Examining the Interaction between Condition Based Maintenance and the Logistics Supply Chain

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Abstract

Condition Based Maintenance (CBM) is an emerging maintenance paradigm in the Land domain. The following study explores the potential impact of the adoption of CBM within an abstracted multi-echelon Army supply chain. A discrete-event simulation model is used to recreate representative dynamics using inventory algorithms in use within the Defence environment. The main metrics chosen reflect the availability of an equipment fleet, the cost of ownership (via the total number of spare parts consumed), and finally the logistic footprint (via the number of spare parts being held). The developed model allows for a better appreciation of the potential impacts of CBM on the supply chain, and hence the potential savings on maintenance. The developed model allows general behavioural trends to be identified and provides a basis for a more realistic multi-indenture, networked multi-echelon system with non-uniform degrees of failure anticipation across subsystems within equipment items.

Keywords: Condition Based Maintenance, Logistics Supply Chain, Pre-emptive Earmarking, Direct Requisition, Discrete Event Modelling.

Introduction

Condition Based Maintenance (CBM) is a maintenance paradigm in which maintenance of an asset is triggered based on the current condition or anticipated future condition of that asset. Such paradigms have long been used on air vehicles where safety has been the preeminent driver [1], including Australian Army aviation assets. Further, CBM and Health and Usage Monitoring Systems (HUMS) have been taken up by the United States and United Kingdom Armies on a range of Land vehicle systems [2-8]. The Australian Army has commenced reviewing the use of HUMS on Land vehicles, hence it is both timely and pertinent that a high-level study be undertaken to explore the potential cost-benefit of CBM for upcoming projects in particular.

The rationale behind the CBM paradigm is widely reported in the literature, e.g. [9-11] and can be encapsulated in three main points. The first is to facilitate a reduced cost of ownership by increasing the life extracted from spare parts. Many spares, particularly consumables replaced during scheduled servicing, such as engine oil, are replaced prematurely and their remaining useful life is wasted. The second relates to the improvements to fleet availability and mission effectiveness, e.g. having confidence that equipment will not fail during the conduct of a mission. The third is due to CBM being a potential 'enabler' of anticipatory logistics[1] [12], by allowing better scheduling of future maintenance activities and stock movement and hence resulting in a more responsive and leaner supply chain.

Many papers in the literature explore specific sensor and monitoring techniques for estimating the remaining life of components [13-17], investigation of the mechanisms and mathematical models of prognostics and predictive ability (e.g. see [11] for a survey) and methods for optimising maintenance intervals based on interpretation of data obtained through condition monitoring [14, 16, 18, 19]. Relatively few investigate the potential impact that CBM and condition monitoring may have on the supply chain.

This paper presents an exploratory investigation into whether introducing a generic prognostic capability into an equipment fleet via condition monitoring can improve operational availability (A_o) and reduce both spare parts consumption and the average stock-holding over time, i.e. spare parts footprint. This paper does not consider the technology of the systems involved. The success of adopting a CBM approach to maintenance will rely on a number of factors that include, among others, sensible incorporation of CBM principles into existing practices. This paper examines two approaches for incorporating anticipation of spares demand into the supply chain: a pre-emptive *earmarking* approach in which spares are set aside for anticipated demand; and a pre-emptive *requisitioning* approach, in which anticipated demand directly generates requisitions for the corresponding spare parts.

CBM solutions for Land vehicles are not well defined in an Australian Army context at present, and thus this work is exploratory in nature and makes a number of assumptions about how Army would support the introduction of CBM for Land systems. Discrete-event simulation and analysis is used to quantify the performance of our abstract logistics system under varying conditions, and conclusions drawn from the observed behaviour.

Model and Experiment Overview

A Coloured Petri Net [20] model was constructed of a simple linear supply chain comprising four nodes at 1st Line, 2nd Line and 4th Line (loosely equated to integral, close, and national types of support) and a supplier node, as illustrated in Figure 1. The 1st, 2nd and 4th Lines of Support each comprised a single spares warehouse (whs), with a single maintenance workshop (wksp) collocated with the 1st Line warehouse. Inventory at each warehouse was controlled using a Re-Order Point/Re-Order Quantity (ROP/ROQ) algorithm [21].

