What did I forget? An Investigation into Refresher Training Intervals For A Multi-Skilled Maintenance Workforce

CAPT Andrew Stark[a,b], Amany Akl[b], Hasan Turan[b], Sondoss Elsawah[b]
Electrical Engineering Student [a]School of Engineering and Information Technology [b]
University of New South Wales [b]
Canberra, Australia [b]
a.stark@unsw.edu.au, amany.mamdouh@adfa.edu.au,
h.turan@adfa.edu.au, s.elsawah@adfa.edu.au

Abstract

Base intuition tells us that if you don't keep practicing a given skill set, it will continue to degrade the longer it goes unused. What does this mean for a skill set that only gets used infrequently? How can one be assured that when they need their skills, that they will be in a state that is reliable? This point becomes even more important when the skills set belongs to a technically skilled worker, within a maintenance facility. Not only does this affect the quality of the work produced, but also the time taken to perform the task. In this study, learning curve theory is applied to the workforce of a military maintenance facility to firstly, identify the changes to job task time that can be expected due to knowledge and skill degradation, and secondly, to determine training intervention types that address the loss of knowledge and/or skill. Through the use of computational experimentation based on Discrete Event Simulation maintenance model output, it was observed that without refresher training intervention, job completion times increased between 14% and 27%. With intervention applied, this increase in completion time can be reduced and maintained at levels as low as 4.14%.

Keywords
Maintenance, Workforce Planning, Defence, Learning Curve and Discrete Event Simulation

1. Introduction

A key measure of a maintenance facility's performance is its ability to adhere to specified task durations, thereby completing a designated amount of maintenance over a given period and thereby maximizing asset availability. This is especially important in Australian Defence Force (ADF) maintenance facilities, as capability system availability is directly tied to the organisation's ability to deliver the service required. Whilst much effort has been applied to the analysis and enhancement of performance in this space, there is a lack of research investigating an individual technician's output - research has focused on factors which effect the facility as a whole, e.g., supply chain issues, (L¨ofsten, 1998, Safaei et al. 2011, de Jonge and Scarf, 2019), Hamimi, Razak et al. 2011). This report attempts to analyse the variances in individual performance.

ADF maintenance facilities do not differ greatly from their civilian counterparts. The most significant difference is the routine high turnover of the workforce due to posting cycles. In this research, the modelled maintenance workforce is that of an unguided weapon maintenance facility employing both ADF and civilian personnel. Effort has been made to maintain a generic approach in the modelling so that the results are useful to maintenance facilities supporting a wide range of equipment. More detail on the workforce and data pool will be provided in Methodology Section.

To analyse the performance of the individual, one must have a proven mathematical means of determining how an individual learns and forgets. Learning Curve (LC) modelling, initially developed in "Factors affecting the cost of airplanes" (Wright, 1936), provides us such a model. LCs have become a verified means of modelling learning and forgetting in fields such as medicine, sports, and software development. This methodology will be adapted in this research to determine the technician's task completion time and therefore the maintenance facility's output.

Refresher training is widely accepted as one of the valid means of maintaining both knowledge and physical skill sets (Sullivan et al. 2019). Numerous professions world-wide employ refresher training as a means of maintaining a prescribed level of competence within a group or workforce. Given the nature of technical maintenance, a physical task requiring a depth of technical knowledge, refresher training is believed to be an effective means of maintaining a competency level within this sector. Refresher training variables are easily incorporated in the LC model, enabling the analyser to predict the effect of the training and the frequency training needs to be conducted.

1.1 Objectives

The objective of this research is to investigate the effects of learning and forgetting behaviours on the output of a military maintenance facility, then implement and investigate different training strategies in order to maintain a pre-determined level of competence within the workforce.

2. Literature Review

Our study intends to develop a model of a maintenance worker's production, which captures their learning and forgetting behaviour of both technical knowledge and physical skills. In doing so, contributing to the overall workforce modelling literature by providing an individual productivity measure for a technician, inclusive of a refresher training regime, to accurately forecast individuals' production levels and staff availabilities.

There is no shortage of studies into the field of maintenance. A simply cursory glance shows that so long as there have been maintenance facilities, there have been studies regarding them. Most of these studies have surrounded the management of such facilities and gaining the highest efficiencies out of them for a business need. Studies have also examined maintenance in production facilities for the upkeep of production machinery. To that end, "management science and operations research journals are replete with optimization models based on statistical analysis of component failures" (Löfsten, 1998).

