = \Pr\{\aleph^2_{155} < 170\} > 10\%$. Thus the hypothesis that the first vendor MTBF fits the observations cannot be rejected. By contrast, the hypothesis is rejected at a risk of < 0.1% with the second vendor MTBF. In all, the observations fit the first MTBF and deviate completely from the second (revised) one.

3.4 Combining the prior MTBFs and observation sets

Second, the random failure rate $\underline{\lambda}$, and its point estimate for the constant rate λ, will be analysed. Recall that the failure rate was, until now, assumed to be both constant in time and the same among numerous ventilators. Here there are 280 electronic components - the same type of ventilator in various servers (HUBs) in the C-SBU of NOKIA. Each of the components has a demand process of Poisson type but with its own specific failure rate of λ = 1/MTBF parameter. Although the demand of one individual ventilator follows the Poisson process (2) its parameter λ varies over the whole population according to some distribution. Consider the random failure rate $\underline{\lambda}$ from the Bayesian viewpoint. In the context of Bayesian estimation the concept of natural conjugate distributions (NCDs) emerges. The NCDs possess the property that the prior and the posterior distributions of $\underline{\lambda}$ have the same functional form. The NCD for the rate parameter λ of the Poisson process is the gamma distribution (Buck et al. 1995), the density function of which is

$$g(\lambda|n,t) = \lambda^{(n-1)} t^n \exp(-\lambda t) / \Gamma(n) \quad \text{for } \lambda \geq 0, \qquad (4)$$

where $\Gamma(\cdot)$ is the gamma function, $n \geq 0$ stands for the number of observed events and $t \geq 0$ for the time units for observing.[4]

Now only the two different MTBFs of 19,272 and 63,265 hours are provided a priori by the vendor. The prior expected number of failures n_0 during the t_0 = 8 month observation period would then be n_0 = 85 and = 26 respectively.

Using the eight month time interval t_0 = 8 and the artificially constructed initial prior points n_0 = 85 and = 26 respectively on the parameter mapping (Buck et al. 1995) the posterior expectation and the variance of $\underline{\lambda}$ is

$$E(\underline{\lambda}) = (n_0 + n_1) / (t_0 + t_1) \tag{5.1}$$

and

$$V(\underline{\lambda}) = (n_0 + n_1) / (t_0 + t_1)^2 . \tag{5.2}$$

The number of observed failures was n_1 = 77 and the observation time t_1 = 8 months. The expectation $E(\lambda)$ would suggest the expected number of failures of 81 when combining the first constructed initial point (n_0 = 81) and the observations. However, when combining the second point (n_0 = 26) and the observations, only 52 failures could be expected.

In all, the expected number of failures at the posterior rate would mean 81 failures instead of 85, and 52 instead of 26 respectively, using the two vendor MTBFs in the initial point estimation. The empirical evidence again supports the former MTBF of the vendor and is against the latter. The parameter mapping is actually aimed at combining sequential observation data sets, say, from different campuses of NOKIA. Using the failure rate expectation $E(\underline{\lambda})$ and variance $V(\underline{\lambda})$, modification formulas above the distribution (4) of the failure rate $\underline{\lambda}$ can be easily updated and tuned for management purposes applying formulas (5.1) and (5.2).

3.5 The Bayesian posterior distribution of the whole NOKIA SBU demand for parameter estimation

Third, the mean number of failures μ of the Poisson process (Formula (2)) has previously been constant – using the case of one ventilator, but from now on a random variable $\underline{\mu}$ - using the case of the whole ventilator population. The random $\underline{\mu}$ is assumed to follow the gamma distribution (Formula (4)). The total "summarised" demand in the whole C-SBU caused by all

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[4] Supposing that the renewal process of each individual ventilator exhibited an exponential distribution $Exp(\lambda)$, the sum of those mutually independent random variables of v ventilators has the distribution of Gamma form with the density function

$$g(\lambda) = \lambda^{v-1} t^v \exp(-\lambda t)/(\Gamma(v)) \quad \text{(Feller 1971).} \tag{4'}$$

the ventilators, each of which is assumed to form a Poisson process, then follows a negative binomial (also called Pascal) distribution (Kendall and Stuart 1977)
(cf. also Lenk and Rao 1995).

