Benefits Analysis of Prognostics & Health Monitoring to Aircraft Maintenance using System Dynamics

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ABSTRACT

The benefits of applying Prognostics & Health Monitoring (PHM) techniques to Aircraft Maintenance are evaluated using System Dynamics (SD). It is well known that a key motivation for PHM is to increase aircraft availability by reducing unscheduled removals and downtime, ultimately reducing Direct Maintenance Costs (DMC). The benefits to aircraft maintenance are tested by modelling two maintenance philosophies using SD: the traditional approach driven by scheduled & reactive maintenance; and through Condition Based Maintenance (CBM) by considering PHM functionality in maintenance practice. The study is focused on an Electromechanical Actuator (EMA) for an aircraft flight control system across a fleet of 25 aircraft over an 8 year maintenance overhaul period. The study indicated there were fewer unscheduled removals as a result of CBM in comparison to the traditional approach. Further sensitivity studies on varying degradation patterns led to instability in maintenance planning with more reactive maintenance due to more abrupt failures of the EMA. The cost effectiveness of CBM as a function of PHM efficiency is demonstrated through DMC accumulation where it was found that CBM is no longer cost-beneficial when over 85% of the EMA life has been used. Overall, the SD models presented a general level of systems understanding of the causalities that are inherent within the two maintenance policies and are a useful methodology to consider PHM benefits through analysing the impact of different policies on the system behaviour.

Keywords—Prognostics; Health Monitoring; Aerospace; Condition Based Maintenance; System Dynamics; Electromechanical Actuators

1. INTRODUCTION

Prognositcs and Health Monitoring (PHM) are becoming more widely applied within the Aerospace industry and it is important to demonstrate the benefits and challenges that are associated to PHM through implementation and application. There are many benefits and drawbacks to account for when considering all stakeholders associated with PHM. It is therefore imperative to capture all of these to make it more receptive and acceptable to the Aerospace industry to fulfil the objectives of PHM which are to improve aircraft availability by reducing equipment downtime by enhanced understanding of health (Wheeler, Kurtoglu, & Poll, 2010).

The impact on aircraft line maintenance actions are a key area of study when analysing the benefits with aircraft operators that are seeking new ways to optimise maintenance practice. Aircaft maintenance forms a significant part of an aircraft's airworthiness criteria, with the key objectives to ensure a fully serviced, operational and safe aircraft (Ackert, 2010). Poor maintenance can have a variety of impacts to an aircraft, its crew and its passengers. Delays to aircraft dispatch time could cause a financial impact to the airline (runway charges) and customer dissatisfaction. In more severe cases, poor maintenance could lead to passenger or crew discomfort in injury or, in the worst case, a flight safety critical situation. It is important to consider the different types of maintenance activities with respect to ‘time’ at a high level as shown in Figure 1. It is desirable for airlines to have maximum operability through optimisation of ‘down time’ activities (Şenturk, 2010).

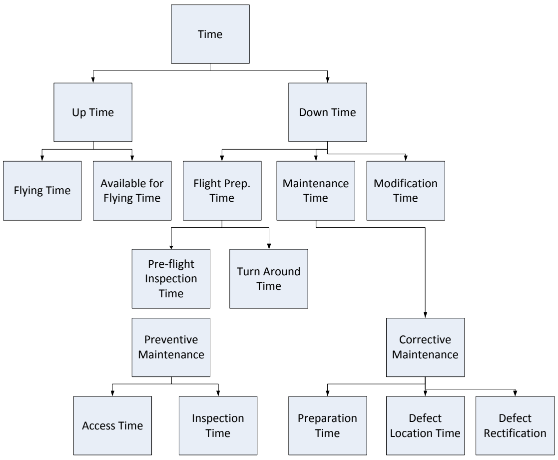

Figure 1. Maintenance Time Relationships (Knotts, 1999).

Aircraft maintenance regimes are generally comprised of activities stemming from preventive, corrective and design-out maintenance. These forms of maintenance are categorised in Figure 2. Corrective maintenance is often classified as ‘unplanned’ or ‘reactive’ and is a form of maintenance based on troubleshooting equipment when it operates under undesirable conditions or its failure results in complete loss of operation thus leading to equipment down time. Design out maintenance stems out of ‘planned’ maintenance as a long term objective and is applied as a means to improve equipment operability and reliability through a process of studies, construction and testing and may serve as part of an iterative design improvement of the equipment being maintained. Preventive maintenance is driven through a culture of planned maintenance. It can be broken down into Systematic (Scheduled) maintenance, where equipment is serviced at periodic intervals to detect the onset of failure and therefore rectify the problem prior to the failure and Condition-Based (Predictive) maintenance (CBM) where continuous monitoring of equipment health to detect potential faults without having to disrupt aircraft operations.

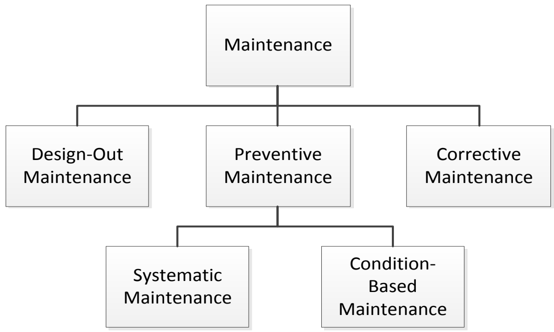

Figure 2. Maintenance Categories (Prokopenko & North, 1997).

General aircraft maintenance is based around a series of Scheduled maintenance for each respective sub-system and components. It is generally comprised of periodic inspections, which are classified into A, B, C and D checks with A & B checks conducted more frequently. They generally consist of visual inspections and general servicing whereas C & D checks are more extensive with checks requiring more man-hours (Ackert, 2010). The D check is the least frequent but the most comprehensive and is factored as an overhaul of the whole aircraft. Corrective maintenance generally arises due to inherent undesirable properties unseen during scheduled maintenance and BITE (Built In Test Equipment) checks where applicable with Condition-based maintenance sparsely applied (Ackert, 2010). This paper therefore intends to capture the shift in maintenance policy as a result of PHM application for an Aerospace application by considering PHM at a component level with continuous monitoring of health considered through use of System Dynamics (SD) modelling.