So, we must begin our study with defining what the term "maintenance" means in our efforts. Maintenance is "the combination of technical, administrative, and managerial actions for the purpose of retaining and restoring an item to a state in which it can perform its required function" (Hamimi et al., 2011). There is sufficient research surrounding the administrative and managerial actions within maintenance and these will be assumed for our purposes. Our focus will be towards the technical actions that are a key component of the maintenance process and can delve further into their analysis and effect within the maintenance space.

The primary input to these technical actions is the human workforce. Previous studies acknowledge that the human resource is the highest priority because of the skilled labour it provides is essential in the process (Safaei et al., 2011). Yet, in most of these studies the technician's output remains at capacity and does not carry any uncertainty (de Jonge and Scarf, 2019). In fact, a very few studies even consider workforce availability and capacity as a restriction (Safaei et al., 2011; Hamimi et al., 2011). It is quite fair to say that if one ignores the capability of the individual, then the evaluation of the output of the workforce may be compromised.

Hence this led us to considering the performance of the worker. There are many ways in which a worker's output can be analysed, from expert analysis (Hamimi et al., 2011), through evaluation of performance against ability (Cooper, 1991), and studies on human reliability (DiMattia, Khan, and Amyotte, 2005). No matter which technique is utilised, a common theme was found - skills that are used regularly are maintained, whilst periods of non-use saw skills deteriorate (Kluge and Frank, 2014). This is also seen in areas such as medicine, where a surgeon does not conduct a certain procedure over time, their ability in this field deteriorated (Sullivan et al., 2019).

Knowledge and physical skill degradation occurs in any profession that utilises physical skills. From surgeons to technicians, chefs to sports people, physical skills can define one's ability to perform their role. It comes as no surprise that, if these skills are not practised regularly then degradation will occur. It is therefore in an organisation's best interest to provide refresher training based off an interval that compliments the tasks completion frequency. In all cases where refresher training has been implemented, workers have been observed to have an increase in both knowledge and skill retention, regardless of the refresher type or interval used (Sullivan et al., 2019; Kluge and Frank, 2014).

Both skill degradation and refresher training can be mathematically modelled and both are encapsulated in the wider category of learning curves (LCs), of which much research has been conducted (Anzanello and Fogliatto, 2011; Valeva

et al. 2017; Keumseok and Hahn, 2009). LCs are a mathematical description of workers' performance in repetitive tasks (Anzanello and Fogliatto, 2011). Originally developed by Wright (Wright, 1936), the concept is that the more frequently an individual performs a task, the familiarity grows and therefore the time per repetition reduces. Similarly, if there are large non-utilisation periods, the skill of the individual will degrade (Kluge and Frank, 2014). Because these LCs have been developed over a multitude of disciplines, with varied control parameters (e.g. cost per unit, accounting for prior experiences, multi-discipline tasks, etc.), analysing for different effects, there is no overall definitive model. For the purposes of this report, a combination LC involving learning and forgetting will be adapted from the works of Keumseok and Hahn (2009).

The last aspect we need to analyse is that of the refresher training; namely the types and intervals between refresher training. From the literature, there are three types of training: maintenance, booster and refresher (Sullivan et al., 2019). Maintenance is delivered regularly and keeps an individual well above the competency level. Booster training is delivered as the individual approaches a non-competency level and is less frequent than maintenance training. Refresher training is delivered to an individual who has dropped below the competency level and is viewed as infrequent. These practices are displayed in Figure 1.

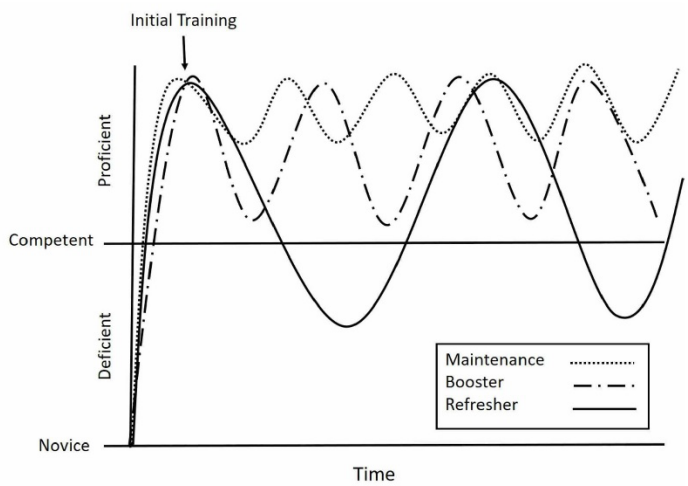


Figure 1. Maintenance, Booster and Refresher Training (Sullivan et al., 2019)

Further to the training types, the literature acknowledges three intervention types which are deemed to be most effective (Kluge and Frank, 2014). These being practice, testing and symbolic rehearsal. As the name implies, Practice is repetitively doing the work until a desired proficiency level is reached. While testing is a test of knowledge and skills after an education phase. Lastly, Symbolic Rehearsal sees an individual visualise the performance of a task, depict or notate the process, without actually performing it.