$$\Pr\{\text{v ventilators and f failures}\} = \binom{\text{v - 1}}{\text{f - 1}} \pi^{\text{f}} (1 - \text{p})^{\text{v-f}}, \quad \text{for v} = \text{f, f} + 1, \text{ f} + 2, \ldots \qquad (6)$$

where $0 < \pi < 1$ is the failure probability and v is the number of ventilators, say 280, and f is the number of failures, say 77. Note that (6) can be interpreted as the probability distribution in which "sample" size v is required to achieve the f:th failure. The negative binomial distribution (6) is applied to the empirical data of NOKIA Corporation and in the Bayesian framework.

If the demand distribution is binomial then the Bayesian posterior distribution $\text{p}(\pi|\text{f})$ of the failure probability $\underline{\pi}$ is the Beta distribution

$$\text{p}(\pi|\text{f}) = \pi^{(\text{f}-1/2)} (1 - \pi)^{(\text{v-f}-1/2)} \Gamma(\text{v} + 1) / \{\Gamma(\text{f} + 1/2)\Gamma(\text{v - f} + 1/2)\}, \qquad (7)$$

where Γ(v+1) is the gamma function and equals v! with integers (Box and Taio 1992). The posterior mean of the failure probability during the 8 months is E($\underline{\pi}$) = (f+1/2)/(v+1) = 77.5/281 = 27.6% and the variance V($\underline{\pi}$) = (f+1/2)(v-f+1/2)/{(v+2)(v+1)^2} (Kendall and Stuart 1977), the latter giving the standard deviation of 2.7%.

In all, the failure risk during an 8 month period follows a Beta distribution (7) with these results when applying (i) the empirical data, (ii) the Poisson process of each ventilator demand (iii) the gamma distribution of the failure rate parameter (iv) compounding the Poisson process and the gamma distribution, and (v) applying the Bayesian methodology in the whole NOKIA SBU. Recall that the original MTBF of 19,272 hours is surprisingly close to the mean above, but the hypothesis that the revised MTBF of 63,265 hours fits the empirical evidence can be rejected using the Beta distribution above with a risk of less than 0.1%. The failure risk distribution is subsequently assumed to follow the Beta distribution (7) with the estimated parameters above, mean of 27.6% and the standard deviation of 2.7%. This result even enables the distribution of the reactive cost C of (1).

3.6 From one ventilator's failure process to the whole NOKIA failure process

Fourth, the HUB failure process of the whole NOKIA SBU will be analysed. Note that the Beta distribution (7) above is that of the failure of any single ventilator. Since each HUB has two ventilators, the service is disrupted only if both of them fail. This means the multiplication of random variables, both of which possess the same Beta distribution above. The multiplication of random variables with Beta distributions is analytically possible only in some special cases (Kendall and Stuart 1977, p. 287).

Here the mixture of binomials is applied (Kendall and Stuart 1977, p. 157). The failure parameter π of both ventilators of a HUB are then distributed in the same Beta form and the failure process of the HUB is a binomial distribution with π the parameter. Now any single HUB with two ventilators is considered. The probability of 0, 1, 2 ventilator failures is that of a Beta-binomial distribution (Kendall and Stuart 1977, p. 157)

$$\Pr\{\text{x ventilators of the HUB fail}\} = \Pr\{x\} = B(f + 0.5 + x, v - f + 2.5 - x) / \{3\, B(x + 1, 3 - x)\, B(f + 0.5, v - f + 0.5)\}, \tag{8}$$

where x = 0, 1, 2 and $B(\cdot,\cdot)$is the beta function. It can be expressed in terms of the gamma function $B(a,b) = \Gamma(a)\ \Gamma(b) / \Gamma(a+b)$. Here, the only relevant combination is the failure of both ventilators and therefore of the HUB. The probability of this specific combination of two failures, x = 2, is

$$\Pr\{\text{the HUB fails}\} = P_h = B(f + 2.5, v - f + 0.5) / \{3\, B(3,1)\, B(f + 0.5, v - f + 0.5\} \tag{8'}$$

Using the case figures v = 280 ventilators and f = 77 failures one obtains the probability of the failure of one HUB as (79 78)/(283 282) = 7.7% .