1.1 Origins of System Dynamics

SD is a methodology used to aid the understanding of nonlinear characteristics of complex processes over time through the use of Stock & Flow diagrams and internal feedback loops stemming from Causal Loop diagrams (Radzicki & Robert, 2008). Historically, SD came into prominence in the mid-1950s from Professor Jay Forrestor through an ambition to understand the core issues which define the success or failure of organisational processes (Forrestor, 1961) .

Complexity within a system is generally defined in terms of the number of components or procesess within it or the number of combinations and scenarios to aid decision making which is termed ‘combinatorial complexity’ (Sterman, 2000). It is often assumed such complexity could arise in a system through additive combinations however, it is also said that complexity may arise in simpler systems with low combinatorial complexity (Sterman, 2000) as dynamic complexity results from the combination of interactions amongst system elements through time. It is a broad-ranging discipline that seeks to integrate several disciplines such as economics, law, management sciences, and management of information systems (Spohrer & Maglio, 2010).

1.2 System Dynamics Application

SD techniques have been applied sparsely as a methodology in demonstrating PHM qualitative and quantitative benefits to aircraft maintenance in general.

Significant research and case studies have been carried out to explore the dynamics of maintenance strategies within production plants with the view to reduce overall plant operation cost and increase uptime (Jabar, 2003). Work conducted by Chumai (2009) included a SD model of plant maintenance systems to simulate plant maintenance behaviour. The results suggest that industrial plants should reduce preventive maintenance practice in a move towards predictive maintenance to achieve plant uptime and keeping maintenance costs to a minimum. The SD model presented could only provide a relative magnitude and direction of system outputs with input data based on a generic plant maintenance system with output data not necessarily representative of all plants (Chumai, 2009).

A dynamic model for estimating the added value of maintenance services was developed using SD techniques for a production plant (Jokinen, Ylén , & Pyötsiä, 2011). It included modelling various maintenance systems to facilitate the service provider’s understanding of its customer’s business as a communication tool and of the added value of services in the hope that it would enhance value propositions. The SD modelling served its initial purpose of providing visualisation of the intricacies of the maintenance system behaviour as a means to identify robust policies and isolate critical areas within the system. However, accurate estimations of the value was seen as unreliable due to uncertainty in the input data.

SD was also applied to evaluate fleet and maintenance strategies in a bus company (Bivona & Montemaggiore, 2005). The objective was to demonstrate how SD could be used to support key decision makers in designing and evaluating their maintenance strategies with reflection on their company performance. Results showed that predictive maintenance would benefit over scheduled maintenance in terms of optimisation of maintenance personnel and reducing equipment downtime (Bivona et al. 2005).

1.3 Aims & Objectives

The purpose of this paper is to demonstrate the benefits of PHM to aircraft maintenance by using SD techniques with emphasis on highlighting causality between two maintenance strategies:

1. Traditional approach driven by scheduled and reactive maintenance;

2. Condition Based Maintenance (CBM) by considering PHM functionality in maintenance practice.

It is intended to provide a wide-ranging understanding of the interconnectedness of the sub-system elements of the two maintenance policies.

PHM within the aerospace industry strives to increase equipment availability, optimise cross-fleet maintenance, reduce Direct Maintenance Costs (DMC), and reduce costs associated with unscheduled maintenance through enhanced understanding of system behaviour (Jennions, 2012). The emphasis of the paper is to illustrate such benefits through rigorous SD modelling by exploring PHM sensitivity and to test its efficiency for aircraft maintenance returns. It also illustrates any emergent characteristics from evaluating the effectiveness of PHM economically with various failure patterns and nonlinear properties explored.

Electromechanical Actuators (EMA) are becoming prominent safety critical applications in next generation fly-by-wire aircraft (Balaban, Saxena, Narasimhan, Roychoudhury, & Goebel, 2011). Therefore, focus on aircraft maintenance at a component level with an EMA for a flight control system is given. The emphasis and the model was based in the context of a medium sized airline consisting of 25 aircraft over a general overhaul period of 8 years (D- Check).

The EMA that was used for this study was a linear ballscrew EMA that provides incremental linear motion powered by a motor.

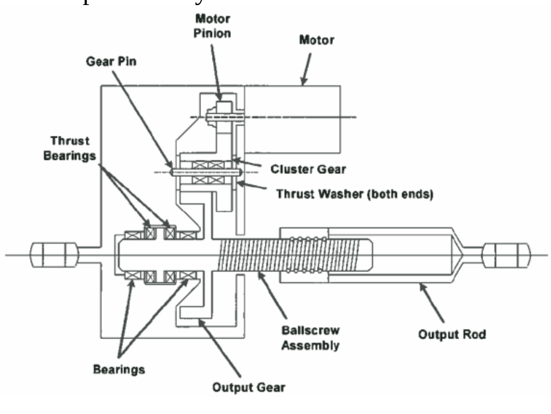

Figure 3. Linear EMA System (Bodden et al. 2007).

Figure 3 shows a baseline schematic of the system to be used consisting of a single actuator assembly driven by a brushless DC motor via a single stage gearbox with the motor mating with a single pinion in the ballscrew assembly (Bodden, Clements, Schley, & Jenney, 2007).

The analysis presented is not necessarily intertwined with other aircraft systems and it is understood that the impacts of other critical components on aircraft availability have been neglected for the purpose of this study.

2. METHODOLOGY

The methodology consists of a series of procedures and equations to develop the finalised SD model. This includes Causal Loop Diagram (CLD) modelling to provide the initial visualisation of the maintenance strategies by modelling the key attributes and parameters through a Stock and Flow model.

CLDs represent a simplistic map of the system being modelled encompassing all the system elements and interactions. CLDs also capture any feedback loops to enable better understanding of the system structure. Thus one can gauge the system behaviour in a dynamic setting. Each system element is given a positive or negative causal link. For a pair of connected nodes, a positive causal link means they are changing in the same direction and a negative causal link means they change in opposite directions. Feedback loops consist of either Reinforcing (+) or Balancing (-) loops. Reinforcing loops are often associated with exponential increases or decreases whereas Balancing loops infer a plateauing effect.