There are two main methodologies regarding the interval between training provisions, being time-based and skill-based (Sullivan et al., 2019). The time-based approach sees all staff conduct the training at a given interval regardless of their individual skill level. While the skill-based approach requires the detection of a decline in skills to trigger the training. The literature also suggests that a hybrid of these to regimes may be best to cater for an individual requirement.

There is much research into the advantages of employing a preventive maintenance (PM) strategy in asset maintenance; cost savings have been observed in the realm of 10% to 30% with an effective PM strategy (Stenström, Norrbin, Parida, and Kumar, 2015). When considering that this approach is aimed at correcting a fault before it is observed, it is plausible that this concept would yield similar outcomes when applied to human element.

2.1 Gaps in the research

In conducting this research, it has become apparent that whilst much effort has been placed into fine-tuning maintenance facility efficiency and cost-effectiveness, it is an area of research which has stagnated. Very few recent papers are available and older papers employ models that do not consider an individual's effect on the overall

performance of the facility. This deficit is believed to have a significant impact on the overall output of a facility and this is the gap in that this research intends to address.

3. Methods

The Simulation Model. This project utilised a large-scale discrete event simulation (DES) to simulate the Asset Management and Maintenance Model activities. This model simulates a maintenance workforce and asset pool over a selected duration. The workforce structure and top-down simulation workflow diagrams are shown in Appendix A, Figures A.1 and A.2. The user is able to simulate hiring and separation rates, technician advancement rates, equipment maintenance requirements and equipment quantities, naming only a few of the parameters. It has been validated and verified by subject matter experts and software developers as an accurate and reliable workforce and maintenance planning simulator.

The LC. The LC used in the experiments for this project is adapted from the recent work of Keumseok and Hahn (2009), which accounts for both learning and forgetting. A power function is employed, beginning at Equation (1) with the simple power law formula, from the original concept of LCs (Wright, 1936).

$$y = cx^{\beta}$$

In Equation (1), the dependent variable y represents the time per task iteration, the constant c is the standard or expected time of the task; x is the number of like tasks completed (or gained experience), and the exponent β is the learning rate parameter - when examining LCs, this value becomes negative in order to reduce the time per task. This is a complete model for the learning aspects and has been implemented in many studies, with the results paralleling real world results.

The next aspect we must account for is forgetting. We can again utilise the simple power function format; however, we must include a forgetting rate and a time between task parameter. Equation (2) displays the forgetting term of the LC model.

$$y = cx^{t\alpha}$$

In this equation, y, c and x retain their definitions from Equation (1). The variable t represents the time between iterations of the task - for this study, the time parameter is calculated as in Equation (3), where T is the number of task iterations per year. The α variable, which facilitates the forgetting rate, is set between 0 and 1, with a value of 1 showing no forgetting and a value of 0 showing no retention.

$$t = 1 - \frac{T}{52}$$

We now combine the models into one that captures the learning and forgetting, resulting in Equation (4). It is to be noted here that this equation is in same form as the literature, however utilising the time parameter in a different manner. Finally, the parameter c is now subtracted at the end of the model, to re-center the curve.

$$y = c\left(x^{\beta} + x^{t\alpha}\right) - c$$

There are only certain parameters of the refresher training that can be altered for our purposes. We can alter the intervention frequency, both through time and skill-based approaches, based on author experience of what is acceptable within the ADF maintenance workspace - as this is not detailed in policy. The intensity of the training can be altered through a manipulation of the β parameter (although as this study is focused on the overall concept, this will not be done) - this is akin to changing between the three training types of maintenance, booster and refresher.

3.1 Assertions and Assumptions

Whilst completing this study, a number of assertions and assumptions were made by the author, in order to complete the simulation. These were:

1. Maintenance task frequencies were set to a weekly domain, as per the simulation settings.

2. Learning and forgetting rates, α and β, taken from literature sources (e.g. (Keumseok and Hahn, 2009)) and were assumed equivalent to what could be expected from technical tradespeople.
3. Refresher training intervals were varied across maintenance tasks, utilising lived experience for numbers that would be acceptable within the military maintenance environment.
4. The average technician works 48 weeks per year, 5 days a week, 8 hours a day which yields 1,920 productive hours per year, per technician.
5. The workforce, assets and maintenance policies are employed in the simulation were kept generic in nature, in order to aide in being applied more broadly.
6. The workforce, at any one point in time during the simulation, comprised a total of 15 technicians, spread across the various positions within the facility. This total number was maintained throughout the simulation, with new technicians being added and older technicians leaving, as per the military posting cycle.