The failure process of the whole HUB population can be described by the binomial distribution in which the failure probability of each HUB is P_h, here 7.7%, and there are h HUBs altogether x of which will fail. Therewith the number of failures distribution is of the binomial form:

$$\Pr\{\text{x HUBs of h fail}\} = \binom{h}{x} P_h^{\,x} (1 - P_h)^{h-x}\ , \tag{9}$$

with mean $E(\underline{x}) = h\ P_h$ and variance $V(\underline{x}) = h\ P_h\ (1-P_h)$. In this special case with h = 140 and P_h = 7.7%, the general formula (9) results in

$$\Pr\{\text{x HUBs of 140 fail} \mid P_h = 0.077\} = P_x = \binom{140}{x} 0.077^{x}\, 0.923^{140-x} \tag{9'}$$

with mean $E(\underline{x})$ = 10.78 and variance $V(\underline{x})$ = 9.95 ventilators, the standard deviation thus being 3.15 HUBs.

3.7 The reactive cost of down time

An evaluation of the failure risk distribution estimated using the empirical evidence is the key to management decision-making and optimisation. A monetary evaluation is often used as the most important measurement, and sometimes the only one, although it should not be the only criterion. Here costs caused by failures are considered. The cost of down time is the proxy of the reactive costs C_r. It is defined on the annual basis, FIM/year, as a kind of shortage cost by:

$$C_r = F * \{N * B_d * MTTR + B_m * RW + 2 * V\} * 12 \text{ months} \tag{10}$$

F = number of network HUB disruptions (failures) per month
N = number of developers behind one HUB
B_d = burden rate per developer per hour
MTTR = duration of network disruption hours (mean time to repair)
B_m = burden rate per maintenance and repair expert per hour
RW = maintenance and repair work required to fix or change the HUB
V = the price of one ventilator.

Recall that the number F of disruptions per month is a random variable. The mean of F during an 8 month period is 10.78 HUB failures, and the corresponding standard deviation is 3.15 HUB failures. Note that the other figures in Formula (10) are assumed to be constant.

A HUB has 24 ports, and there are typically 22–24 PCs linked to it. Some equipment has only 12 ports, especially in the Campus A unit. In all, calculations are based on the estimate N = 24 developers behind each HUB. Burden rate B_d describes the contribution of a developer, which is obtained from the cost accounting systems at B_d = FIM 350/hour. If the missed opportunities of developers indicate an alternative burden rate for sales, then the turnover divided by the number of personnel and by working hours suggest the burden rate $B_{d'}$ = FIM 750/hour.

The MTTR, the duration of network disruptions, varies from hours to half a day, the last of which is used as the estimate, MTTR = ½ a day = 4 hours. Although MTTR is actually also a random variable, its variation is so small that it can be considered as constant.

The burden rate of the repair person, B_m = FIM 300 / hour, comes from the cost accounting system. The repair work typically lasts less working hours than the whole out-of-service time of the network and is estimated to be RW = 2 hours. The price of a ventilator is FIM 300. When a HUB fails both ventilators are broken, i.e. two units are needed.

In all, the cost of one failure is FIM 34,800, with the burden rate based on a sales-limiting effect of FIM 73,200. The reactive costs of down time is on average FIM 562,716 with a sales-based burden rate of FIM 1,183,644 annually. Note that the interval: mean +/- the standard deviation is (FIM 398,286 and FIM 727,146) and with +/- two standard deviations (FIM 233,856 and FIM 891,576) annually. Whenever the sales-based burden rate is accepted the corresponding intervals are with +/- one standard deviation (FIM 837,774 and FIM 1,529,514) and with +/- two standard deviations (491,904 and 1,875,384).