The Stock and Flow diagram provides a more detailed impression of the CLD allowing the user to analyse the system in a more quantitative manner. A 'Stock' depicts any entity in the system can accrue or lessen over time and a 'Flow' is the rate of change of a Stock.

2.1 Causal Loop Diagrams

Two CLDs were constructed using the software 'Vensim'. The first CLD presented in Figure 4 provides an intitial visualisation of the processes involved in the traditional maintenance approach driven by scheduled & reactive maintenance for an EMA in a commercial aircraft.

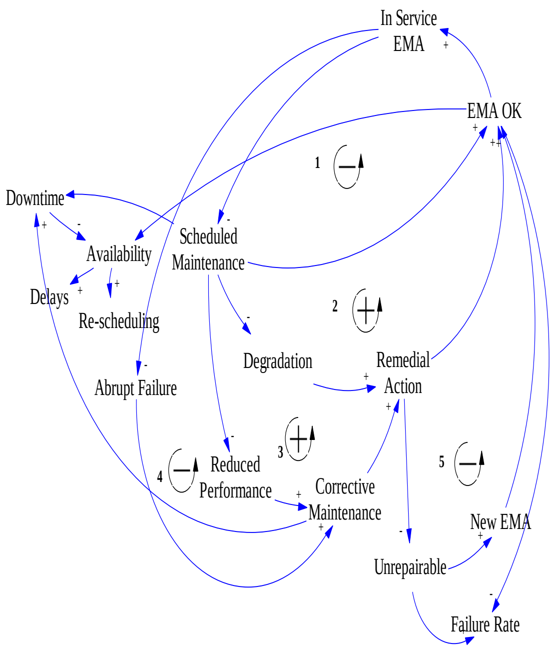

Figure 4. Scheduled & Reactive Maintenance processes CLD.

A 'Uses Tree' is a good way to illustrate the causalities in a more comprehendible format as shown in Figure 5.

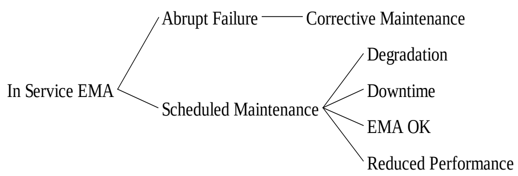

Figure 5. Scheduled & Reactive Maintenance Uses Tree.

The traditional maintenance process is simplified through the Uses Tree to show the in-service component to be subjected to Scheduled maintenance at a defined period with failures occuring sporadically.

Five feedback loops were identified in the CLD presented in Figure 5 with the nature of the feedback and behaviour described in Table 1.

Table 1. Feedback Loops for Scheduled & Reactive Maintenance CLD.

Loop	Inference
1:In-service EMA →Scheduled Maintenance→EMA OK→In-service EMA	This is a 'balancing' feedback loop where the behavioural pattern of the loop suggests a temporary null in operation due to the EMA experiencing downtime due to mandatory maintenance.
2:In-service EMA→Scheduled	This is a 'reinforcing' feedback loop due to the

Loop	Inference
Maintenance →Degradation→ Remedial Action→EMA OK→In-service EMA	gradual wear that occurs within the EMA.
3:In-service EMA →Scheduled Maintenance→ Reduced Performance→ Corrective Maintenance→ Remedial Action→ EMA OK→In-service EMA	This is a 'reinforcing' feedback loop like loop 2 due to the attributes associated to gradual wear within the EMA.
4:In-service EMA→Abrupt Failure→Corrective Maintenance→ Remedial Action →EMA OK→In-service EMA	This is a 'balancing' feedback loop as abrupt failures would lead to reactive maintenance due to more severe degradation trends within the EMA system.
5:In-service EMA→Scheduled Maintenance→Degradation→Remedial Action→Unrepairable→New EMA→EMA OK	This feedback requires the need for EMA replacement as a result of the workshop deeming the component unrepairable. It was envisaged that the majority of these outcomes would arise from abrupt failures and so this was a deemed a 'reinforcing' loop.

The same process was followed for modelling the CBM approach with PHM associated processes added in – the corresponding CLD is shown in Figure 6.

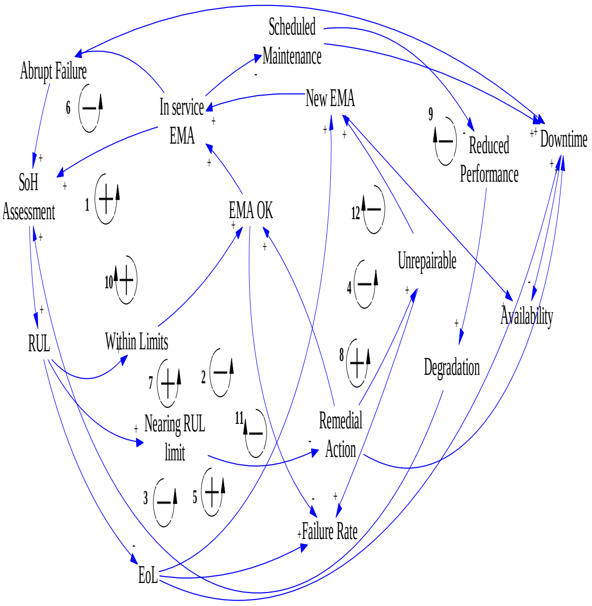

Figure 6. CBM processes CLD.

The additional steps relating to PHM processes were added in to the CLD with State of Health (SoH) assessment a governing feature to aid maintenance personnel at a workshop to get a better understanding of component health.

As shown in the Uses Tree in Figure 7, the SoH is a sequential step as it is something intended to be performed offline (at a frequent interval) and becomes a dominant feature within CBM.

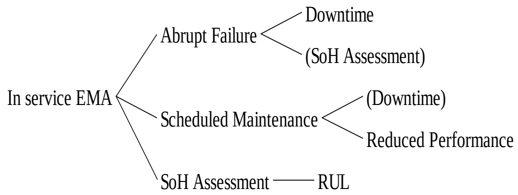

Figure 7. CBM Uses Tree.

There were considerably more feedback loops in the CLD model with PHM processes added in. the feedback loops were broken down into 3 groups as shown in Tables 2-4.

Table 2. Feedback Loops for SoH assessment within CBM-CLD.

