

Recognizing Significant Human-Related Factors Affecting System Reliability

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System reliability can be affected by many factors, some of which are not machine-related. An important category of these non-traditional factors are human-related (HR) factors, such as expertise, collaboration, and motivation. Operational systems consist of machinery as well as human operators and decision makers. Therefore, a risk analysis is incomplete if the probability of human error is not considered. The paper discusses a method for recognizing human-related factors affecting the system reliability and evaluating their impact. Factors are analyzed to determine their significance. The insignificant ones are then eliminated. Various Human Reliability Analysis (HRA) techniques have been developed in order to identify factors that influence human and system reliability. Among the many HRA techniques developed for various applications, this paper uses Cognitive Reliability and Error Analysis Method (CREAM) due to its cognition approach for identifying the factors affecting human reliability. Once identified, factors are utilized in the Proportional Hazards Model (PHM), a well-known failure prediction and reliability analysis model. The inclusion of HR factors will expand the traditional focus of PHM, thus making it an all-encompassing approach.

Keywords: Human Reliability Analysis (HRA), Proportional Hazard Model (PHM), Maintenance, Reliability Optimization.

1. INTRODUCTION

A Reliability expert who disregards the role of the human in the overall failure risk of a system exaggerates the role of machine-related failure modes in the overall unreliability of the system. This is quite common and, consequently, identical machines used across various sites may exhibit varying reliabilities. The skill level, motivation, work place politics, and many other intangible factors play a role that should be taken into account when devising reliability estimates and maintenance strategies.

There is quite a strong desire to provide a coherent strategy to maximize human performance and to minimize human error in every working context. Accident analysis forecasting techniques and Human Reliability Analysis (HRA) methodologies are doing so in complex systems with hazardous operations (Cacciabue, 2000), such as nuclear power stations (Swain and Guttman, 1983) and petrochemical processes (OGP, 2002) as well as in railway transports (Cacciabue, 2005) and aviation maintenance (Chang and Wang, 2009) but can be both onerous and time demanding.

The main goal of this paper is to discuss the integration of significant human-related (HR) factors into maintenance optimization models. One strategy under maintenance optimization is condition-based maintenance. In this strategy, the objective is to gain the maximum useful life of the machine and all its components. On the one hand, the components should not be replaced too soon because that would not be economical. On the other hand, the machine should not be stopped too late because unplanned downtime may be quite costly. These two conditions are contradictory and one needs to balance the two against each other in order to predict the perfect replacement time. One approach to estimate the failure time of any given equipment is the Proportional Hazards Model (PHM). The PHM is a method that relates the time of an event, such as failure or breakdown, to a number of explanatory variables known as covariates (Vlok et al, 2002). From a maintenance point of view, the idea behind the PHM is that obvious and/or hypothetical factors, including the equipment age, may act as reliability criteria that influence the hazard rate of the equipment. The hazard rate is the rate of transition out of the non-failed state to a failed

state. The optimal hazard rate as a threshold, or the optimal risk level, is calculated based on the cost of preventive replacement and the cost of machine failure, along with a model for considering the covariates. When the hazard rate exceeds this pre-determined threshold, it acts as an alarm to the maintenance decision maker to take proactive steps as there is a high probability of a functional failure.

The hazard rate can be affected by factors specific to the machine or by factors that are related to the environment or the human decision makers within the man-machine system. Traditionally, PHM has always been used with quantifiable covariates that are machine-related. However, this usage can be expanded to enlarge the scope of PHM by including non-machine-related factors (Kiassat and Safaei, 2009). This is the essence of Human Reliability Analysis (HRA) where the knowledge of the human involved with the system may play a deciding factor between the survival and the failure of two otherwise identical machines. This may be especially true in the case of new machinery where operator unfamiliarity plays a larger role in failure frequency compared to the machine degradation. If HR failures are not taken into account in the early stages, the major contributor to the total failure frequency is mistakenly assumed to be machine-related (MR). This may lead to a waste of resources in a maintenance optimization strategy.