3.2 Constraints and Limitations

As for the limitations of this research; evidence cannot be found that LC theory has been applied to the military maintenance workforce and more broadly, only specific instances of maintenance have been studied in this manner. Therefore, known learning and forgetting rates are not recorded. To fill this void, results from studies within the software development and medical fields have been used; as both industries rely on underpinning technical knowledge using a physical skill-set for implementation. This approach was considered flexible enough to fulfill a proof on concept approach, opening an avenue for future research. The research required to obtain these numbers from the military maintenance workforce was outside the scope of this project. However, this may become prudent in future to clearly ascertain learning and degradation rates so as to correctly calculate required refresher training intervals.

3.3 Experiments

Access to the DES model is provided to the user via an Excel spreadsheet where one can build their organisation - simulation duration and known idle periods, equipment types and quantities, maintenance policies and frequency of breakdown during simulation, warehousing and spares, technician pool and hierarchy, and hiring and separation rates. As mentioned earlier, the data used in this study was the same as used in Withers et al., This data set employed a mixed ADF/Australian Public Service (APS) workforce, with the hiring/separation policies aligning with ADF posting policies. The equipment numbers and maintenance policies were also maintained. Table 1 details the variables which were altered per experiment.

The baseline (control) experiment was a ten-year simulation conducted within the confines of the simulation model . The simulation is conducted weekly steps and was computed on the author's Dell XPS 15 9500. This experiment utilised ideal conditions and controlled the rotation of staff throughout the simulation, maintaining the aforementioned 15 technicians at any one time. There are 23 maintenance tasks to perform within the simulation, duration's for these tasks ranging from one to seven hours - the frequency of these tasks is dependent on the maintenance policy . For this experiment, task duration remained fixed and no learning, forgetting or retraining was conducted. The results of this experiment form the control data for the remainder of the study.

The first computational experiment on the control data was to calculate an LC which encapsulated the learning and forgetting aspects only. This process involved stepping through the data, amending the task completion time for the organisation based on the task iteration number and the LC variables as described previously.

The second computational experiment implemented refresher training, with intervention frequency based off task iteration amounts. we determined the interval duration was utilising the technician and trade supervisor personal experience. Considerations for this duration included current task time, specified task time and calendar year, owing to the ADF posting cycle. From experience, trade section training within the ADF can be determined by the trade section supervisor, in the first instance, to address a skill or knowledge deficit, or to raise the group's performance to a desired level. This process is not detailed within policy, however, has been witnessed as acceptable practised many times.

The third computational experiment again implemented refresher training; on this instance the intervention frequency was based off the percentage of specified time that the current iteration of the task took. The determination of how much time the job was permitted to overshoot by came down to the judgment of the author and their application of experience-based knowledge of acceptable limits within Defence maintenance facilities.

Table 1. Experiment testbed

Experiment	Task Duration	Learning and Forgetting	Refresher Training
Control	Fixed	×	×
1	Calculated	✓	×
2	Calculated	✓	Iteration based
3	Calculated	✓	Completion time based

4. Data Collection

The Data. To ensure our study remained relevant to ADF Maintenance facilities, the equipment, technician pools and maintenance strategies were adopted from Withers et al. (2021). This dataset is a replication of a maintenance facility which employs both ADF and Australian Public Service (APS) maintainers. The maintainers are of different ages and seniorities within the facility, fulfilling roles of technician, inspector and verification, as per the workforce structure depicted in Figure A.1. Throughout the simulation, individuals progress through the positions, including separating from facility, with new personnel arriving.

5. Results and Discussion

Figure 2 displays the organisational maintenance hour totals for idealised conditions (baseline experiment), no refresher training (first computational experiment), refresher training based off task iteration number (second computational experiment) and refresher training based on task completion time (third computational experiment). Without refresher training, a 14.86% increase in total hours is observed over the span of the simulation. Under the two refresher training continuum's, we observe this number reduce to 5.22% for the iteration-based approach and 4.14% for the completion time based approach.