Loop	Inference
1:In-service EMA→SoH Assessment→RUL→ Within Limits→EMA OK	This is a 'reinforcing' feedback loop due to the principal nature in which the SoH assessment is performed at a frequent interval as a mandated process in which there is no disruption or reduction in aircraft availability.
2:In-service EMA→SoH Assessment→RUL→ Nearing RUL Limit→Remedial Action→EMA OK	This is a 'balancing' feedback loop due to the SoH assessment bringing about need for remedial action and therefore prompting the aircraft to go out of service momentarily.
3:In-service EMA→SoH Assessment→RUL→EoL (End of Life)→ New EMA	This feedback loop is similar to Loop 2 in that this has a 'balancing' feedback loop where the EMA has reached the end of its useful life and therefore a replacement is prompted.
4:In-service EMA→SoH Assessment→Nearing RUL limit→Unrepairable→ New EMA	This is a 'balancing' feedback loop attributed from the aircraft experiencing downtime due to EMA replacement.

Table 3. Feedback Loops for Abrupt failures within CBM-CLD.

Loop	Inference
5:In-service EMA→Abrupt Failure→SoH Assessment→RUL→EoL→Remedial Action→New EMA	This was deemed to be a ‘reinforcing’ feedback loop due to the equipment being forced out of service prior to the SoH check thus subsequently leading to a replacement.
6:In-service EMA→Abrupt Failure→SoH Assessment→RUL→ Within Limits→LG EMA OK	This is a ‘balancing’ feedback loop because the abrupt failure may not be applicable to the EMA itself and therefore there is no resulting effect on parts inventory with the EMA showing satisfactory health.
7:In-service EMA→Abrupt Failure→SoH Assessment→RUL→ Nearing RUL Limit→Remedial Action→EMA OK	This process is similar to loop 6 however there is a need for prolonged downtime with the EMA deemed repairable and this was deemed to be a ‘balancing’ feedback loop. This is the same for loop 8 where the EMA is declared unrepairable following remedial action.

Table 4. Feedback Loops for Scheduled Maintenance within CBM-CLD.

Loop	Inference
9:In-service EMA→Scheduled Maintenance→Degradation→SoH Assessment→RUL→ EoL→New EMA	This is a ‘balancing’ feedback loop due to the planned downtime for Scheduled Maintenance with poor health reading giving rise to EMA replacement. The same applies for loops 11 & 12 where the outcome of SoH check lead to remedial action and possible replacement.
10: In-service EMA→Scheduled Maintenance→Degradation→SoH Assessment→RUL→ Within Limits→EMA OK	This is a ‘reinforcing’ feedback loop because the EMA is deemed to be in satisfactory condition for continued service. This is assumed to be the majority case scenario.

Further learning can be achieved from CLDs where the broadness of the system can be broken down and therefore one can begin to quantify the system in a more tangible representation by using a Stock & Flow diagram.

2.2 Stock & Flow Diagram

The CLDs presented provides an initial overview of the system with the top level processes involved in maintenance and such a technique enabled the identification of any feedback and key attributes to take forward to build a detailed sub-system model through Stock & Flow diagrams.

Many sub-systems can be developed from the CLDs and for the purpose of this research the objective was to build a Stock & Flow diagram of a sub-system evaluating EMA maintenance and availability. The intention was to exemplify the effect of PHM on corrective maintenance and how advanced prediction in the onset of a degrading failure can reduce the rate of failure and unscheduled removals and thus boost availability.

Prior to modelling the Stock & Flow diagram of the sub-system, it was necessary to define the stocks (state variables) and flows (state changes) necessary to model the sub-system.

Table 5. State Variables.

Stocks	Definition
Working EMAs	EMAs that are fully operable and functioning for safe intended purpose.
Degrading EMAs	EMAs that are starting to lose efficiency as a result of mechanical wear.
Working EMAs to undergo CBM	EMAs that are subject to PHM.
Degrading EMAs to undergo CBM	Queue for EMAs to undergo CBM.
EMAs under Scheduled Maintenance	All EMAs are subject to system level periodic checks.
Failed EMAs	EMAs that have failed to operate at design operating conditions.
EMAs failed prematurely	EMAs that have failed before MTBF.
EMAs under remedial action	Failed EMAs at workshop for repair.
Direct Maintenance Costs	Incurred costs as a result of scheduled or unscheduled maintenance activities.

Table 6. State Changes.

Flows	Definition
Failure Rate	The frequency at which the EMA fails.
Premature Failure Rate	The frequency at which the EMA fails before the MTBF.
Failure Rate (following CBM)	The frequency at which the EMA fails post-CBM.
Repair Rate	The frequency at which remedial action is conducted by workshop engineers.
False PHM Rate	The frequency at which False Positives/Negatives occur.
Rate of Detected Failures	The frequency at which failures are detected through CBM.
CBM Work Rate	The frequency at which PHM is performed.

Based on these Stock & Flow attributes and system level information from the earlier CLD modelling a Stock & Flow diagram was constructed and is presented in Figure 8.

From Figure 8, there are many parameterised attributes that impact each stock and flow, which demonstrates causality and therefore adds granularity to the model.

EMA ballscrew actuator failures are most often a result of gradual degradation of the ballscrew surface through metal to metal contact of the re-circulating balls to the hardened metal surface of the ball screw shaft (Jin, Chen, & Lee, 2013). Therefore the 'Rate of Wear' component was initially modelled to reflect a gradual degradation of the EMA in terms of its MTBF as shown in Figure 9.