The human characteristics that may normally be considered as intangible, or qualitative, can be captured through HRA methods to be turned into quantitative data. They can then get integrated with the overall PHM for the purpose of predicting the risk of failure. If asset managers can make more informed maintenance-related decisions, the operating cost of the organization can be directly affected. The PHM, along with a model for the covariates, is an appropriate tool to predict the failure time of the system under the condition-based maintenance (CBM) policy (Jardine and Banjevic, 2005). The general form of the Weibull PHM is as follows:

$$h(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} \exp\{\gamma_1 z_1(t) + \dots + \gamma_n z_n(t)\} \quad (1)$$

The first part of the equation is a baseline hazard function, sensitive to the age of the equipment. The individual z_i 's are covariates that are supposed to affect the overall hazard. As pointed out earlier, in an all-encompassing analysis, some z_i 's will be MR, while others may be HR. We will investigate which HR covariates affect the hazard rate of a given system. Eventually, we will also look at how they would affect the covariates. A hypothetical case study of a manufacturing company, Alpha, is created in order to demonstrate the entire process of modeling and using an enhanced PHM.

Research has been conducted on the role of Human Reliability in maintenance activities and various approaches for incorporating it into maintenance strategies. Some of the related research, such as Barroso and Wilson (1999), has been conducted in manufacturing environments where the context is similar in focusing on estimating the overall effect of human unreliability in a manufacturing environment. However, the approach used in that paper is not based on PHM. Other papers, such as Blanks (2007), discuss the need for improving reliability prediction, with special attention to human error causes and prevention. However, there are no mentions of PHM or any predictive techniques for human reliability. There are also other papers, such as Zimolong and Trimpop (1994), and Dhillon and Liu (2006) that focus on the maintenance workforce performing repair work while the machine is not being used for production purposes. There is a main difference among the aforementioned papers and the discussions in this paper. In the context of maintenance optimization, the enhanced usage of PHM by integrating HR factors as covariates distinguishes our paper from previous research.

2. FACTORS INFLUENCING HUMAN RELIABILITY AND PERFORMANCE

In modeling human performance for probability risk analysis, it is necessary to consider those factors that have the most critical effect on performance. Many factors influence human performance in a complex man-machine system such as the industrial context (Cacciabue, 2000). These factors can be both internal and external to the human decision maker. A global view of these factors must include a wide range such as:

- 1) The human characteristics, such as physical, psychological and mental conditions, stress and fatigue levels,
- 2) Working environment and the equipment state, such as operational conditions, design, maintenance, availability and reliability of equipment, and
- 3) Managerial and organizational factors, including the safety culture and policy, management commitment, procedures and training, risk assessment, and incident analysis. Important factors are also the ones that are influenced by the cultural environment like the national culture and the societal values.

To perform an HRA, an analyst must identify those factors that are the most relevant and influential in the jobs studied. CREAM methodology (Hollnagel, 1998) uses a group of factors named Common Performance Conditions (CPC) to define sets of possible error modes and probable error causes. The CPC's provide a comprehensive and well-structured basis for characterizing the conditions under which the performance is expected to take place. These CPC's are briefly presented hereunder:

Adequacy of organization: Defines the quality of the roles and responsibilities of team members, additional support, organization communication systems, safety management system, instructions and guidelines for externally oriented activities, role of external agencies.

Working conditions: Describes the nature of the physical working conditions such as ambient lighting, glare on conditions screens, noise from alarms, interruptions from the task.

Adequacy of Man-Machine Interface (MMI) and operational support: Defines the MMI in general, including the information available on MMI and control panels, computerized workstations, and operational support provided by operational specifically designed decision aids.

Availability of procedures and plans: Describes procedures and plans and includes operating and emergency procedures, familiar patterns of response heuristics, routines.

Number of simultaneous goals: Enumerates the number of tasks a person is required to pursue or attend to at the same time (i.e., evaluating the effects of actions, sampling new information, assessing multiple goals).

Available time: Depicts the time available to carry out a task and corresponds to how well the task execution is synchronized to the process dynamics.

Time of day: Denotes the time of day (or night) and describes the time at which the task is carried out, in particular whether or not the person is adjusted to the current time (circadian rhythm). Typical examples are the effects of shift work. It is a well-established fact that the time of day has an effect on the quality of work, and that performance is less efficient if the normal circadian rhythm is disrupted.

