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Improving the Dependability of Existing System via Maintenance

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Abstract

Maintenance consists of several actions which are performed on a given component to improve its dependability and performance, and subsequently that of its overall system. Maintenance policies are advocated for consideration right from the infancy stage of system design. However, existing systems or legacy systems may not have been designed with maintenance in mind. Additionally, the data required to carrying out the improvement analysis of such systems may not be available. Therefore, it is helpful to investigate how the dependability of existing systems could be improved and this is the focus of this paper.

Keywords: *Maintenance, parts count, dependability, failure analysis, expert judgement*

1. Introduction

Dependability is a discipline that comprises of safety, reliability, availability and maintainability [1]. Improving the dependability of a system would imply improving the four attributes. These four attributes are usually interwoven, for instance, when the reliability of a system is improved, the availability and safety of the system are also improved. However, maintainability of the system may not have improved since maintainability is a property of the system. As it is with reliability, maintainability should be built into components right at their design stages since maintainability cannot be easily predicted and a maintainability improvement often requires important changes in layout or construction of the component under consideration [2].When the frequency of failure of a system is reduced, it would suggests that the likelihood of the system failing to cause loss of life, damage to property and environment is also reduced, in which case safety is improved. Similarly, the number of downtime to be experienced by the system throughout its useful life is reduced and hence, availability is improved. Subsequently, the likelihood of successful operation of the system from time t_i to t_j is improved, in which case reliability is improved.

Typically, system reliability is improved via component replication and, or redundancy. For instance consider Figures 1 and 2 which depict a simple case of component replication and redundancy respectively. In both figures, X and Y are components, 'in' and 'out' indicate input and output respectively while S_w and S in Figure 2 represent switch and sensor respectively.

In Figure 1, X and Y could either be same implementations of same component having same failure data or varying implementations of the same component with varying failure data. The same scenario though applies to Figure 2. Under replication, the components (X and Y) are active at the same time and this implies that they both function as the system operates.

Under redundancy as indicated in Figure 2, X and Y do not function at the same time. Component X is functional when the system is operating while Y remains in a waiting

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state and only functions when X has been identified to have failed. The manner in which X is detected to have failed is when the sensor S detects no output from X while the system is operating. The sensor S then activates the switch S_w.

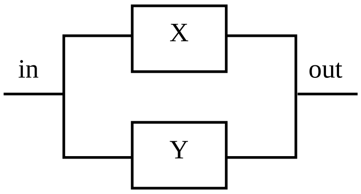

Figure 1. Component Replication

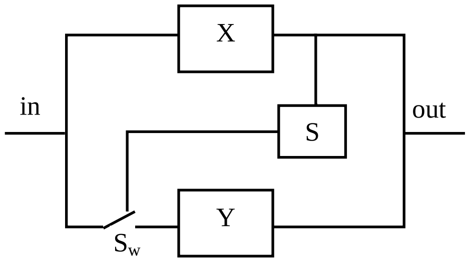

Figure 2. Component Redundancy

The limitations of such architecture are increase in weight and size. Additionally, they also add to the design complexity of the system by increasing the number of components. One of alternative approaches to improving dependability is via maintenance.

Maintenance refers to set of actions taken to retain a system in or restore a system to its operational state when the actions are performed according to prescribed procedures and standards. The term retain refers to keeping the system functional when failure has not occurred. Restore refers to bringing back the system into its functional state after a failure has occurred. The former is referred to as preventive maintenance (PM) while the latter corrective maintenance (CM). In order to get the best performance or reliance out of a system, PM is usually performed periodically. Typically, when a component is maintained its condition is improved. It has been shown by Nggada *et al.*, [3] that maintenance improves (i) the reliability of components and consequently the system, and (ii) the availability of components and consequently the system. Similarly, according to Moghaddam and Usher [4] maintenance activities improve the overall reliability and availability of a system. When maintenance activities are performed on a component, this reduces the occurrence of failure [5] and hence, improves the safety of the system.

The dependability analysis of a system right from its infancy stage through to completion where presumably there is availability of failure data is fairly straightforward. For existing systems such as those that have been procured and are being used in industries where the manufacturer has not provided such data to the client, it becomes a difficult task. Improving the dependability of systems under such scenario is the focus of this paper. Thus, this paper is organised as follows. Preventive maintenance is discussed in Section 2, followed by a discussion on failure data in Section 3. The elicitation of failure data in the absence of its availability is then discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. Preventive Maintenance

Maintenance consists of several activities such as lubricating, adjusting/calibrating the position or load carried to mating parts, tightening loosed parts, cleaning dust, jam and rust, etc [6]. Under preventive maintenance policy, the maintenance actions on a given component are performed at intervals referred to as PM time T_p. This implies that the PM time for all the components may differ. To illustrate this, Figure 3 is a series system with five components; X1..X5. Each of these components has a PM time as arbitrarily represented in Figure 4.

