CHAPTER 6

CLOSURE

6.1 Overview

At present, there is a world-wide drive to optimize maintenance decisions in an increasingly competitive manufacturing industry. Preventive maintenance is often the most organized and cost efficient strategy to follow, but a decision still has to be made on the optimal instant to perform preventive maintenance. Use based preventive maintenance decisions have been optimized through statistical analysis of failure data while predictive preventive maintenance (condition monitoring) has been optimized by utilizing more sophisticated technology. Very little work has however been done to combine the advantages of the two schools of thought. This thesis originated from a realization of the potential improvement in maintenance practice by combining use based preventive maintenance optimization techniques with high technology condition monitoring.

A literature survey showed that only one established technique exists to optimize preventive maintenance decisions by considering failure time data and condition monitoring information. That is the approach followed by Makis and Jardine (1991) where the PHM is utilized to describe the failure process and decisions are then made by performing cost trade-offs in terms of risk. Although this technique has a sound theoretical base and has produced many successful results, it is not always well accepted by maintenance practitioners. The technique produces results that are difficult to understand and the underlying model, the PHM, has certain limitations.

Following the literature study, it was decided to pursue an approach that produces results that are much easier to understand, i.e. residual life estimates. The RLE approach developed in this thesis is similar to that of Makis and Jardine in that it also bases estimations on a PIM (the PHM is a special case of a PIM) but the limitations of the PHM are largely overcome. A combined PIM for non-repairable systems and a combined PIM for repairable systems were

developed that contains the majority of the enhancements of conventional PIMs in literature as special cases. Any data set under consideration dictates which enhancements are applicable in the combined PIM and the combined PIM can be simplified to fit the attributes of the particular data set.

A data set was obtained from SASOL and both Makis and Jardine's approach and the RLE approach were applied to it. The two techniques produced very similar results with the RLE approach performing marginally better in certain cases.

6.2   Recommendations for future research

Clear objectives for this thesis have been set in Chapter 1 and although these objectives were largely achieved there are still areas where further research can improve the results obtained. A few recommendations for future research are discussed in this section.

6.2.1   Upper and lower bounds on residual life estimates

Upper and lower residual life bounds in Chapter 4 and 5 were calculated directly from the conditional expectation of an event produced by the combined PIM. In doing this it was implicitly assumed that the covariate behaviour was predicted without error. By evaluating the graphs of actual vs. estimated covariate values of Appendix E, it is clear that this implicit assumption is questionable. The influence of the quality of covariate behaviour predictions on residual life estimates is also a function of a a particular combined PIM. Combined PIMs with relatively high regression coefficients would be more sensitive to the quality of covariate behaviour predictions than models with relatively low regression coefficients.

Although the combined PIM used in the Chapter 5 produced relatively good results, the influence of the quality of covariate behaviour predictions is not known and and was not formally taken into account in upper and lower confidence bounds. Further research on this aspect could make residual life estimates more reliable.

6.2.2   Covariate and combined PIM selection

Two of the most difficult steps in a proportional intensity analysis such as this are the selection of appropriate covariates for a particular combined PIM and the selection of the most relevant combined PIM. These steps were addressed as follows in the case study of Chapter 5:

(i) It was assumed that covariates RF53H and RF54H are good descriptors of the failure

process of the pumps based on the tests of significance of these covariates in a Weibull PHM done by Vlok (1999). The validity of this assumption was not verified for every model that was evaluated. It was however decided to sustain with these covariates because their physical significance was confirmed by technician experience.

(ii) A trial and error method was used to determine the most applicable combined PIMs for the SASOL data set. This was possible because the generic algorithm that was developed to fit any simplification of the combined PIM in equation (3.30) could easily be adjusted to evaluate numerous different combinations of enhancements. This is one of the biggest advantages of the combined PIM.

Reasonable results were obtained by dealing with the two steps in the manner outlined above but a formal mathematical methodology confirming these selections could benefit future application of the combined PIMs.

6.2.3 Using variable regression coefficients to limit the number of parameters in models

It was on numerous occasions pointed out that in practice reliability data is often very limited. Small data sets are desirable because that indicates that a system is performing well (Ascher (1999)). For the complete combined PIMs in equation (3.13) and (3.30), large data sets are required to be able to estimate parameters with reasonable certainty. Simplifications of the combined PIMs requires much smaller data sets but fewer regression coefficient are always desirable. For this reason regression coefficient elimination techniques should also be implemented.

One method that could be used to reduce the number of parameters in models (especially stratified models), is to define regression coefficients as functions of external influences. This concept is illustrated by the following example. Suppose $k = 1, 2, ..., w$ single part system copies are studied and the position of each copy, $p_k = 1, 2, ..., w$, is expected to influence the survival time of a particular system. Allocate position 1, i.e. p_1, to the system that is least affected by its position and p_w to the system that is most affected by its position. If a stratified combined PIM is used to model event data and the number of parameters should be reduced, regression coefficients can be defined as a function of p_k. For example, if a linear relationship between the regression coefficients and the position exists, γ_s can be defined as $\gamma_s(k) = ap_k + b$. In such a case, only a and b need to be determined.

This method is appropriate provided that there is a valid reason to define a certain relationship and in practice such relationships often exist. It is very difficult to formulate a single technique or procedure that would lead to an optimal combined PIM with the minimum number of parameters. Each data set should be modeled on merit.

6.3   Conclusion

The RLE approach followed in this thesis originated directly from an industrial need and was constructed in a formal and structured manner after a thorough literature survey. Results obtained from the RLE approach compares favourably with those of an established approach. This verifies that the RLE approach is relevant and practical.