An abstract fleet of 50 identical vehicles operating at 1st Line and experiencing a constant and ubiquitous rate of usage was considered. Each vehicle was decomposed into 5 major subsystems, with a specific failure rate, spares requirement and duration for both Preventative Maintenance (PM) and Corrective Maintenance (CM) assigned to each subsystem uniformly across the fleet.

[1] Technologies, information systems, and procedures to better predict and prioritise customer requirements.

A failure forecasting capability was considered that could detect failures a certain time period in advance (the 'failure forecast horizon') with a constant degree of accuracy. This anticipatory capability enables the maintenance workshop to act pre-emptively regarding provision of spares for anticipated maintenance tasks. We considered two alternative anticipatory strategies:

- Pre-emptively *earmarking* spares in the 1st Line warehouse for future use, setting spares aside in response to anticipated demand, thereby effectively reserving these spares and making them unavailable for other maintenance tasks; and
- Pre-emptively *requisitioning* spares in response to anticipated demand directly from the 2nd Line warehouse, outside of the ROP/ROQ stock replenishment process.

For brevity, the pre-emptive earmarking and pre-emptive requisitioning strategies will henceforth be known as the earmarking and requisitioning strategies, respectively.

Three PM policies were considered:

- *Scheduled PM* only, in which all subsystems undergo regular scheduled maintenance;
- *CBM* only, in which all subsystems are maintained based on condition, without regular scheduled maintenance; and
- *Scheduled+CBM*, the combination of Scheduled PM and CBM, in which condition monitoring is used to initiate maintenance between regular scheduled maintenance.

Further, two key input parameters were varied: the failure forecast horizon (FFH) and the *K*-factor (a multiplier used in ROP/ROQ algorithms to scale the amount of safety stock held in warehouses).

In the absence of concrete cost data, analysis of the model has focussed on three key performance metrics as proxies for cost: total fleet A_o[2]; 1st Line spares footprint; and overall parts consumption. These three metrics have been measured both in terms of instantaneous values and averages over all replications of the simulation for a given set of parameters. For this work, we consider all three metrics to have equal importance, although in practice this is likely to depend on operational context.

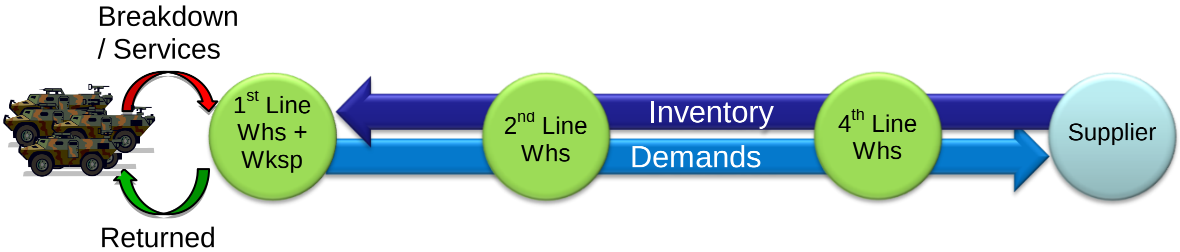

Figure 1: An abstract view of a generic simplified linear supply chain, comprising a single supplier, three warehouses and a single maintenance workshop integrated with the 1st Line warehouse.

[2] In this paper, A_o refers to the proportion of a fleet that is available for assignment to missions at any given time.

Experimental Results

General Model Behaviour

To provide insight into the general behaviour of the system, Figure 2 and Figure 3 present both instantaneous and time-weighted average statistics for a single exemplar 10-year simulation run of the Scheduled PM policy. Figure 2 depicts A_o while Figure 3 depicts 1st Line spares footprint. The metric of spares consumption is not shown, as trends in spares consumption generally follow trends in A_o. In this specific simulation run, the two significant dips in A_o are due to significant 'stock-outs' of one particular spare part reaching back to the supplier node. Footprint is seen to increase rather than decrease during these dips in A_o as replenishment actions initiated previously for other spare parts are fulfilled, noting that those spare parts cannot be consumed until the stocked-out spare part is once again available.