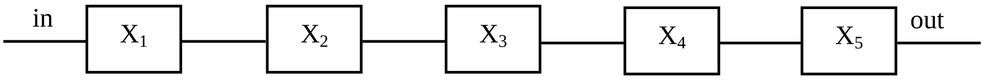

Figure 3. Series System

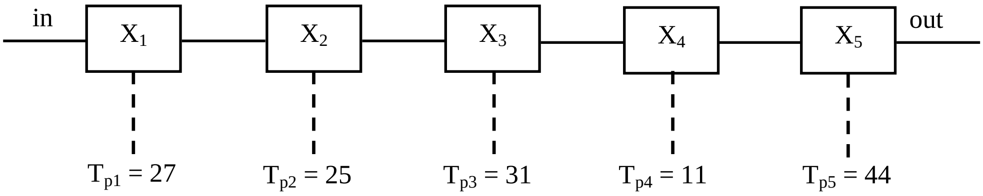

Figure 4. Series System Components and PM Times

PM scheduling (PMS) is represented as follows.

PMS = $\{T_{p1}, T_{p2}, T_{p3}, .., T_{p(m-1)}, T_{pm}\}$

Where: T_{pi} is the PM time for the *i-th* component; i = 1..*m*.

m is the number of components of the system

Hence, the representation of the PM scheduling of Figure 4 is as follows.

PMS = {27, 25, 31, 11, 44}

The PM scheduling above does not follow any defined pattern. Nggada *et al.*, [3] established that the PM time of a component can be expressed as shown in equation 1.

$$T_{pi} = \alpha_i T \quad (1)$$

Where: α_i is the coefficient of maintenance interval (CoMI) for the *i-th* component

T is the system's shortest PM interval

The system's shortest PM interval takes into account the component that fails most often in the system. Hence it is chosen such that it does not exceed (i) the mean time to failure (MTTF) of the component when the maintenance policy is a perfect one, or (ii) the mean time between failures (MTBF) of the component when the maintenance policy is an imperfect one. Under perfect maintenance, the condition of a component is restored to as good-as-new (GAN) while under imperfect maintenance, the condition is improved to a certain degree. However, if the maintenance actions are not carried out properly, the condition of the component could be as bad-as-old (BAO); implying that the maintenance actions had no effect on the component. It is also possible that the condition of the component could be worse-than-old (WTO); implying that the maintenance actions did damage to the component.

According to Nggada *et al.*, [7], the CoMI for the *i-th* component lies between 1 and its maximum CoMI α_{imax}; $1 \leq \alpha_i \leq \alpha_{imax}$. The maximum CoMI is an integer value determined using equation 2 below [7].

$$\alpha_{imax} = \begin{cases} Q\left(\frac{AFT_i}{T}\right) & ; \; AFT_i \leq RT \\ Q\left(\frac{RT}{T}\right) & ; \; AFT_i > RT \end{cases} \tag{2}$$

Where: Q is the integer quotient of the division

RT is the system risk time, also referred to as useful life

AFT_i is the average failure time for the *i-th* component

The average failure time as seen in equation 2 is defined as follows.

$$AFT_i = \begin{cases} MTTF_i & ; \; if \; under \; perfect \; maintenance \; policy \\ MTBF_i & ; \; if \; under \; imperfect \; maintenance \; policy \end{cases} \tag{3}$$

Assuming the system's shortest PM interval is 10 (T = 10), then Figure 5 illustrates the PM times of the series system.

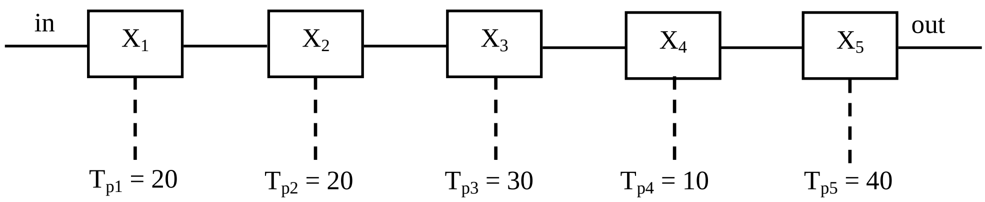

Figure 5. Comi Based System Components PM Time

The PM scheduling follows a particular pattern in line with equation 1 and could be represented in terms of CoMI as shown below since T is a constant.