Adequacy of training and experience: Describes the level and quality of training provided to operators as familiarization to new technology, refreshing old skills, etc. It also refers to the level of operational experience.

Crew collaboration quality: Declares the quality of the collaboration between crewmembers, including the overlap between the official and unofficial structure, the level of trust, and the general social climate among crewmembers.

3. SCENARIO DESCRIPTION

In order to better describe the process of integrating HR factors into an existing condition-based program that only considers MR factors, a hypothetical scenario is described. Alpha is a machining department producing high-precision parts. There are 15 machines in Alpha, running in series. Eight of these machines are made by the same machine manufacturer, Beta, and are quite similar. Due to the extremely high precision of the product, Beta machines are complex and sensitive. There is a much higher occurrence of unplanned breakdowns related to the Beta machines compared to the other machines. The Mean Time Between Failures (MTBF) of the Beta machines is low and the Mean Time To Repair (MTTR) is high.

The maintenance manager has put an emphasis on the Beta machines by starting a condition-based maintenance program in the form of oil and vibration analysis. Oil samples and vibration readings are taken once every week. In addition to the regular, age-based data being collected, oil and vibration analysis data has been collected from all eight of the Beta machines over the last few months. The necessary analysis has been performed and a proportional Hazards Model (PHM) has been developed. In this model, in addition to the working age of each machine, certain metal contents in the machine oil, as well as a vibration reading on a certain bearing are used as covariates. He employs a policy of simple interval-based preventive maintenance on the other machines. He has asked each of his shift supervisors to use the PHM on their first shift of the week for each of the Beta machines. The purpose of the usage of the PHM is to determine the failure risk of the Beta machine for the upcoming week based on the latest information. Each supervisor is obligated to capture all shift events in the Computerized Maintenance Management System (CMMS). All downtimes are noted along with durations, causes, and remedies.

The department's regular operation is three shifts per day, around the clock. As a result of the current high demand, and the inefficiencies within the system, the department runs frequent overtime shifts on the weekends. It is a new department currently running at full capacity after only a quick ramp-up period. Consequently, there is much strain on the system. This strain affects the system in terms of the equipment, maintenance activities, and human resources.

The maintenance manager is recently becoming aware that non-machine related factors can play a major role in the equipment MTBF and MTTR. He is losing confidence with the PHM currently in use as it is not predicting failures accurately.

In addition, there have been numerous cases where the PHM has called for machine stoppage and immediate preventive maintenance. However, all components replaced have looked almost brand new after removal from the machine.

He has made several observations that are not related to the machines. There seems to be a significant shift-to-shift difference in terms of production counts and the frequency and duration of machine failures. In addition, he knows there are some operators that can operate the machines much better than others. These operators are more in-tune with the machine and can detect abnormalities through sound and/or part measurements. He notices the lower occurrence of breakdowns when certain operators are working. There is one operator assigned to each of the beta machines. These operators have varying skill levels, ranging from novice to excellent. Some are very well motivated and are dedicated to their jobs. However, there are a few that will just do the bare minimum requirement. Lastly, there have been some training programs in the past for both the machine operators as well as the maintenance tradesmen. The maintenance manager has noticed that the MTBF and MTTR have been positively affected after these training programs.

The highlights of the above scenario and the possible effects of these points on this paper are summarized in Table 1.