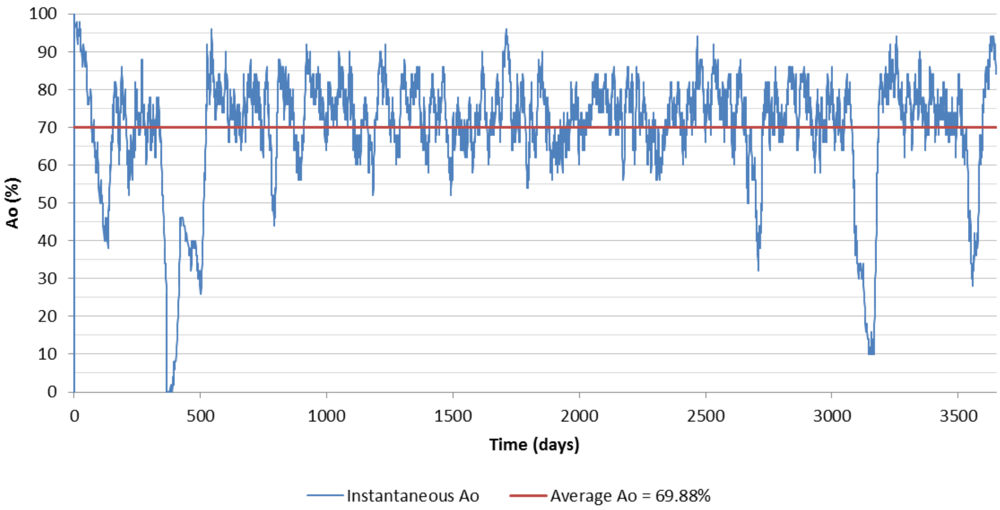

Figure 2: Instantaneous and Average A_o, for a single run of the Scheduled PM policy.

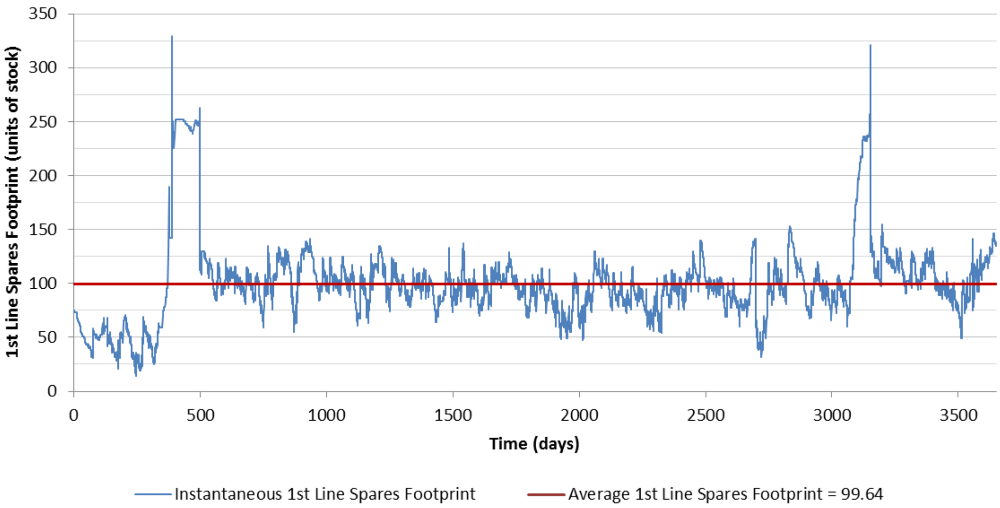

Figure 3: Instantaneous and Average 1st Line Spares Footprint, for a single run of the Scheduled PM policy.

For comparative purposes, Figure 4 shows histograms of instantaneous A_o for single runs of all three PM policies for both the earmarking and requisitioning strategies. Corresponding histograms of 1st Line spares footprint are shown in Figure 5. Making some general observations from these figures, we see that, at least for this run:

- The CBM and Scheduled+CBM policies provide similar increases in average A_o when compared to the Scheduled PM policy, from approximately 70% for Scheduled PM up to approximately 80% under earmarking and 75-77% under requisitioning (Figure 4);
- The average footprint of the Scheduled+CBM policy under the earmarking strategy is comparable to that of the Scheduled PM policy (Figure 5 (left)); and
- CBM exhibits a smaller average footprint than Scheduled+CBM, 72 vs. 102 units of stock under earmarking and 42 vs. 66 units of stock under requisitioning (Figure 5).