PMS = {2, 2, 3, 1, 4}

As mentioned earlier, one of challenges of existing systems is the availability of failure data especially the MTTF or MTBF. Hence, it is difficult to stochastically determine the CoMI and consequently the PM time as illustrated by Nggada *et al.*, [7]. In respect of this, there is need to investigate the elicitation of failure data in the absence of one. Therefore, the next section discusses failure data.

3. Failure Data

A system model is the design representation of an actual system and therefore, analysis performed on the model would be applicable to the actual system. The design would consist of components and sub-systems or even sub-sub-systems. A detailed design would consist of broken-down sub-systems design into their constituent components. A complex system would usually consist of either several sub-systems or numerous components, or both. To analyse the system model for one or more of dependability attributes such as reliability, availability, safety or maintainability, the model is augmented with failure data [8]. Additional requirements to the analysis may also suggest cost analysis such as those illustrated by Nggada *et al.*, [7] in optimising preventive maintenance schedules and architecture. Thus, in this case the failure data would also include cost.

Typically the failure data of a component whose dependability is to be improved via maintenance would consist of the following.

- Cost of the component when it was new
- Cost of performing maintenance actions on the component – this could include cost of repair or cost of replacement as appropriate.
- Mean time to failure (MTTF) – for non-repairable component
- Mean time between failures (MTBF) – for repairable component

More failure attributes could be added to those enumerated above depending on requirements. The above are generic to maintenance problem. Other maintenance parameters are usually derived from the MTTF or MTBF. However, none of these may be available especially for existing systems.

If the dependability attribute of the overall system is to be evaluated through synthesised fault tree which is supported by HiP-HOPS [9] then each component will have logical expression of failure behaviour. HiP-HOPS defines a language for the description of failure behaviour at component level, and in its basic version the failure behaviour is specified as a list of internal failure modes of the component and a list of deviations of parameters as they can be observed at component outputs [3]. HiP-HOPS is a state-of-the-art compositional system dependability analysis technique and offers a significant degree of automation [10]. It was first developed by Papadopoulos and McDermid [9].

4. Elicitation of Failure Data

In the absence of available data or complete data regarding the MTTF or MTBF of the components of a system, there are methods that could be used to determine such data. Although this may not be an exact figure to the actual MTTF and, or MTBF it provides an approximation with which the engineer could use to evaluate the system.

4.1. Parts Count Prediction Method

Under certain circumstances there may be available data that could be used to estimate the required and missing data. One of such methods which could be adopted to improving the dependability of existing systems is parts count prediction method. The parts count method assumes the time to failure of the parts (components) is exponentially distributed [11]. This method is useful when the engineer is aware of the (actual or estimated) number of components in the system and their types. A component type provides a generic type of function. Components which are designed to generically provide same function are categorised under the same type.

The parts count prediction method is used to approximate the failure rate of a system. Failure rate is defined in terms of MTTF or MTBF. Failure rate is the inverse of MTTF or MTBF as appropriate. The technique used is to multiply the number of components in each component type by the generic failure rate of the component type. The individual products are then summed to give the approximate failure rate of the system. This value can then be used in performing other evaluations of the system. The general model used for this method as expressed in MIL-HDBK-338B [11] is shown in equation 4 below.

$$\lambda_s = \sum_{i=1}^{n} N_i(\lambda_{Gi}\pi_{Qi}) \tag{4}$$

Where: λ_s is the approximated system failure rate.

n is the number of component types.

N_i is the number of components for the *i-th* component type.

λ_{Gi} is the generic failure rate for the *i-th* component type.

π_{Qi} is the quality factor for the *i-th* component type.

The quality factor refers to the level of function or performance that the component can still provide. The quality factor data could be assumed or predicted by the engineer if it does not exist. However, the generic failure rate for a component type and the quality factor data could be obtained from manufacturer's data [11].

Certain portions of the parts count method prediction could be applied in the approximation of the average failure time (AFT) of a component. This is illustrated in equation 5.

$$AFT_i = \frac{1}{\lambda_{Gi}\pi_{Qi}} \tag{5}$$

Where: AFT_i is same as stated in equation 2; the average failure time for the *i-th* component

4.2. Expert Judgement

The parts count prediction method uses trace of data such as the generic failure rate of component type to predict AFT. Under certain scenarios, there may be complete lack of trace of any form of failure data. The elicitation of the failure data then becomes more challenging and in general expert judgement is employed. The role which the expert plays is to subjectively suggest the MTTF or MTBF of the component informed by knowledge and experience about the component. If there is certainty regarding the opinion of a single expert then there is no need to seek for further experts' opinion. However, in most cases opinions will be sought from several experts. In such cases, the different opinions are aggregated (or combined) to give the final value. There are existing approaches that are used to aggregate opinions from several experts, such as linear opinion approach [12], logarithmic opinion pool [13], and Bayesian approach [14, 15]. The linear opinion pool is investigated in this paper, from which its applicability in preventive maintenance is modeled.