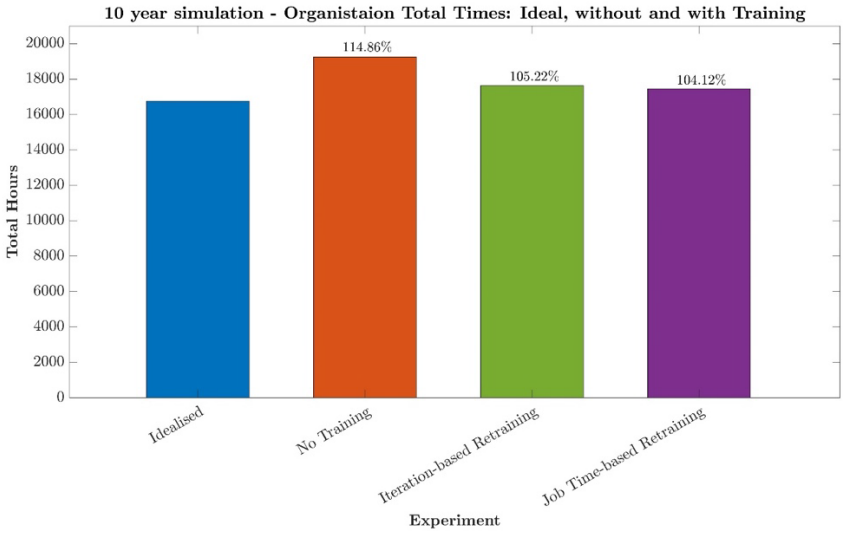


Figure 2. Organisational Maintenance Hours – Totals

When conducting the analysis for individual technician's total maintenance hours, an anomaly was encountered - the initial configuration of the calculation treated each technician's first completion of each task as their first completion after becoming qualified. Given the low number of task iterations per technician and the nature of the LC, this led to every technician yielding total hours less than the ideal case, which is unrealistic. To remediate this issue, each technician was assigned a starting value, per task, which represented the number of historical completions at the start of the simulation. This approach proved to be effective, the results are displayed in Figure 3. For the no refresher case, total hours increased some 27.78% when compared to the ideal total. For the iteration-based training, this figure reduces to 25.58%, and for completion time-based training to 15.77%.

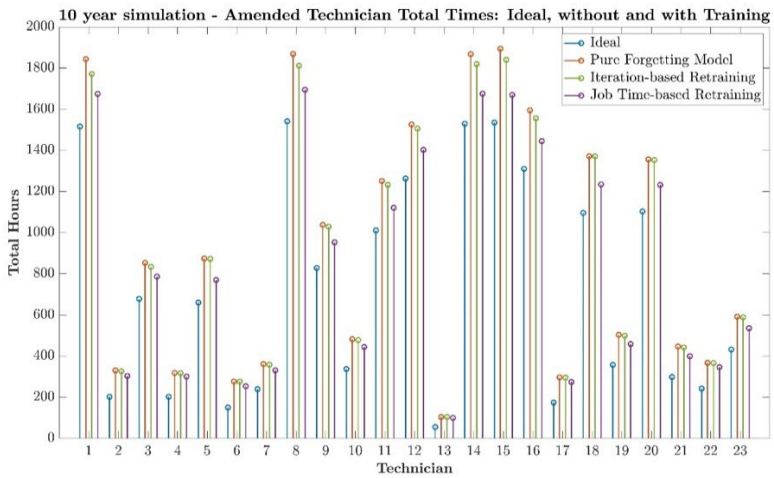


Figure 3. Adjusted Technician Maintenance Hours – Totals

For the individual task completion times, as shown in Figure 4, we notice that the lower frequency tasks (tasks 1-8, tasks completed approximately once a month) benefit from the completion time-based training regime, while the higher frequency tasks (tasks 9-23, tasks completed approximately once every two weeks) benefit from the iteration-based approach. This is further confirmed in Figures 5a and 5b, for low repetition and increased repetition respectively. The vertical line in these plots represent the years over which the simulation was conducted.