Detail	Effect on the Case
Total 15 machines, 8 are Beta machines, almost identical. Most unplanned maintenance due to Beta machines.	Condition-based maintenance focuses on ‘family’ of Beta machines.
PHM currently in use, all 3 covariates are machine-related (iron and lead content in oil, and vibration readings on the main axis bearing).	Company is sophisticated and knowledgeable to have PHM as a tool in maintenance optimization decision making. May be enhanced by the possibility of adding HR factors.
Shift supervisors keep detailed logs on CMMS on all downtimes encountered, including causes, remedies, and durations.	The necessary data is collected and stored for possibly enhancing PHM to include additional covariates.
Oil analysis and vibration readings are performed once per week on each of the Beta machines. Each machine’s readings are plugged into the general PHM equation and analyzed for each machine on the first shift of each week.	Relatively short time-horizon of decision making using PHM.
PHM is not working well for predictive purposes. Failures have occurred when hazard rate was calculated to be low. There have also been cases where hazard rate was high and the machine was stopped. However, components replaced looked new.	Current usage of PHM is not yielding satisfactory results. It needs to be enhanced by adding factors not yet considered.
Department runs Monday to Friday, on three shifts, around the clock.	Operators on the off-shifts may experience inefficiencies due to disruptions on their Circadian rhythms.
Operators are assigned to each machine and this assignment is long term.	As time goes on, operators gain specific experience on their assigned machines. This may also produce a negative effect due to boredom and repeatability of tasks.
There are many overtime shift scheduled on the weekends.	Element of fatigue is likely. Possible decrease in motivation also if the weekend work is repeated frequently with no significant remuneration.
There seems to be a significant shift-to-shift difference in output, frequency, and duration of failures. There seems to be a wide range in skill level among the operators. There seems to be a difference among the operators in terms of motivation to perform high-quality work.	The highly skilled operators are more in-tune with the machines. They can detect abnormal conditions by the sound the machine is making or trends in product quality. Possibility of consideration for additional covariates.
After some training programs in the past, performance has improved and breakdowns have decreased.	Operator skill has a direct relationship on MTBF and MTTR.

Table 1: Summary of points of the hypothetical case

4. INCLUSION OF NEW COVARIATES

Data has been collected for every shift since the start of production. The data is captured in shift logs in the CMMS. Production volumes as well as planned and unplanned maintenance activities are captured in these shift logs. Table 2 is a typical maintenance shift log. Production shift logs are also kept which look very similar to the maintenance log shown but explain the shortfall of actual to forecasted volume.

Date	Shift	Total Planned Downtime (min)	Total Unplanned Downtime (min)	Total Unplanned Downtime from Beta Machines (min)	Operator	Machine issues	Duration	Operator Issues	Duration	
May 3, 10	D	30	90	85						
				Beta 1	10	John	Alignment sensor bent	10	-	-
				Beta 2	10	Bill	-	-	Out of sequence	10
				Beta 3	15	Chris	-	-	Part out of tolerance	15
				Beta 4	10	Tom	-	-	Part out of tolerance	10
				Beta 5	35	George	Overheat alarm	25	Reset button not pressed	10
				Beta 6	20	Joe	-	-	Wrong set-up at tool change	20
				Beta 7	0	Paul	-	-	-	-
				Beta 8	10	Jessica	-	-	Start button not pressed after break	10

Table 2: A Typical Maintenance Shift Log

In addition to the shift logs, results of the weekly oil and vibration analysis are also kept for each machine. Based on the historical data and failure times, a PHM has been developed for the Beta machines. The PHM in current practice only includes MR factors. This is the current model:

$$h_1(t) = \frac{\beta_1}{\eta_1} \left(\frac{t}{\eta_1} \right)^{\beta_1 - 1} \exp \left[\gamma_{11} Z_1(t) + \gamma_{12} Z_2(t) + \gamma_{13} Z_3(t) \right],$$

where in addition to the characteristics included in the baseline hazard, there are three MR covariates included in the model. These are the concentration of iron and lead in the machine oil, and the vibration reading of the main axis bearing. Time is measured in hours.

The maintenance manager wants the PHM to be re-evaluated for possible enhancement. He would ask for input from the system experts for an initial list of additional factors that affect Beta machine failures. He is considering the possibility of including Human-related factors to the model.

In order to possibly enhance the PHM by including human related factors as mentioned above, we need a way to identify those factors, to determine their significance and to objectively measure them. By using CREAM with its nine CPC families as presented in section 2, we can focus more on the plant-related and people-related factors. The process continues with the use of the taxonomy of Kim and Jung (2003). This work aids the analyst in the recognition of important parameters that should be taken into account in each CPC category. The taxonomy of Kim and Jung allows the analyst to take into account all the possible Performance Shaping Factors known from the literature and to combine them into a single and global list.