4.2.1. Linear Opinion Pool: Most of the solutions to the aggregation problem require that each individual's opinion be encoded as a subjective probability distribution [12]. Subjective probability distribution is also referred to as subjective probability measure. Such individual probability measures are then combined into a single probability measure. One of ways to achieving this is through linear opinion pool. Assuming k subjective probability measures P_1, P_2, .., P_k, equation 5 is a model which could be used to combine such subjective opinions [12, 13].

$$P(\theta) = \sum_{j=1}^{k} w_j P_j \tag{6}$$

Where: θ is a vector of subjective probability measures; $\theta = (P_1, P_2, .., P_{k-1}, P_k)$.

$P(\theta)$ is the combined (aggregated) probability measure.

k is the number of experts; implying the number of subjective probability measures.

P_j is the *j-th* subjective probability measure from the *j-th* expert.

w_j is the relative quality of the *j-th* subjective probability measure.

It could be observed that the linear opinion pool is a weighted linear combination of the experts' subjective probability measures and as such it is easily understood and calculated [13]. The source of information consulted by the expert is one of parameters which could influence the value of the weight. Another factor is the level of knowledge and experience of the expert. However, the total weight must be equal to one as illustrated in equation 6 [12]. There is currently no suggestion in literature that a weight cannot have a negative value if need be.

$$\sum_{j=1}^{k} w_j = 1 \tag{6}$$

The approach of combining expert judgements as illustrated in equation 5 could be applied in the elicitation of the AFT (MTTF or MTBF) of a component from where its PM time could be derived. Therefore, in terms of preventive maintenance, equation 5 could be adopted as shown in equation 7.

$$AFT = \sum_{j=1}^{k} w_j AFT_j \tag{7}$$

Where: AFT_j is the average failure time (MTTF or MTBF) specified by the *j-th* expert.

$0 < w_j < 1;\ j > 1$ and equation 6 applies.

However, estimating the quality level in terms of percentage is much easier than picking a value between 0 and 1. Hence, the level of quality for each expert's subjective probability measure can be specified in percentage while a model that converts it into its equivalent value between 0 and 1 is applied. This is modeled as follows.

Let P_j be the percentage quality level of expert j.

Let S_p be the total sum of the percentage qualities from k experts.

Then:

$$S_p = \sum_{j=1}^{k} P_j \tag{8}$$

The quality level for each expert can then be calculated as follows.

$$w_j = \frac{P_j}{S_p} \tag{9}$$

The linear opinion pool's modeling as it relates to preventive maintenance is a bit more complicated than the parts count analysis. Therefore, Table 1 demonstrates using arbitrary values how the linear opinion pool works as applied to preventive maintenance time. It consists of 6 experts each with his or her own subjective AFT. The expert combining the experts' opinions then provides the percentage quality level for each expert opinion. Equation 8 is used to obtain the total sum of the percentage quality level S_p; giving 486 as shown in the table. Equation 9 is then used to obtain the quality level for each expert w_j, the summation of these gives 1 as desired. The combined subjective AFT is then evaluated using equation 7; giving 450.1282051 time units as shown in the table.

Table 1. PM Time Elicitation from Linear Opinion Pool

Expert *j* (*j* = 1..6)	1	2	3	4	5	6	**Total**
Subjective AFT_j	300	500	400	450	520	470	2640
Percentage Quality Level P_j	60	90	70	75	92	81	468
Quality level w_j	0.12821	0.19231	0.14957	0.16026	0.19658	0.17308	1
Aggregated $(w_j AFT_j)$	38.4615	96.1538	59.8291	72.1154	102.222	81.3462	450.128205

Although the values used are arbitrary, the evaluations suggest the validity of the approach and the models. Hence, the approach could be used for the elicitation of component average failure times which could then be used in analysis to improve the dependability of a system.

5. Conclusions

The unavailability of failure data especially the average failure time (mean time to failure – MTTF or mean time between failures - MTBF) is a challenge in the dependability analysis of a system. In preventive maintenance the MTTF or MTBF could be used in determining the preventive maintenance (PM) time of a given component. Such PM time is then used in analysing system requirements.

This paper has investigated existing approaches through which expert opinion is used in the elicitation of missing data. In particular, parts count analysis and linear opinion pool were investigated, and models as applicable in preventive maintenance were developed. The model developed using the approach of parts count analysis is straightforward. However, the one developed based on linear opinion pool approach is a bit more complicated, and its evaluation suggested its validity and applicability in preventive maintenance.

Further work is required in the following areas.

- Inclusion of several expert opinions in the parts count analysis approach
- Investigation of the applicability of Bayesian approach in the elicitation of failure data

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