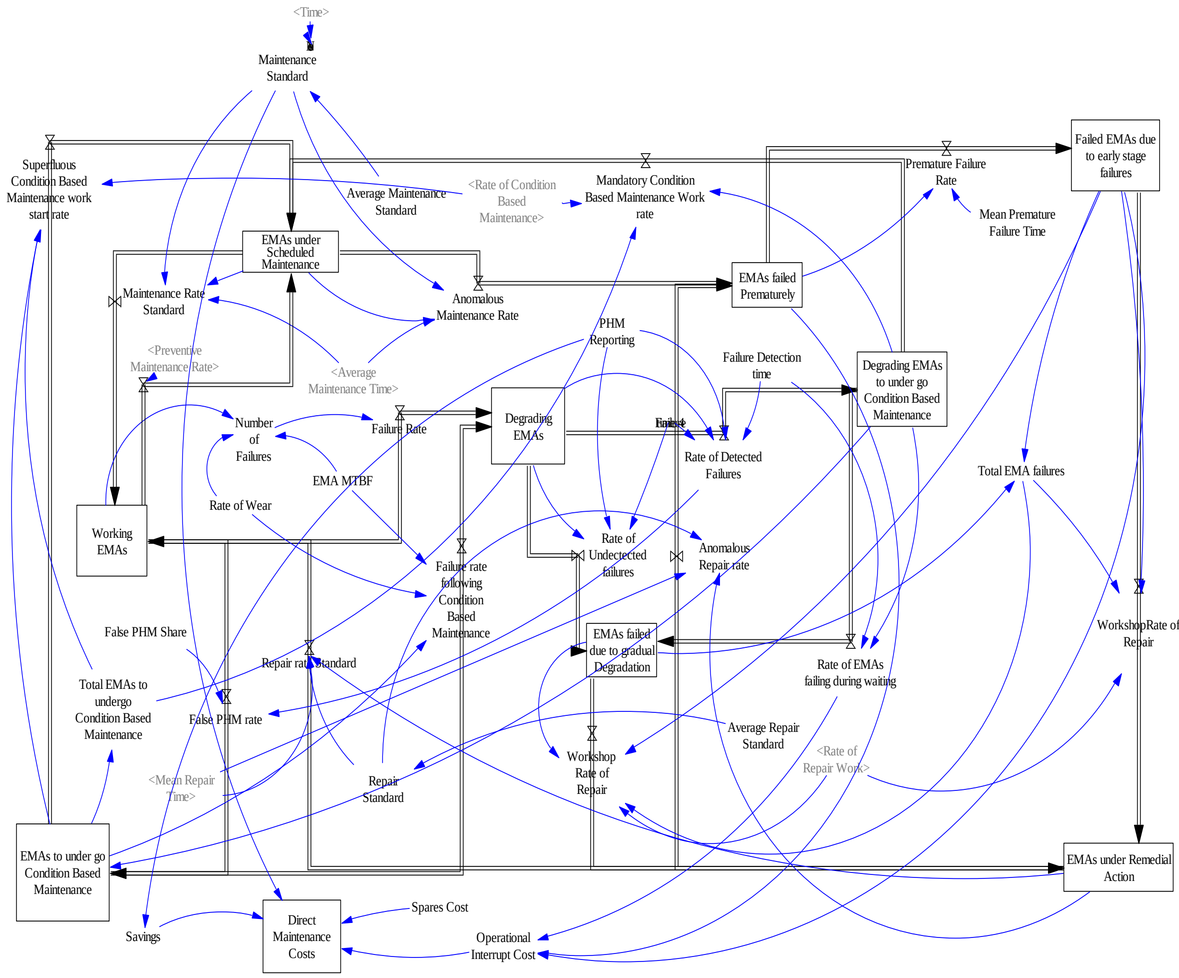

Figure 8. Stock and Flow Diagram of EMA Maintenance Sub-system.

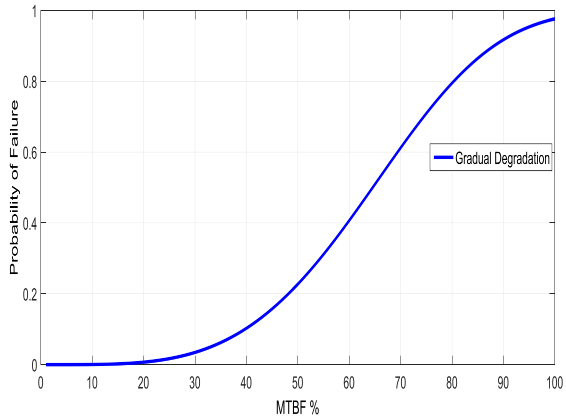

Figure 9. Probability of Failure under Gradual Degradation.

Subsequent simulation sensitivity studies were conducted to further demonstrate the effect of more severe failures as a means to examine the effect on EMA availability and the resulting number of failures over the overhaul period.

3. RESULTS AND DISCUSSION

This section presents the results of the simulation studies following the methodology described in Section 2 to demonstrate the usability of the Stock & Flow diagram in Figure 8. The analysis was based on two metrics: EMA availability (total number of EMAs deemed to be in an operable state at the beginning of a flight at any point of time during the maintenance overhaul period), for the two maintenance policies modelled. Additionally, sensitivity studies explored the effects of efficiency of PHM reporting and of differing types of component degradation. The impacts on DMC were also explored with a view to demonstrate the effectiveness of CBM as a function of PHM efficiency by considering DMC accumulation through EMA life. The SD analysis conducted are based on a continuous simulation of discrete events as is the case for most SD simulations (Tako & Robinson, 2008).

3.1 EMA Availability

The first simulation, shown in Figure 10, was based on the traditional maintenance approach of scheduled and reactive maintenance.

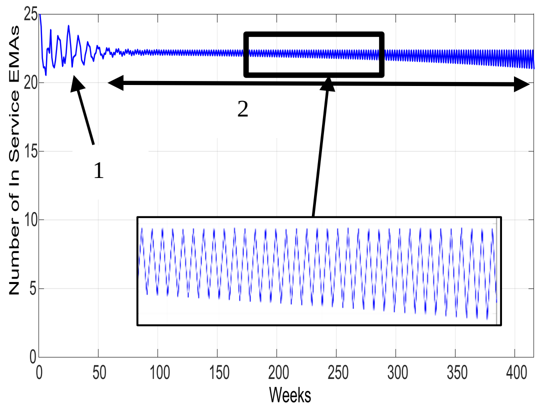

Figure 10. EMA Availability through Maintenance overhaul period with no CBM.

The simulation response of Figure 10 shows two distinct regions. The region labelled ‘1’ displays decaying oscilations and is an artifact of the simulation start-up and thus can be ignored. The region labelled ‘2’ displays an oscilation at the scheduled maintenance interval that grows over time. This is congruent with the observation that over time the rate of component failure increases hence more failures are detected at each inspection.