Recall that the empirical observations confirm the original MTBF of the vendor, 19,272 hours. These results can be considered pessimistic supposing that the vendor’s new revised MTBF of 63,265 hours holds instead of the original.

3.8 The proactive and management costs

The **proactive cost** C_p consist of several types of system administration activities, such as (i) system and service monitoring, (ii) network monitoring, and (iii) preventive corrective actions before troubles appear for the users (called troubleshooting). In NOKIA neither (iv) system backups nor (v) disk space management are affected by the HUB risk consideration. In all, the annual proactive costs, FIM/year, for the whole network management can be calculated as a kind of holding cost using the formula:

$$C_p = B_a * (SM + NM + TS)* 46 \text{ weeks} \qquad (11)$$

B_a = burden rate per system administrator per hour
SM = hours per week spent on system and service monitoring
NM = hours per week spent on network monitoring
TS = hours per week spent on troubleshooting.

The burden rate is, according to the cost control, FIM 300/hour. The corresponding weekly hours altogether in the three business units of NOKIA, are SM = 15, NM = 15 and TS = 10. The weekly proactive cost is FIM 12,000, and the yearly cost C_p = FIM 552,000.

The proxy of **management cost** C_m includes system investment for service and network monitoring. This cost is based on investment calculation for three years. One system (210,000 FIM) costs FIM 70,000 annually. It provides proactive monitoring for 500–1000 end-users. Note that the pros and cons of automated systems have been discussed by Welch (1997) among others.

3.9 The cost of ad hoc actions

The additional preventive actions of network management in NOKIA nowadays consist of general network monitoring such as focused fault anticipation and preventive maintenance actions before potential failure, including preventive maintenance work. The cost component for actions C_a related to and allocated to the HUBs are calculated on a monthly basis

$$C_a = HUB * (NM + FA + SP + PW * POW) \qquad (12)$$

HUB = the number of HUBs
NM = general network monitoring FIM /HUB
FA = focused fault anticipation FIM /HUB
SP = spares and other maintenance facilities FIM / HUB
PW = preventive work hours /HUB
POW = price of the preventive work.

The number of HUBs is 140. The general network monitoring, according to the cost control, is NM = 150 FIM/HUB, focused fault anticipation FA = 50 FIM/HUB, spares SP = 50 FIM/HUB, preventive work required after diagnosis is PW = ½ hour, and PW = 300 FIM/hour.

The monthly action cost C_a total FIM 56,000, and annually FIM 672,000, exceeding the annual proactive cost C_p and the expected reactive cost C_r of the base burden rate case by more than FIM 100,000, but remain below the expected reactive cost of the sales-based burden rate case by more than FIM 500,000.

4 Management policies, IT investments and the factors affected

The reactive, proactive, management and action cost components have been aggregated on an annual basis in each case. Different policies provide their summarised, related annual cost figures. The key requirement is to analyse the total cost as a function of the various background factors affecting the service (cf. Figure 1) applying the ceteris paribus rule, i.e. only one variable is considered at a time.

The basic proactive costs remain constant, with each management policy being kFIM 552 in size in accordance with the traditional NOKIA policy. However, if ad hoc preventive actions have been taken in advance in NOKIA to find and fix possible problems, then the action costs would charge the HUBs at an annual kFIM 672.

In contrast to the deterministic proactive and action costs, the stochastic reactive costs vary according to the risk distribution, which is built on the demand processes of electronic components, Bayesian estimation techniques, and on the empirical failure findings of NOKIA’s three business units. The expected reactive costs would be kFIM 563 if the cost-accounting-based developer’s burden rate is applied, and kFIM 1184 if a burden rate affecting sales is used. The standard deviation is kFIM 165 or as much as kFIM 346 if the burden rate affects the sales.

