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Retention in the Royal Australian Air Force Aviation Technical Workforce: Is it Changing and how Feasible is the Future Demand?

March 2022

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ABSTRACT

Recently, the Royal Australia Air Force (RAAF) has embarked on a large-scale expansion of its air and space power capabilities to better achieve joint effects. The RAAF fleet currently comprises both legacy and advanced aircraft with differing maintenance requirements. In order to deliver air and space power effects, the RAAF needs to recruit, grow, and retain personnel with specialized aviation maintenance skills. The focus of this thesis is the enlisted aviation technical categories of Avionics, Aircraft, and Armament technicians, which represent approximately 15% of the RAAF's full-time members.

This thesis develops Markov models for time in service and time in rank to determine transition rates within this workforce and to predict future inventories until fiscal year 2030–31. These predictions are compared to a fictitious demand profile to determine the feasibility of the demand and system behaviors that need to be changed. A one-year time in service and one-year time in rank model perform well in predicting system behavior in recent years. The results show that the RAAF will not meet future demand for the aviation maintenance workforce by 2030–31, particularly at the E05 and E06 ranks. E03 personnel are leaving sooner in their time in rank, and retention rates are too low at E05 and E06 ranks. The RAAF either needs to adjust the future demand or attempt to modify the behaviors in this workforce; adjusting promotion rates is one lever to modify retention behavior.

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I owe a great deal of thanks to my family and friends in Australia for their support and ongoing words of encouragement, particularly when I broke my wrist … and then ruptured the tendon to my thumb … adding more challenges to the mix. To my family, Dad, my brother Paul, and Aunty Ros, thank you for being there to encourage me and to make me feel like I'm still connected to Australia. To Katrin, Mia and Robbo, Steph, Tricky, Annie, Cara, CK, BJ, Jacqui, and others who sent me messages of support, thank you for being there; this would have been so difficult to get through without you.

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LIST OF ACRONYMS AND ABBREVIATIONS

1RTU	1 Recruit Training Unit
ADF	Australian Defence Force
AFS	Average Funded Strength
ARMTECH	Armament Technician
ATECH	Aircraft Technician
AVTECH	Avionics Technician
BAM	Base Armament Manager
CMB	Career Management Board
DASR	Defence Aviation Safety Regulations
DFR	Defence Force Recruiting
DFRDB	Defence Forces Retirement and Death Benefits
DGPERS-AF	Director General Personnel Air Force
DWP-AF	Directorate of Workforce Planning – Air Force
EASA	European Aviation Safety Association
EO	Explosive Ordnance
EOD	Explosive Ordnance Detection
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
IET	Initial Employment Training
IMI	Independent Maintenance Inspector
IMPS	Initial Minimum Period of Service
LSC	Line Safety Controller
MM	Maintenance Manager
MPIP	Maintenance Productivity Improvement Program
MRO	Maintenance Repair and Overhaul
MSBS	Military Superannuation and Benefits Scheme
RAAF STT	Royal Australian Air Force School of Technical Training
RAAF	Royal Australian Air Force
SRG	Surveillance and Response Group

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I. INTRODUCTION

A. OBJECTIVE

The purpose of my thesis is to determine whether the separation behavior of the Royal Australian Air Force (RAAF) enlisted aviation maintenance workforce is changing, utilizing a Markov modeling approach. I develop two manpower inventory models and compare them through a rigorous cross validation process to determine which performs better in predicting a set of known data. Then I use the best model to derive future inventory of the workforce. This inventory is compared to a fictitious future demand profile to determine its feasibility over the next 10 years until fiscal year 2030–31. The results show that the RAAF is unlikely to meet future demand for the aviation maintenance workforce by 2030–31, particularly at the E05 and E06 ranks. E03 personnel are leaving sooner in their time in rank and retention rates are too low at E05 and E06 ranks. The RAAF either needs to adjust the future demand or attempt to modify the behaviors in this workforce; adjusting promotion rates is one lever to modify retention behavior. My results can be used by the RAAF to investigate policies that may improve retention, for example, through fixed promotion rates.

B. BACKGROUND

To meet Australia's national security interests, the Australian government has invested a significant amount of spending in the Australian Defence Force (ADF) over the last decade. Subsequently, the RAAF has embarked on a large-scale expansion of its air and space power capabilities through acquisition programs, upgrades, organizational transformation, and integration programs that aim to better achieve joint effects (Department of Defence, 2020). The government expects the RAAF to have a serviceable, operational fleet of aircraft that are ready to be tasked as required. The RAAF fleet currently comprises both legacy and recently acquired, advanced aircraft. Airframes include AP-3C Orion, C-130J Hercules, C-27J Spartan, C-17 Globemaster, E-7A Wedgetail, F/A-18F Super Hornet, F-35A Lightning II, and new remotely piloted aircraft.