The next step was to introduce the effect of CBM by tuning in the frequency of PHM into the existing maintenance schedule. The PHM schedule was adjusted through ‘the CBM Work Rate’ parameter to analyse the effects on availability and downtime with PHM occuring for every aircraft at the following intervals:

- At the end of every Week;
- At the end of every Day;
- At the end of every Flight Cycle (FC).

The mean values of In Service EMAs over the entire maintenance overhaul period was also calculated for varying PHM frequencies and also other failure distributions as presented later in this section.

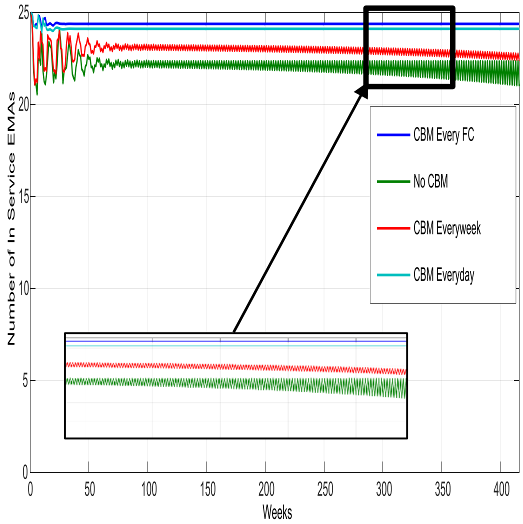

Figure 11. EMA availability with varying frequencies of CBM.

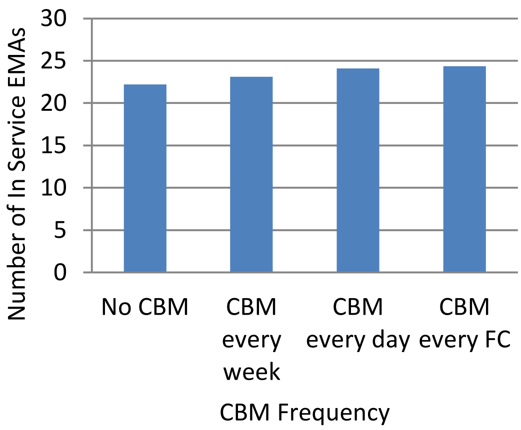

Figure 12. In Service EMAs Mean Availability for varying CBM frequencies over the entire overhaul period.

Figure 11 indicates that as CBM becomes more frequent within the CBM schedule the mean availability number of In Service EMAs over the maintenance overhaul period increased as shown in Figure 12. There is also a higher degree of stability when CBM is conducted on a daily basis and at the end of every FC with the reduced transient behaviour. This can be attributed to the more continuous health monitoring in place where the constant steady state responses are indicative of the reduced reactive maintenance events and therefore increased uptime. This would enable maintenance engineers to monitor the SoH offline without operational interrupts. Any impending failure dealt with in advance would enable better optimisation to schedule in component replacement effectively.

3.2 Degradation Sensitivity

The analysis considered only gradual failures up until this point. It is more challenging for aircraft operations and maintenance teams using CBM when the component degrades at a faster rate (Li, Wang, Liu, & Bu, 2014). This was tested to demonstrate the effectiveness of PHM in such situations by adjusting the 'Rate of Wear' setting in the Stock & Flow diagram.

The component degradation in Figure 9 was modelled through Weibull Probability Density Function (PDF).

$$f(x, \alpha, \beta) = 1 - e^{-(x/\beta)^\wedge\alpha} \tag{1}$$

The sensitivity study for degradation involved varying the function arguments for the Weibull PDF to reflect more severe failure distributions.

Where x is the value at a point of time in the MTBF curve, α is the shape parameter and β is the scale paramater to the distribution. α & β were adjusted to reflect different failure distributions, these are presented in Figure 13.

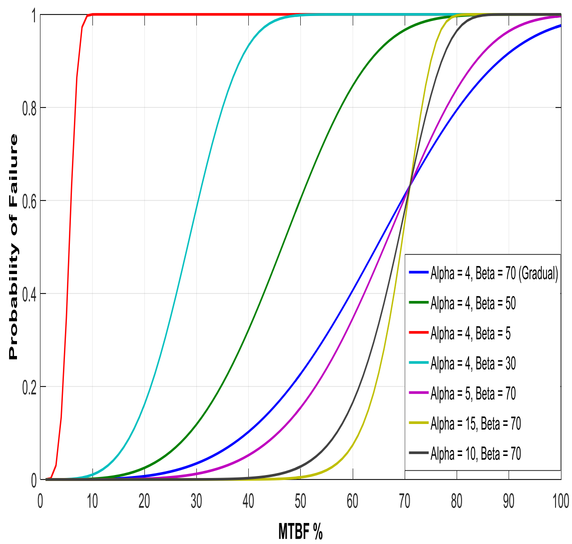

Figure 13. Weibull curves for various EMA failure distributions.

The β parameter was increased to indicate failures of an abrupt nature at the early stage of the EMA life. These failures could arise from actuator misalignment leading to mechanical seizure of the ballscrew assembly (Balaban, et al., 2015). The α parameter was increased to indicate gradual degradation initially but then exhibit sharper degradation towards the end of the EMA life. Such failures can often be attributed to abrupt seizures in the bearings or the screw shaft from a build up of debris or loss of lubrication (Balaban et al. 2015).

Each of these failure distributions were tested in the Stock & Flow diagram with CBM implemented at the end of every FC.

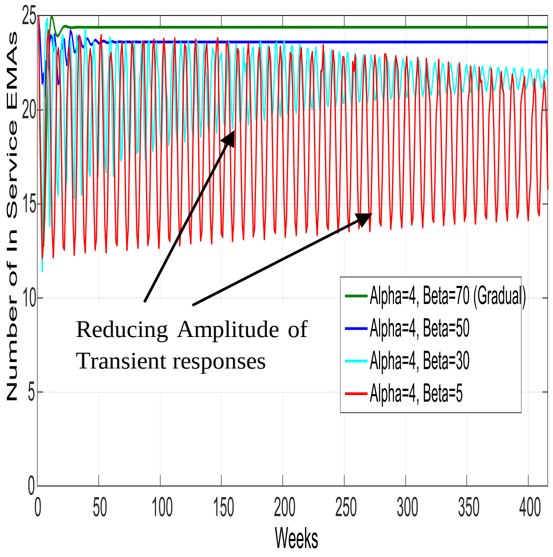

Figure 14. EMA availability for more abrupt failure distributions.