Comparing reactive and proactive costs, it turns out that the proactive management policy would save money. If a sales-based burden rate is used the costs would cover even systematic additional preventive actions such as semi-annual action. Moreover, the reactive costs could also then cover service and network monitoring investment of kFIM 210. Where only the salary costs of the burden rate are recognised, the investment could be considered, but only if the systematic preventive maintenance actions could be ignored.

Recall that the reactive costs C_r are random. Their distribution has an interval of mean +/- the standard deviation (kFIM 398 and kFIM 727) and mean +/- two standard deviations (kFIM 234 and kFIM 892) at the annual level using the cost-accounting-based developer burden rate. If the developer burden rate affecting sales is accepted, the corresponding intervals are (kFIM 838 and kFIM 1530) and (kFIM 492 and kFIM 1875). The mean of the reactive costs was kFIM 563 in the former burden rate case, and kFIM 1183 in the latter, and the proactive costs kFIM 552. This suggests that a management monitoring investment of kFIM 70 could be considered with the lower burden rate if the mean reactive costs are accepted for decision-making. However, the additional preventive actions, with costs C = kFIM 672, could wait until additional empirical evidence can be obtained from the failures, preferably with different policies in different business units (see Figure 4).

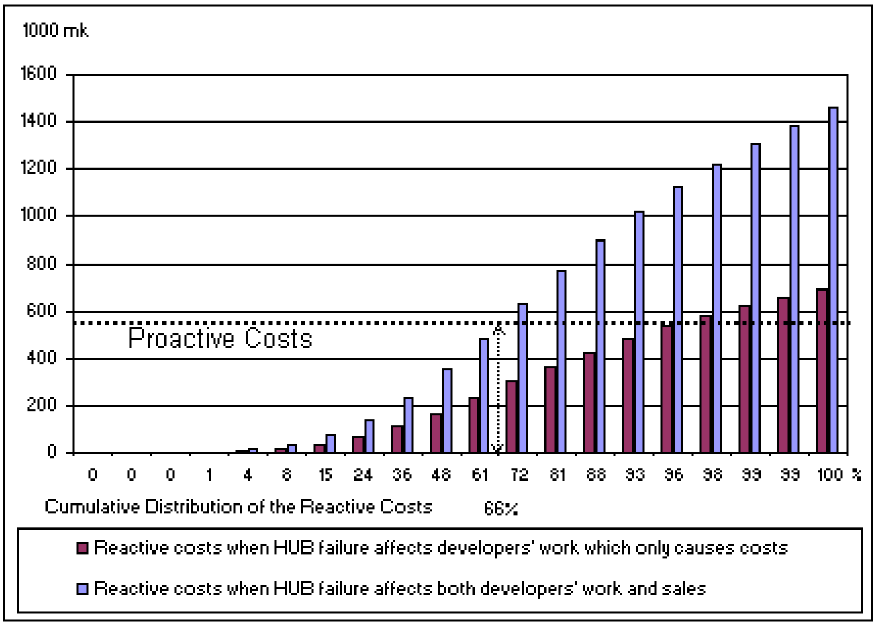

Figure 4. Proactive as against reactive costs

Alternative calculations, with an optimistic revised MTBF of 63,265 hours, are against the monitoring investments. However the original MTBF of 19,272 hours of the vendor is nearly in balance with the empirical failure observations. In all, the economic calculations show that proactive and reactive costs are quite well balanced, supporting even the management monitoring investment, but additive preventive actions are not yet justifiable.

Suppose that SBU and IT management costs were estimated separately for both proactive and reactive policies. Although failures cause management involvement and even crises, one might assume that a proactive policy would necessitate kFIM 50-100 more management cost than the reactive one, which would be seen as the upper limit of cost difference. Even these costs could be covered by the difference between the proactive and the expected reactive costs, but the management monitoring investment would then be questioned.