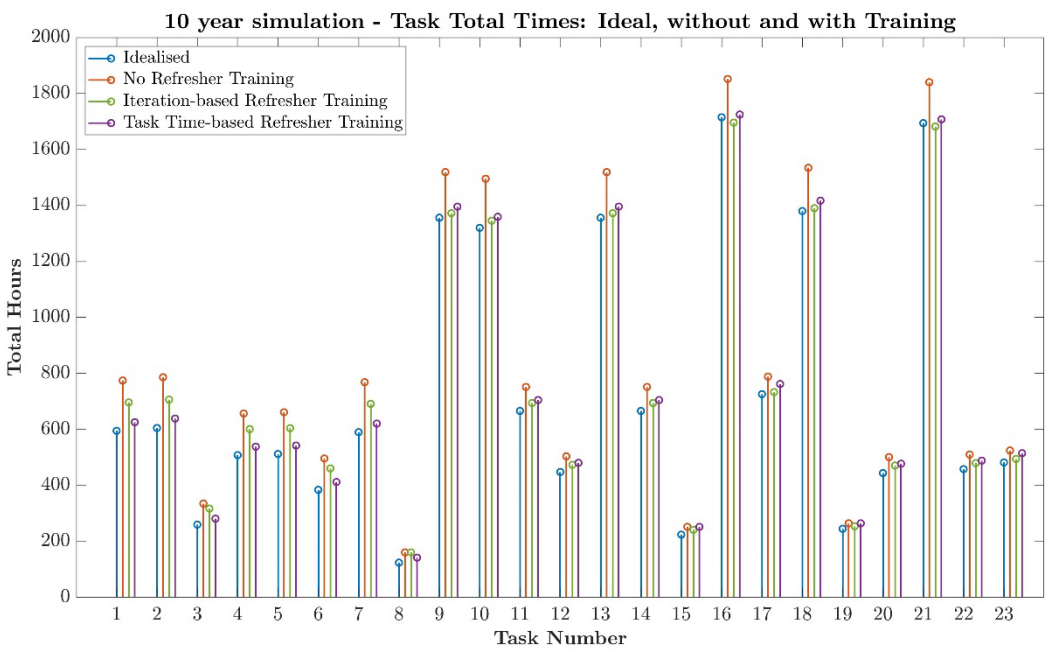
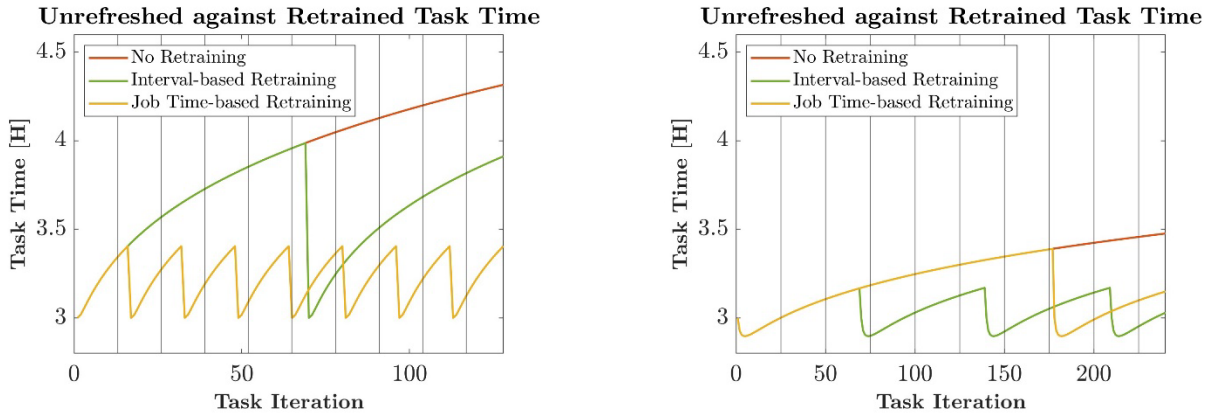


Figure 4. Specific Task Total Hours



a. 3 Hour Task with Low Repetition

b. 3 Hour Task with Moderate Repetition

Figure 5. Effects of Task Frequency

The first compelling finding in the results came from the first computational experiment - the discrepancy between idealised time reporting and the actual time to complete a task without refresher training. Whilst this simulation is conducted in a very controlled environment where each technician adheres to the parameterised learning curve values, the revelation is that the time to complete a task can be seen to increase by 27.78% over the ten-year period, if that technician receives no refresher training. Thus, if the technician is completing a task specified at seven hours, this task will almost take 9 hours.

From the second and third computational experiments, we find that from an organisational point of view, a balanced approached to training is required. Figure 2 shows that both refresher interval approaches yield similar results because of the correlation between task frequency and retraining regime. This is highlighted when analysing Figure 5, it is noted that the low frequency tasks, conducted at a rate of once every four to five weeks, respond with a task completion time approach, while tasks with higher frequencies were maintained through the task iteration based approach. An organisation would need to analyse their tasks and completion data to ensure training policies are aligned correctly.

While analysing the data of individual technicians in the second and third computational experiments, we find that a task completion time approach to refresher training yielded the best results. This is due to total individual task completions being small. If training were based off the individual's total task iteration number, the threshold would need to be much lower to have significant impact. Therefore, planning refresher training at an individual level is far more effective if it is based off their task completion time.