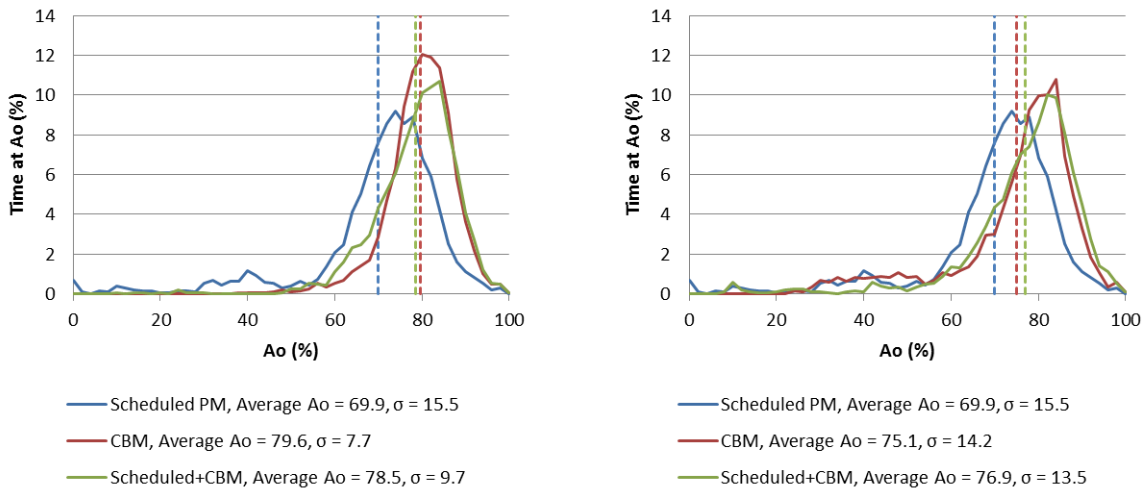

Figure 4: Histograms of Instantaneous A_o (average A_o shown as dashed vertical lines), for pre-emptive (left) earmarking, and (right) requisitioning.

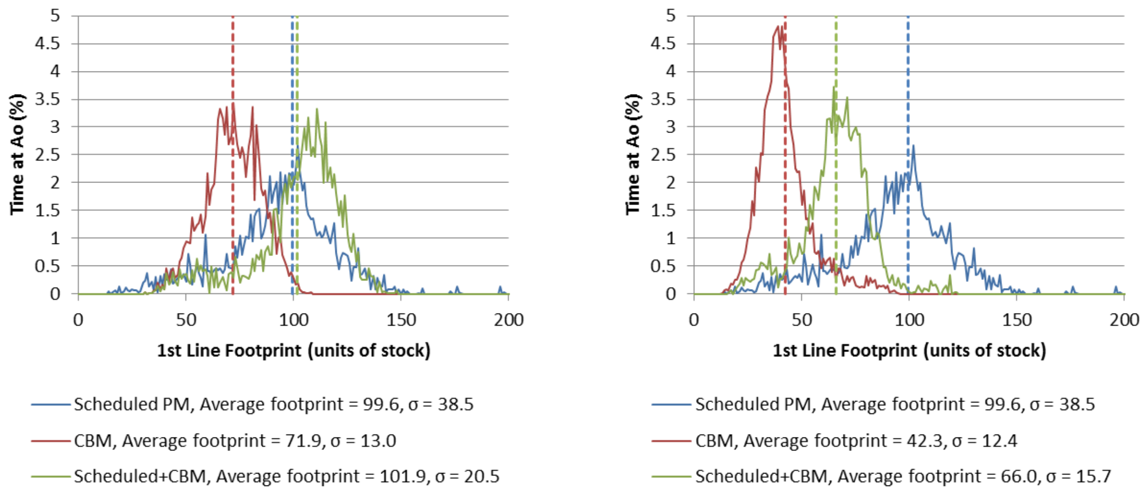

Figure 5: Histograms of 1st Line Spares Footprint (average footprint shown as dashed vertical lines), for pre-emptive (left) earmarking, and (right) requisitioning.