After the completion of the process, three additional very specific and human-related factors are identified that may play a significant role in the reliability of the Beta machines. These factors are:

1. Machine operator expertise: This is the ability of the operator to detect anomalies early and act to remedy them. The system experts have been called on to place the operators into skill categories.

2. Shift: Once again, this may affect the ability of the operator to detect anomalies and their action to remedy or call the proper maintenance tradesman. Disrupted circadian rhythm on off-shifts may negatively affect detection or action abilities.
3. Day of the week: The operators work five eight-hour shifts during the weekdays. They are also asked to come in on many weekends on overtime shifts to make up the demand shortfall. Fatigue may get accumulated and have a negative effect on performance.

The following table summarizes the process and the effort required to identify these factors:

CPC from CREAM	Sub items according to Kim and Jung (2003)	Specific factors related to case-study
Adequacy of training and experience	Adequacy of training	Adequate on the job training
	Experiences/practices of real operating events	Troubleshooting of real events
	Learning of past events/experiences	
	Career of operators	Years of experience
Time of the day	Day of the Week	Weekdays and weekends
	Shift Time	Morning / Afternoon /Late

Table 3: Items and sub-items used to identify human-related factors

The determination of significance and possible ways of quantifying the human related factors are presented in the following section.

4. QUANTIFICATION OF FACTORS

Two of the three factors under analysis, Shift Time and Day of the Week, are related and the same methodology, the Fatigue Index, may be used for their quantification. The third one, Operator Expertise, will be quantified using expert knowledge.

4.1 Shift Time and Day of the Week

These two factors may affect the ability of the operator to detect anomalies. They can also affect their troubleshooting activities or to call the proper maintenance tradesman. Disrupted circadian rhythm may negatively affect detection or action abilities. Whether the operator is rested after a relaxing weekend or if he/she has been working for 20 days straight, with plenty of overtime and no rest day in between, makes an impact on his performance and the risk of error. In addition, the operator working on the night shift and having a disrupted circadian rhythm also impacts the performance and the risk of error.

For the analysis of operator fatigue, the work done by HSE (2006) is referenced. There is a method of assessing the risk arising from fatigue associated with work patterns and this methodology involves the calculation of a Fatigue Index. This index includes five factors associated with the development of fatigue, namely: time of day, shift duration, number of rest days, quality of breaks, and cumulative fatigue. The scores from each of these factors are summed to provide an overall index for the pattern of work.

The final form of the Fatigue Index is given by the following equation:

$$FI = 100 \{1 - (1-C) (1-J-T)\},$$

- C is the cumulative fatigue component, with values based on trends from large studies.
- T is the duty timing component. This component is calculated by multiplying the risks associated with two individual factors, namely the time of day and the length of the shift.
- J is the job type / breaks component. It captures the increase in risk as a function of the time since the last break.

In this formula, C, J and T correspond to probabilities and therefore take values between 0 and 1.

4.2 Operator Expertise

This is the ability of the operator to detect anomalies early and to act to remedy them. There may be cases where the troubleshooting is beyond his capabilities. But the early recognition of the issue based on machine sound, vibration, or part quality may result in more economical reaction by the maintenance tradesman. This can be in the form of less component replacements and/or keeping the machine down for a shorter duration.

A group of system experts intimately familiar with the man-machine system are used for the skill classification. This group consists of Manufacturing Engineers, shift supervisors, and some outstanding machine operators. The system experts have classified the operators into four skill categories, namely Novice, Acceptable, Good, and Excellent. The classification is done based on subjective evaluations of the individuals by the experts. The shift logs are consulted and data is used wherever possible to support opinions provided by the experts. The operators are evaluated based on the following criteria, in conjunction with the years of operational experience they have and the number of hours spent on specific on-the-job training:

1. Production volume per shift by the individual over a one-month period.
2. Trouble shooting time and the application of knowledge when the machine has a fault.
3. Number of scrap parts produced during set-up, tool change, or regular production.
4. Number of errors made during set-up, tool change, part measurement, and machine operation.