5 Conclusions and recommendations

The IT investment and factors influencing it were investigated considering both proactive and reactive costs, as well as the influence of additional preventive actions and purchase of a management monitoring device. The essential empirical data was obtained from the failure statistics of three business units of NOKIA Corporation. The real case was managed proactively, however, and the potential losses in productivity could be avoided

The cost of proactivity was small compared to the potential loss caused by reactive policy. When using the developer's burden rate based on sales impact especially, the costs of annual failures were intolerably high. The reactive approach would have caused considerable productivity losses and damage to the business and user satisfaction. Fortunately, the threat was identified in this case; surprisingly though, not as a result of systematic LAN monitoring, but by IS management. Recall that proactivity has even been studied as a personality property (Crant 1996), which might be of help in managing IS departments.

It has been stated that ‘all end-user costs must be identifiable, comparable and assigned directly to the departmental projects or personnel who "drive" the costs' (Hoshower and Verstraete 1989). Moreover, 'today's information service marketplace requires unbiased appraisals of the cost and risk associated with various technologies, and accurate assessment of current operational costs.' The IS management is facing difficulties in allocating reactive costs after failures, but might be authorised to allocate proactive costs to the end-users in the context of the firm’s accounting procedure.

The analysis also emphasises the selective role of proactivity, which should be focused on the areas of the main potential loss. The analysis additionally shows that there is room for management to monitor investments. In practice, investments could be considered only after the HUB management policy was tuned and more failure statistics and cost information gathered.

Recall the maturity stages: start-up (initial nine months), mid-life (nil to 24 months) and maturity (more than 24 months) suggested by Hecht (1994), which contains the notion of a learning process. The results can be generalised in the form that comprehensive problem analysis for finding the root cause is an economical tool both for proactivity and investment planning.

For a practitioner our work reveals the risks of the networked computing environment and the managerial options for making reactive and proactive choices. Our analysis makes the point that significant proactive measures are justified for isolating the business from technical risks. It also becomes clear that active management is required to identify the potential risks in a rapidly changing, complex technical environment.

Summary

This paper has used LAN availability as a case for analysing the balance and differences between reactive and proactive end-user support. The productivity of a knowledge worker depends heavily on the availability of LANs. Lower LAN availability hurts the productivity of the end-users of NOKIA, most of whom are high-level SW development specialists.

Our case material shows that the failure of a LAN component (HUB) caused a decrease in productivity of 34,800 FIM when a cost-accounting-based development specialist hourly cost is applied. If the developer’s inability to work affected sales, the cost of the failure would be FIM 73,200. The failure process of the HUBs was analysed using three different approaches. However, all of them were based on the same known empirical failure behaviour of HUBs, as well as on the so-called posterior Bayesian test and estimation methodology.

The annual reactive cost distribution was estimated at a mean of kFIM 562 and standard deviation of kFIM 164 with cost-accounting-based hourly developer cost, and kFIM 1184 and kFIM 346 respectively, with a sales-limitation-based hourly developer cost. The proactive cost components were analysed both in the basic case and with ad hoc preventive maintenance actions before potential failure. The cost of the proactive basic case was kFIM 552 and that of the additional preventive maintenance actions kFIM 672.

We have analysed the justification for proactive LAN management on the basis of different cost components and options. The conclusion is that proactive support management results in better user productivity and can be considered a sound focus for resources. Moreover, investing HW for network management, such as systems for service and network monitoring (kFIM 210), could be considered when expected reactive costs only are recognised. The pay-back period would then be roughly three years. However, preventive maintenance actions before a potential failure should not be carried out before more precise hourly developer costs and additional empirical failure statistics become available.

In all, the optimal management policy is as follows: a careful proactive policy and fault cause recognition and cost estimate update should be implemented. If the sales limitation hourly developer cost is accepted, even the cost of systematic preventive maintenance actions, e.g. semi-annual action before potential failure are covered by the potential cost caused by the failures with less proactive effort. Moreover, additional ventilators and even an additional HUB in each of the three NOKIA units could be considered as decreasing the mean time to repair (MTTR). Additionally, the network monitoring investment with a three-year pay-back period can be justified by the expected reactive costs where no additional preventive actions are taken.

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