Figure 14 indicates the increasingly variable EMA availability with more early stage failures of the ballscrew. The transient response of the simulation becomes more apparent and remains prevalent throughout whole overhaul period with reducing β values. The reducing amplitude of these responses never reach steady state equilibrium and is indicative of the CBM striving to cope with the demands of component uptime in the face of a high frequency of early stage EMA failures.

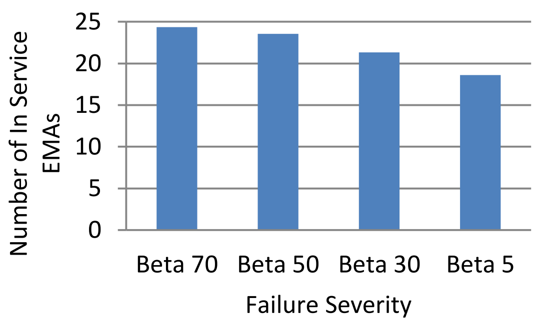

Figure 15: In Service EMAs Mean Availability for varying failure severities (β values) over the entire overhaul period.

Figure 15 illustrates that EMAs failing more abruptly results in there being significantly less mean availability throughout the whole maintenance overhaul period.

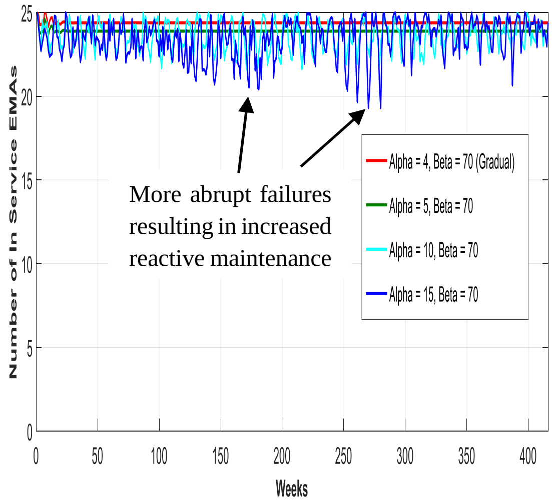

Figure 16. EMA availability for gradual failure distributions leading to abrupt failures.

Figure 16 shows the tendency of the EMA availability to become sporadic over the duration of the overhaul period with increasing α values. This can be attributed to the sporadic health pattern of the EMA where initially it exhibits gradual degradation however a sudden failure leads to component downtime. Therefore, the mean in service EMAs remains relatively constant with PHM functionality enabling maintenance teams to plan in reactive maintenance when sharp degradations begin to manifest themselves.

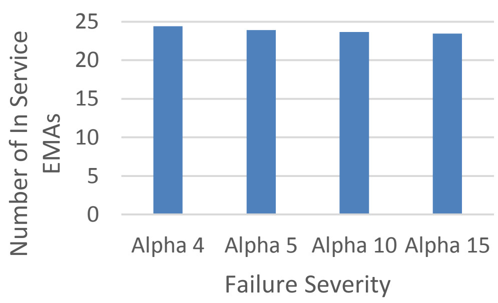

Figure 17. In Service EMAs Mean Availability for varying failure severities (α values) over the entire overhaul period.

As can be seen from Figure 17, the mean availability of in service EMAs reduces with increasing α values over the whole maintenance overhaul period.

3.3 Cost Effectiveness of PHM

An emerging feature of the analysis was the increase in 'False Positives/Negatives' readings as a result of the PHM functionality. This is a common issue encountered when considering the economics of CBM through PHM (Feldman, et al., 2010).

Additional studies were conducted to demonstrate the effectiveness of CBM as a function of PHM efficiency by considering DMC accumulation through EMA life where minimal costs would be incurred at the early detection of the onset of a failure through PHM.

This was conducted using the Stock & Flow diagram (as was presented in Figure 8) with the following inputs:

MTBF = ~18000 FH (Weiss, 2014)
Operational Interrupt cost = £3360.00/FH (Airlines for America, 2014)
DMC = £586.00 (IATA, 2011)
Spares cost = £5500.00 (Exlar, 2016)

Figure 18 illustrates the trend in which DMCs are accumulated through incremental PHM intervals (time to detect fault as a percentage of overall EMA life) from which it was ascertained that if PHM were to identify the onset of a failure at an early stage minimal DMCs would be incurred. An exponential rise in DMCs follows as failure detection occurs towards the end of component life. This can be attributed to the degradation becoming more prevalent over time and therefore it costs much more to repair.

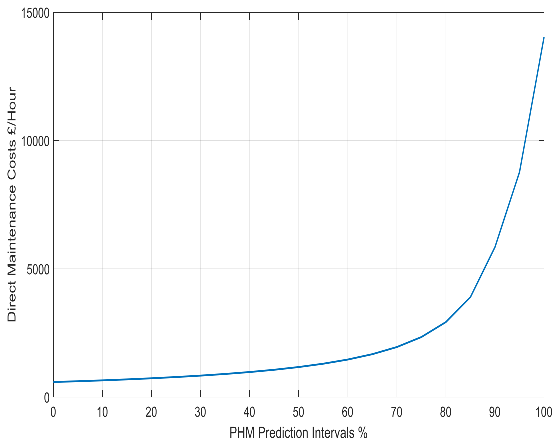

Figure 18. Direct Maintenance Costs for CBM at the end of each FC.

Using the data from DMC accumulation over PHM prediction intervals, the overall savings were deduced and they enabled the calculation of where the PHM predictions would start to incur a loss.