Overall, in this instance, earmarking outperformed requisitioning in terms of average A_o whereas requisitioning outperformed earmarking in terms of average footprint. To understand the observed behaviour, we consider how the effect of condition monitoring is taken into account in our model. Firstly, the presence of the failure forecasting mechanism in our model results in fewer breakdowns than would occur in its absence, through early maintenance intervention. Our scenarios are defined so that PM takes less time and consumes fewer parts than the corresponding CM action on the same subsystem, hence this means that less time is spent in maintenance and less spare parts are consumed. This has a tendency to increase A_o while decreasing the footprint for both the CBM and Scheduled+CBM policies.

Secondly, our earmarking strategy can cause replenishment to be triggered earlier than would otherwise be the case. In our model, the earmarking procedure sets aside spares in anticipation of future maintenance, resulting in a time gap between the point at which spares are reserved for a maintenance task and the physical consumption of those spares by the maintenance task. During this time gap, the earmarked spares are still physically present, hence still count toward 1st Line spares footprint, but are viewed by the ROP/ROQ replenishment algorithm as having been consumed. This has the potential to trigger replenishment earlier than if the spares were not earmarked, and hence has a tendency to increase the footprint.

Thirdly, the requisitioning strategy in our model will requisition spares as soon as the future demand is anticipated, but no earlier than the mean lead time between the 2nd and 1st Line warehouses. Given a normally distributed lead time between the 2nd and 1st Line warehouses, this will mean that the requisitioned spares will, at best, be late 50% of the time[3]. This has a tendency to decrease A_o through an increase in the time spent waiting for spares.

Model Parameter Sensitivity

To more closely observe the effect of FFH, we consider a 2nd to 1st line Lead time of four weeks[4] and adjust the FFH from zero weeks to eight weeks in one-week increments. A FFH of zero weeks corresponds to no ability to forecast failures in advance, but in our model this still allows for CBM to detect failures as they happen and hence avoid corrective maintenance. The results shown in Figure 6 compare A_o with 1st Line spares footprint for both the earmarking and requisitioning strategies. As above, we do not report results relating to spares consumption, as spares consumption closely follows A_o for each particular PM policy, with the Scheduled PM policy consuming the most spares and the CBM policy consuming the least.

In our model we see that extending the FFH improves A_o. There are two reasons for this: the ability to earmark or requisition spares earlier, giving more time for the supply chain to respond; and a higher degree of *aggregation* of maintenance tasks, hence reducing the costs associated with repeatedly calling vehicles into the maintenance workshop.

Figure 6 (a) considers the default level of safety stock (K=1.375, relating to a default 87% service level) at the 1st Line warehouse. It indicates that requisitioning is more

[3] Note that a condition based maintenance task can consume spares other than those in the corresponding requisition, hence does not necessarily have to wait for the spares in the corresponding requisition to arrive.
[4] Unrealistic for a practical system, but suitable for model exploration.

sensitive to FFH than is earmarking in terms of A_o, and that the CBM policy is more sensitive than the Scheduled+CBM policy. We observe that, when compared to the Scheduled PM policy, it is possible in some circumstances for:

- The footprint of Scheduled+CBM to worsen (under earmarking); and
- The A_o of CBM to worsen (under requisitioning).

The former occurs when the FFH nears or exceeds the 2nd to 1st Line lead time, as spare parts are earmarked progressively further in advance. The latter occurs when the FFH falls below about one quarter of the 2nd to 1st Line lead time[5]. It is clear that the ability to forecast failures in time for the supply chain to respond is critical for the success of the requisitioning strategy.

Mirroring the results observed for the single runs depicted in Figure 2 and Figure 3, we can see in Figure 6 (a) that the requisitioning strategy exhibits a smaller footprint than earmarking, and the CBM policy exhibits a smaller footprint than the Scheduled+CBM policy. Further, it is evident (and expected) that extending the FFH beyond the 2nd to 1st Line lead time of four weeks has a progressively reduced impact on A_o and footprint. The small variations that are observed when FFH exceeds four weeks are related to an increased ability to aggregate maintenance tasks further in advance of their occurrence.