For computational experiments number two and three, the retraining intervals were decided by the author lived experience over a decade of working within the military maintenance field and employment as a technician through to coordinator. These intervals are believed to be based on what are acceptable task overshoot times. Therefore, it is recommended that organisations engage expert opinion to decide what is best for their situation.

The importance at an organisational level to accurately track completion times, even if they exceed the specified task times, cannot be understated. Without this being done, analysis is nearly impossible and therefore training regimes will not be able to cater for the actual deficiencies.

6. Conclusion

This study has endeavoured to forecast the knowledge and skill degradation of a technically skilled, military maintenance workforce and suggest retraining options to ensure a prescribed level of competency is retained. Through the use of LCs, we are able to model learning and forgetting behaviours, and also the effect of training during the simulation. This approach combined with the validated and verified the simulation workforce model, has demonstrated not only the effect of forgetting and skill degradation on the output of a maintenance facility, but also the possible improvements to productivity by the employment of a well-directed refresher training policy.

Through the experiments detailed in this report, we have seen that, when viewed from the organizational point of view, maintenance tasks with a relatively low repetition frequency (occurring monthly or less than) benefit from monitoring tasks completion times and implementing training when these times exceed a predetermined level. Whereas tasks that occur more frequently (every two weeks or so), had their completion tasks well maintained with a refresher training program driven off the number of task completions.

If one were to consider a refresher training program aimed at the individual, the results favoured the task completion time approach, as individual task iteration numbers increase slowly. This may only be required where an individual's performance has been observed to be lapsing.

Finally, the results confirm the hypothesis that without refresher training being implemented, the time taken to complete infrequent tasks will increase. It is therefore in the interest of the organisation to conduct maintenance task completion analysis, both in the frequency of the task and the time taken to complete the task, and implement a refresher training regime to address the shortfall.

6.1 Acknowledgements

We qualify that the analyses in this paper are not a reflection of the position, intent or opinions of the Australian Army or any defence organization but are solely the opinions of the authors of the paper.

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Appendix A - DES Workforce Structure and Top-Level Visualisation of the DES Model

Figure A.1 depicts the workforce hierarchy as used by the DES model. Throughout the simulation duration, staff are progressed through the positions over time-frames that are commensurate with military time-inrank requirements.

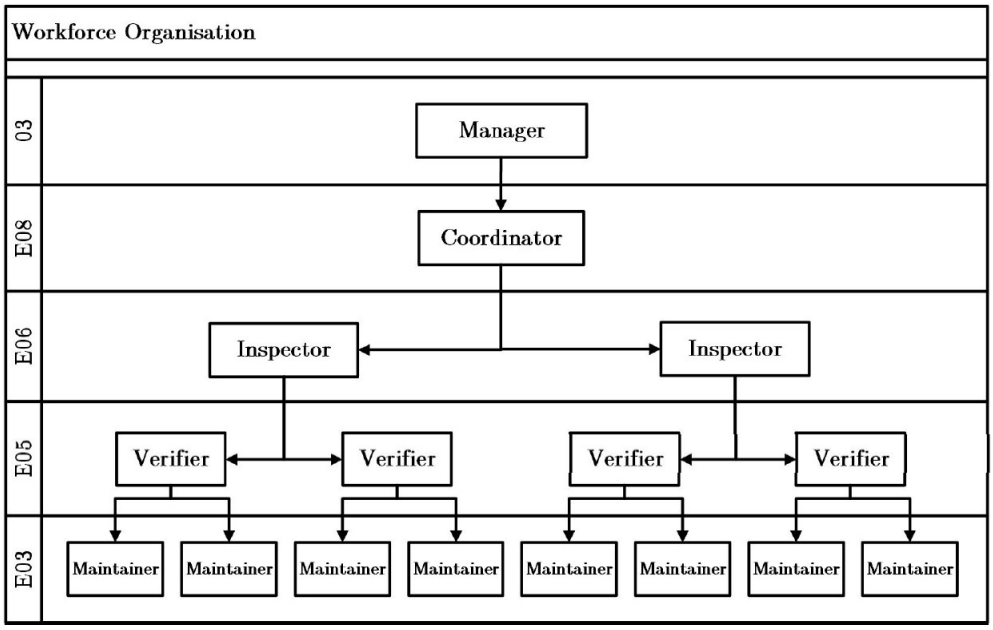

Figure A.1: DES Workforce Hierarchy Model

Figure A.2 shows the top-level simulation workflow of the DES.