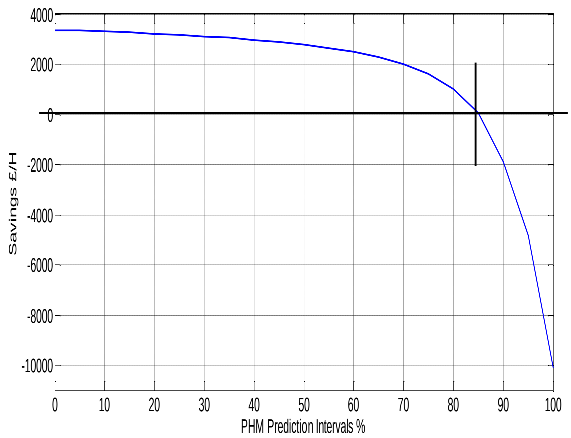

Figure 19. Savings per Flight hour for CBM.

Figure 19 shows that early replacement detectable through PHM starts to become no longer cost beneficial if more than 85% of the EMA life has been used.

4. CONCLUSIONS

Two maintenance policies have been modelled and analysed through SD as a means to demonstrate the potential qualitative and quantitative benefits to aircraft maintenance teams using CBM.

The analysis initially considered the EMA to deteriorate gradually over a maintenance overhaul period of 8 years, which would result in a surge in reactive maintenance near the end of the overhaul period. CBM was added into the model to improve availability of the EMAs and to bring stability to the maintenance planning as the frequency of the PHM was increased.

The study also explored the effects on EMA availability as a result of varying failure patterns. This included introducing more severe failure distributions, which resulted in more unscheduled removals and an increased need for reactive maintenance due to these abrupt failures. The increased frequency in PHM also resulted in a higher number of 'False Positives/Negatives' which prompted a further study to demonstrate the PHM performance in terms of cost effectiveness. It was established that PHM becomes no longer 'cost beneficial' to maintenance when over 85% of the EMA life has been used.

The analysis was modelled using failure distributions based on literature featuring test stand degradation of ballscrew actuators. These were used to map specific failure patterns to test PHM functionality within the SD model. It is envisaged that such work should be extended to consider real failure distribution data on ballscrews undergoing wear to factor in other non-linear effects.

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REFERENCES

Ackert, S. P. (2010, October 1). Basics of Aircraft Maintenance Programs for Financiers. *Evaluation & Insights of Commercial Aircraft Maintenance Programs*.

Airlines for America. (2014). *Per-Minute Cost of Delays to U.S. Airlines*. Retrieved December 2015, from Airlines for America: http://airlines.org/data/per-minute-cost-of-delays-to-u-s-airlines/

Balaban, E., Saxena, A., Narasimhan, S., Roychoudhury, I., & Goebel, K. (2011). Experimental Validation of a Prognostic Health Management System for Electro-Mechanical Actuators. *American Institute of Aeronautics and Astronautics*.

Balaban, E., Saxena, A., Narasimhan, S., Roychoudhury, I., Koopmans, M., Ott, C., & Goebel, K. (2015). Prognostic Health-Management System Development for Electromechanical Actuators. *Journal of Aerospace Information Systems*, 329-344.

Bivona, E., & Montemaggiore, G. (2005). Evaluating Fleet and Maintenance Management Strategies through System Dynamics Model in a City Bus Company. *The 23rd International Conference of the System Dynamics Society.* Boston.

Bodden, D. S., Clements, S., Schley, B., & Jenney, G. (2007). Seeded Failure Testing and Analysis of an Electromechanical Actuator. *Aerospace Conference IEEE*, 1-8.

Chumai, R. (2009). System Dynamic Modeling of Plant Maintenance Strategy in Thailand. *The 27th International Conference of the System Dynamics Society.* Albuquerque.

Exlar. (2016). *Exlar Product*. Retrieved December 2015, from Exlar: http://exlar.com/resource/

Feldman, A., Kurtoglu, T., Narasimham, S., Poll, S., Garcia, D., Kleer, J., . . . Gemund, A. (2010). Empirical Evaluation of Diagnostic Algorithm Performance Using a Generic Framework. *International Journal of Prognostics and Health Management*.

Forrestor, J. W. (1961). *Industrial Dynamics.* Cambridge, MA: The M.I.T Press.

IATA. (2011). *Airline Maintenance Cost Executive Commentary.*

Jabar, B. H. (2003). Plant Maintenance Strategy: Key for Enhancing Profitability.

Jennions, I. (2012). *Integrated Vehicle Health Management: Business Case Theory and Practice.* SAE International.

Jin, W., Chen, Y., & Lee, J. (2013). Methodology for Ball Screw Component Health Assessment and Failure Analysis. *International Manufacturing Science and Engineering Conference.* Wisconsin.

Jokinen, T., Ylén , P., & Pyötsiä, J. (2011). Dynamic Model for Estimating the Added Value of Maintenance Services. *The 29th International Conference of the System Dynamics Society.* Washington DC.

Knotts, R. M. (1999). Civil Aircraft Maintenance and Support Fault Diagnosis from a Business Perspective. *Journal of Quality in Maintenance Engineering*, 335-348.

Li, L., Wang, Z., Liu, Z., & Bu, S. (2014). Trend Prognosis of Aero-Engine Abrupt Failure Based on Affinity Propagation. *First Symposium on Aviation Maintenance*, 13-22.

Prokopenko, J., & North, K. (1997). Productivity and Quality Management. In *Productivity by Maintenance.*

Radzicki, M. J., & Robert, T. A. (2008). Origin of System Dynamics: Jay W. Forrester and the History of System Dynamics. *U.S. Department of Energy's Introduction to System Dynamics*.

Şenturk, C. (2010). Optimization of Aircraft Utilization by Reducing Scheduled Maintenance Downtime. *10th AIAA Aviation Technology, Integration and Operations (ATIO).* Fort Worth, Texas.

Spohrer, J., & Maglio, P. (2010). Service Science: Toward a Smarter Planet. *ntroduction to Service Engineering*, 3-30.

Sterman, J. D. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World.* Jeffrey J. Shelstad.

Tako, A. A., & Robinson, S. (2008). Model Building in System Dynamics and Discrete Event Simulation: a quantitative comparison. *The 2008 International Conference of the System Dynamics Society*. Athens.

Weiss, J. (2014). Control Actuation Reliability and Redundancy for Long Duration Underwater Vehicle Missions with High Value Payloads. *Underwater Intervention*.

Wheeler, K. R., Kurtoglu, T., & Poll, S. D. (2010). A Survey of Health Management User Objectives Related to. *International Journal of Prognostics and Health Management*.

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