Figure 6 (b) presents results from repeating the experiments depicted in Figure 6 (a) but with no safety stock (*K*=0.0) at the 1st Line warehouse. In this case, both the Scheduled+CBM and CBM policies can provide a more significant improvement to A_o, as indicated in the figure. However, we also observe that the A_o performance deteriorates more rapidly with decreasing FFH than when safety stock is present. This suggests that the ability to forecast failures has a greater impact in the absence of safety stock: this potential trade-off is explored in the next section.

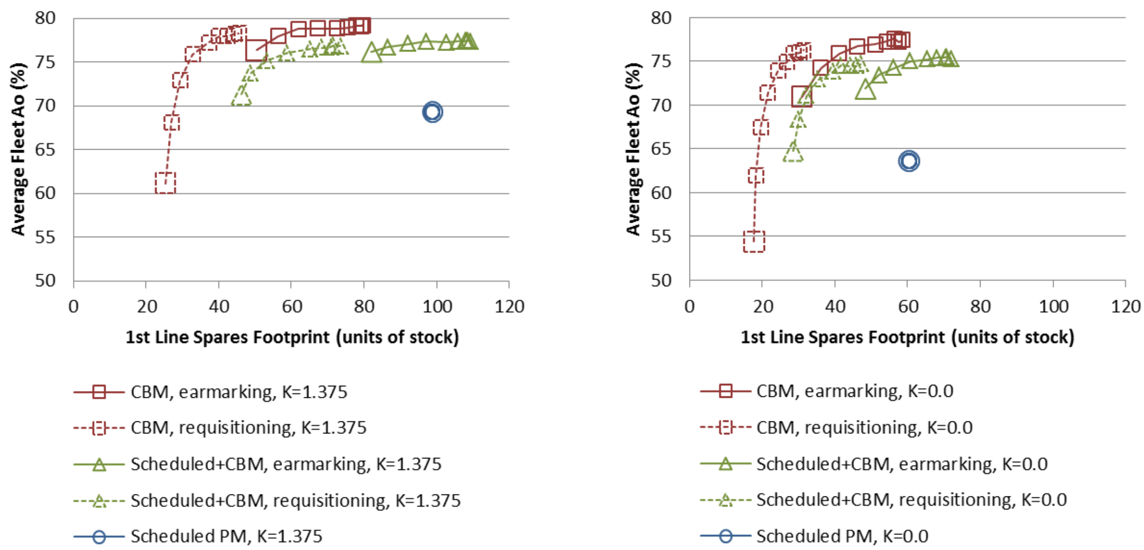

Figure 6: Comparison of A_o and 1st Line Spares Footprint when sweeping Failure Forecast Horizon through 0 to 8 weeks, for (left) the default level of safety stock, and (right) no safety stock at 1st Line. For all curves, a Failure Forecast Horizon of zero is depicted by an enlarged point, and increases from left to right.

[5] Whether these results hold for lead times other than four weeks was not explored in this study.

Trade-off Between Forecast Horizon and Safety Stock

The trade-off between *K*-factor and FFH in terms of A_o and 1st Line spares footprint is depicted in Figure 7 and Figure 8 for the earmarking and requisitioning strategies respectively. *K*-factor is varied from 0.0 (no safety stock) to 1.375 (the default level of safety stock) and FFH from zero to four weeks[6], both in four equal increments, with a 2nd to 1st Line lead time of four weeks. The same scale has been used for corresponding graphs in Figure 7 and Figure 8 to ease comparison.