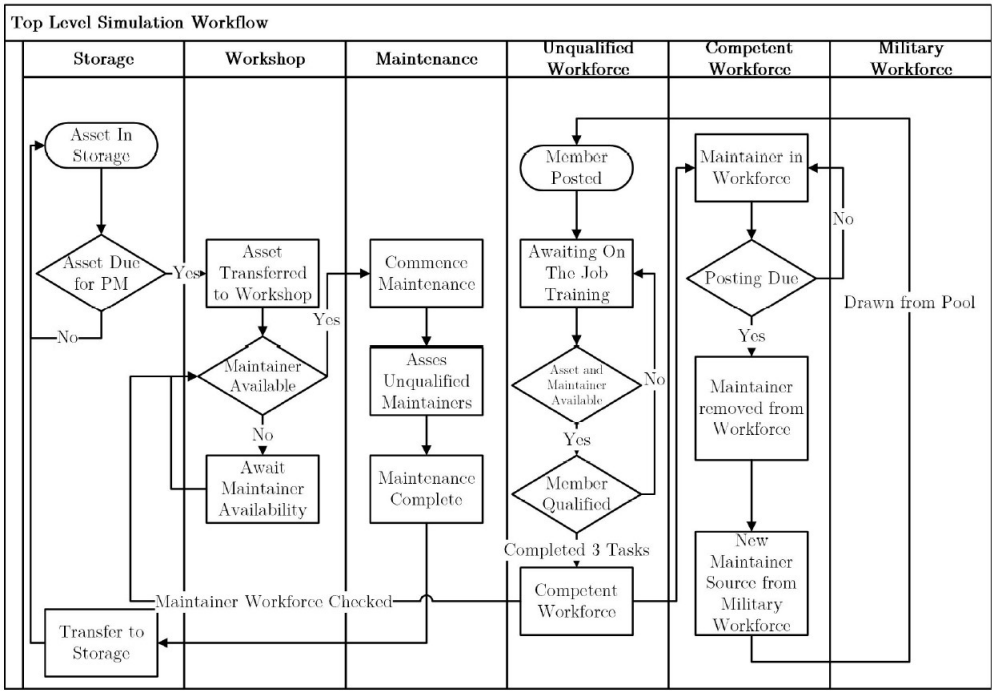

Figure A.2: DES Top Level Workflow Chart

Biographies

Andrew Stark,UNSW-C at Australian Defence Force Academy
Andrew is a fourth-year electrical engineering student at ADFA. He has served in the Australian Army for 20 years, working primarily as an electronics technician, across a vast array of equipment fields. Through his career he has worked as a technician, small team leader, section supervisor and workshop commander. His experience within ADF maintenance facilities includes the training of established trades-people and ab-initio personnel.

Amany Akl,, Research Associate Post-Doc UNSW at Canberra
Dr. Amany Akl is experienced in Operations Research and Decision Support. Her research interests cover operations research, decision support, simulation-optimization, evolutionary computation, machine learning, development of optimization models such as those of cybersecurity and power systems. She has a solid background and long-established experience and capability of building mathematical and statistical models and developing software programs for such systems. She has 10 years of professional experience as an Assistant Lecturer, a Research Assistant in the Centre of Excellence in Data Mining and Computer Modeling (CoE), Cairo University, PhD researcher, and currently Research Associate at the Capability Systems Centre, SEIT, UNSW at ADFA.

Hasan Turan, Lecturer and the Research Lead at Capability Systems Centre, UNSW Canberra
Hasan H. Turan obtained his Ph.D. and master's degrees both in Industrial and Systems Engineering from Istanbul Technical University and North Carolina State University, respectively. Dr. Turan's research interests revolve around the development and application of data-driven optimization algorithms and simulation models arising in different domains including service and maintenance logistics, defense applications (fleet management, workforce, and resource planning), energy capacity expansion, and telecommunications networks.

Sondoss Elsawah (Associate Professor at UNSW Canberra) Sondoss Elsawah' expertise lies in the area of the design of multi-method and collaborative modelling methodologies to support decision making, learning, and design. She has published widely including journal articles, conference papers, book chapters, and technical reports. She has attracted research grants from Government and industrial agencies in Australia and overseas, including Australian Research Council (ARC) and US National Scientific Fund (NSF). Her research has been recognized by multiple prestigious awards, such as: the Best Paper Award by the International Council on Systems Engineering (2017), and The Australian Society of Operations Research Rising Start Award (2016). She is an editor of the Journal of Environmental Modelling and Software.