As a first step though, the system experts assign a score to each operator based on the above four criteria. This is an ordinal score, ranging from 1 to 4, corresponding to Novice, Acceptable, Good, and Excellent.

4.3 Effects on Human Reliability

Despite the definition of the influencing factors, there is still the unresolved issue of how to measure the induced changes in human and therefore system reliability from adjustments in the aforementioned parameters. Naturally, optimizing the input parameters will lead to the optimization of human reliability and performance. However, this cannot always be achieved practically or in some cases the improvement of human reliability does not rationalize the high costs of such adjustments. Consequently, the decision maker needs to be able to identify the critical and necessary improvements in the influencing parameters, as well as to measure the effect of these improvements, upon human reliability and performance.

A model has been previously developed to calculate human error probabilities in specific working contexts. As an operator becomes more skilled and as the working environment is more conducive to good performance, the error probability is reduced. A specific application of a model on calculating human error probability is presented in the paper by Konstandinidou et al (2007). The model has been used in order to define the critical transitions in the influencing factors of human reliability. In order to evaluate the combined effect of multiple influencing factors in HRA this model can be used. The model may help us identify, and subsequently work on, improvements that lead to significant reductions in human error probability. The results of the application of the model can help introduce the new covariate values into the PHM.

5. REVISED PHM AND USAGE

The analysis for the inclusion of the HR factors is performed. The maximum likelihood method to determine the covariate coefficients is applied, as discussed by Vlok et al (2002). As a result, the previous model is updated to the following:

$$h_2(t) = \frac{\beta_2}{\eta_2} \left(\frac{t}{\eta_2} \right)^{\beta_2 - 1} \exp \left[\gamma_{21} Z_1(t) + \gamma_{22} Z_2(t) + \gamma_{23} Z_3(t) + \gamma_{24} Z_4(t) + \gamma_{25} Z_5(t) \right], \text{ where the two additional}$$

$Z_k(t)$'s are variables representing operator skill and operator fatigue. Operator fatigue consists of "Shift Time" and "Day of the Week". It should be noted that it is not always the case that all candidate covariates eventually get included in the PHM. In some cases, after the data analysis, the coefficient for a covariate may not be found to be significantly different from zero. This will signify the covariate to not have a significant impact on the hazard rate.

In this particular case, the PHM is used on a weekly basis to calculate the hazard rate for the upcoming week. This is a relatively short period of time and significant changes in the individual covariates are unlikely in this relatively short duration. Therefore, the PHM can be used on its own to supply the hazard rate for predictive purposes. However, if the decision maker decides to use this model for predictions over the longer term, this model will not be sufficient on its own. As Vlok et al (2002) have discussed, it would be necessary to predict the behaviour of the covariates using transition probabilities. The PHM can be combined with a Markov process to predict the future state of covariates and failure times.

5. CONCLUSION

In this paper, the impact of human reliability is discussed along with a possible method to identify the significant factors and integrate them into a maintenance optimization model. If there are significant human-related factors present in the man-

machine system that can affect machine reliability, the lack of consideration for these factors in a maintenance optimization strategy will significantly reduce the effectiveness of the strategy utilized.

A maintenance manager may utilize the proportional hazards model for condition-based maintenance decision-making. In cases where significant HR factors exist, the PHM will only be complete if the covariates consist of both types of machine-related, as well as human-related factors affecting machine reliability. Human reliability analysis techniques are utilized to identify the significant HR factors. In this paper, CREAM has been used to assess the various possible HR factors in a hypothetical case study. Once the significant factors are identified, they can be integrated into the PHM which had originally only included MR factors. The enhancement of the PHM enables the maintenance manager to make more accurate decisions on preventive maintenance. The improved predictions of maintenance decisions result in financial gain for the company which is the ultimate goal of any physical asset manager.

The future work stemming from this paper may include other factors not considered here. One important such factor may be employee motivation which requires more sophisticated methods to turn into concrete measurements. In addition, the detailed methods for the actual quantification of the factors for inclusion into mathematical models remain as future work. An actual case study must be referred to in order to use real data to clearly show the various steps required to integrate HR factors into an existing PHM.

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