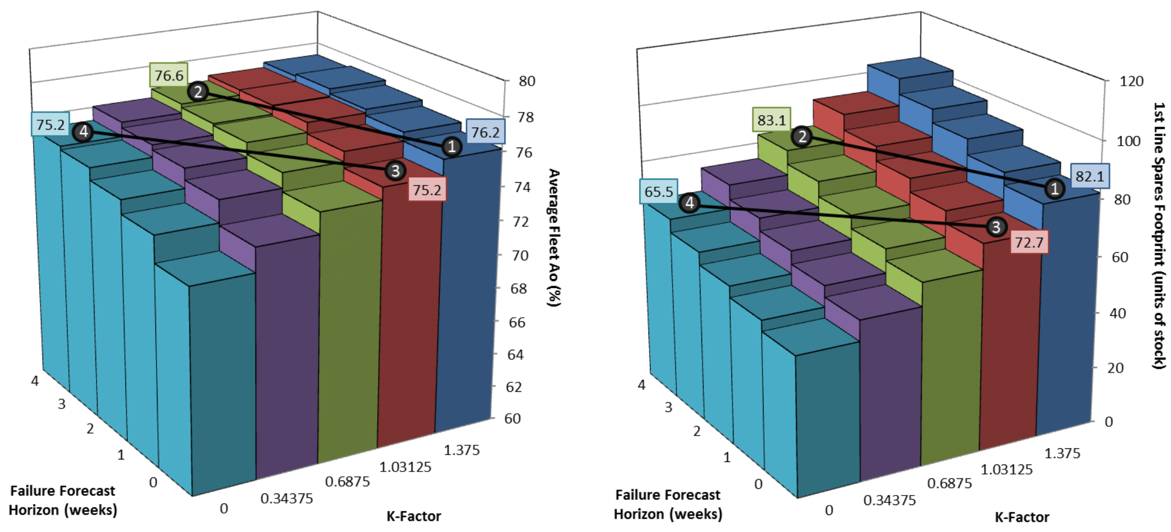

Figure 7: Trade-off between K-factor and FFH for the Scheduled+CBM policy under pre-emptive earmarking, for (left) average A_o and (right) 1st Line Spares Footprint.

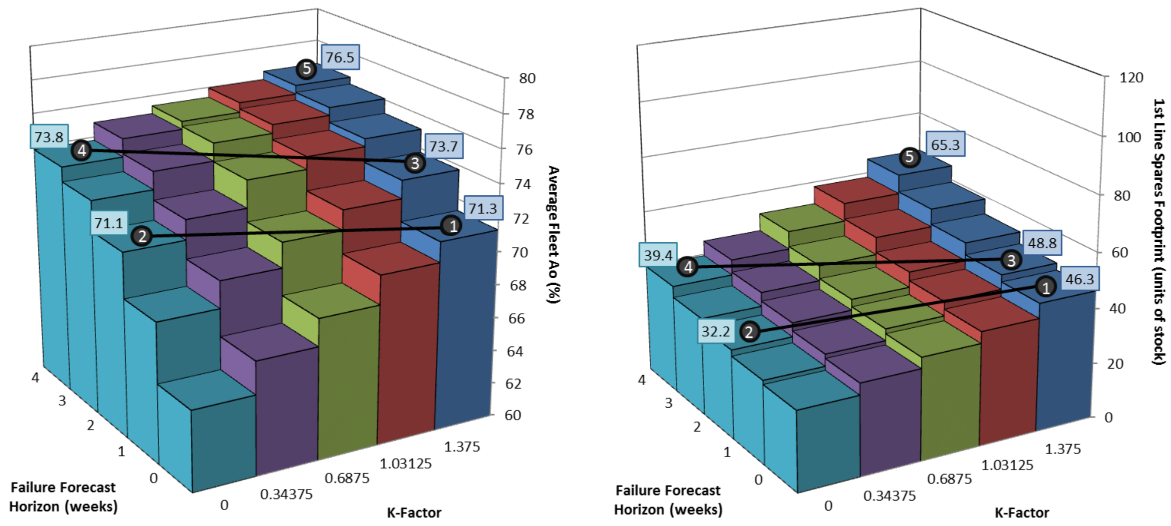

Figure 8: Trade-off between K-factor and FFH for the Scheduled+CBM policy under pre-emptive requisitioning, for (left) average A_o and (right) 1st Line Spares Footprint.

[6] As observed previously, extending failure forecast horizon beyond lead time provides only a minimal impact on A_o and footprint, hence a failure forecast horizon of four weeks is close to the optimum for this lead time.

Under the earmarking strategy, a FFH of four weeks is able to offset around one half of the default level of safety stock in terms of A_o (point 1 to point 2 in Figure 7 (a)) without having a significant impact on average 1st Line footprint (point 1 to point 2 in Figure 7 (b)). Conversely, a FFH of four weeks with *K*=0.0 (point 3 in Figure 7 (a)) provides about the same benefit to A_o as is provided by three-quarters of the safety stock with FFH=0 (point 4 in Figure 7 (a)). Further, it provides a modest improvement in footprint (approximately 10%, points 3 and point 4 in Figure 7 (b)).

Under the requisitioning strategy, a FFH horizon of only two weeks (half of the 2nd to 1st Line lead time) is able to completely offset the default level of safety stock (point 1 to point 2, Figure 8 (a)) while providing a significant decrease in footprint (point 1 to point 2 in Figure 8 (b)). Conversely, a FFH of four weeks with no safety stock (point 3 in Figure 8 (a)) provides the same benefit to A_o as the system with the full default level of safety stock and a FFH of one week (point 4 in Figure 8 (a)). Again, the former provides a reduction in footprint (nearly 20%, points 3 and 4 in Figure 8 (b)).

Although A_o is in general modestly lower under requisitioning than under earmarking, the 1st Line spares footprint tends to be significantly lower. For example, consider an A_o of around 76-77% under both the earmarking strategy (points 1 and 2, Figure 7 (a)) and the requisitioning strategy (point 5, Figure 8 (a)). To achieve this level of A_o under requisitioning requires a combination of a high-performing failure forecasting capability and all of the default level of safety stock, but this comes with a footprint reduction of around 20% (points 1 and 2 in Figure 7 (b) vs. point 5 in Figure 8 (b)).

Conclusions

Whilst the use of Condition-Based Maintenance (CBM) has been well established in the aerospace community over many years, CBM remains a relatively new concept within the Defence Land environment. As such, there remain many uncertainties as to the potential costs and benefits, including the savings in terms of inventory that can be realised by introducing sensors onto vehicles. One such uncertainty is how the use of vehicle-based prognostics would interact with the existing supply chain processes, and how this might impact on the Operational Availability (A_o) and inventory footprint for a given vehicle fleet.

Whilst the system representation is currently too abstract to inform projects directly, our experimental results confirm the belief that CBM has the potential to increase fleet operational availability, and reduce the spares footprint. The normal mechanism for managing supply chain uncertainty, i.e. safety stock, can be traded off with prognostic CBM capability. However, the improvement in A_o generally comes at a cost that is dependent on the specific implementation of inventory algorithms. Whilst increasing the degree of prognostics with pre-emptive earmarking improves A_o, it does so at the cost of footprint. Indeed, at higher forecast horizons there may be a net gain in stock held at the lowest level. Pre-emptive (or just-in-time) requisitioning based on condition monitoring is much more efficient, and the increase in footprint with forecast horizon saturates when looking ahead approximately twice the lead time. The reduced impact on footprint from the pre-emptive requisitioning is however accompanied by both a reduced A_o benefit and a higher vulnerability to uncertainty when the forecast horizon is not realised.

Our investigations have highlighted the importance of considering the maintenance and supply chain policies holistically. It further demonstrates that the question of cost-benefit of solution space should depend not only on the degree (and expense) of sensor-based prognostics, but also how this is employed within the supply chain, and what is done with the foreknowledge they provide. As an example, the increase in footprint for the pre-emptive requisitioning case is due to the complex interaction with the work aggregation heuristics, and suggests much more sophisticated risk-based analysis might be required to control the scheduling of tasks. As such, whilst implementing CBM programs into new systems almost certainly improves A_o through avoiding more time consuming repairs, corresponding improvement in logistics footprint requires more careful consideration of the supply chain. Such considerations unfortunately are often not considered when assessing systems for acquisition.

Future Directions

The future direction of this work is to consider the costs and benefit associated with CBM in the broader logistics context, against a backdrop of current and future Army acquisition projects. This includes costs and benefits that are both monetary and non-monetary and may potentially involve: investigating how to make better use of prognostics and foreknowledge; the degree of networking and global visibility of information within the logistics information system; and the evaluation of proposed future support structures both with and without CBM. An important component of this analysis would be the development of applicable risk-based heuristics for the supply chain controls that consider the appropriate scheduling and aggregation of events based on the probabilities of further as yet un-detected events occurring.

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