These aircraft have differing maintenance requirements as newer generation airframes require significantly more specialized maintenance regimes than legacy models. Aviation maintenance personnel need to be able to adapt to, and master, modern technology. Consequently, new technicians need to possess mechanical skills but also need to have "expertise in computer systems, advanced analytics, electrical systems, and other new disciplines" (Committee on Small Business, 2018, p. 5). The Air Force Workforce Plan 2019–2024 states that the organization faces the risk that it may not be able to sustain, grow, skill, resource, and/or rebalance our workforce to meet current and future capability requirements, resulting in our inability to meet organizational priorities (Department of Defence, 2018). Part of this risk lies in the enlisted aviation technical categories, as the consequences of under-manning or errors include an inability to project airpower in support of a mission; loss of life; damage to, or loss of, assets, or facilities; and damage to the RAAF's capability and reputation. Further, there is a long lead time to develop personnel with these technical skills. To deliver air and space power effects, the RAAF needs to recruit, grow, and retain personnel with specialized aviation maintenance skills.

My research is specifically aimed at the full-time, enlisted aviation technical categories of Avionics, Aircraft, and Armament technicians. On average, these three categories comprise 15% of the RAAF's full-time, active-duty members (DWP-AF, personal communication, August 12, 2021). I develop Markov models to determine transition rates within this workforce and identify if separation behavior is changing over time. I then utilize these models to predict a future inventory and compare this to a fictitious demand profile. The latest Air Force Workforce Plan (Department of Defence, 2021) states that workforce structures need to be responsive and flexible to generate effective air and space influence in the joint force. My thesis assists in achieving this initiative by addressing how flexible the system needs to be in the future enlisted aviation maintenance workforce. Further, this modeling can be extended to other workforces to identify behaviors that will derive feasible future demand profiles. The study will not provide insight into the reasons for separations, but it may identify correlations with some of the changes to conditions of service.

1. RAAF Aviation Maintenance Technicians

My thesis analyzes the three categories of Avionics, Aircraft, and Armament technicians as one workforce to provide a strategic overview of the separation behavior of the RAAF's aviation technical workforce. Practically, the categories are managed as separate workforces with separate recruiting and promotion targets. However, they are similar in that they are highly technical, largely work on the RAAF's airborne assets, attend training at the RAAF School of Technical Training (RAAFSTT) and have some similarities with career progression requirements, such as the completion of workplace journals (K. Longman, email to author, October 05, 2021). They are employed at a range of bases across Australia and deploy on exercises or operations within Australia and overseas. Entry pathways for these categories are via general entry through Defence Force Recruiting (DFR) centers, through remuster (changing category) of serving members, lateral and Service transfers, and re-entry.

a. Aircraft Technician

The RAAF employment profile for Aircraft Technician states:

> Aircraft technicians are responsible for the maintenance, sustainment and certification of aircraft airframe and propulsion systems, including: hydro-mechanical, pneumatic, landing gear, flight controls, gas turbine engines and associated components, fuel transfer and control, environmental control and propeller systems. (RAAF, 2013, p. 1)

b. Armament Technician

The RAAF employment profile for Armament Technician states:

> Armament technicians are responsible for maintaining aircraft armament systems and associated support equipment. They are also employed in non-aircraft roles including air weapons range duties, training, Explosive Ordnance (EO) management and EO Disposal (EOD) related functions. (RAAF, 2019, p. 1)

c. Avionics Technician

The RAAF employment profile for Avionics Technician states:

> Avionics technicians are responsible for the maintenance, sustainment and certification of aircraft avionic systems, including: instrumentation,

> communication, navigation, surveillance, radar, automatic flight control, fuel management, warning and alert, fatigue management, oxygen, lighting, environmental control, electrical power distribution, electronic warfare, self-protection, and explosive ordnance. (RAAF, 2013b, p. 1)

2. Ranks and Career Progression

General entry enlisted members attend recruit training for 11 weeks at 1 Recruit Training Unit (1RTU), RAAF Base Wagga, where they undergo initial military training and indoctrination and wear the rank of E00 (AC/W REC). Following graduation from 1RTU, aviation, armament and avionics technicians attend the RAAFSTT for their Initial Employment Training (IET). During IET, technicians wear the rank of E01 (AC/W TRN). Course length varies, with 53 weeks for Avionics, 46 weeks for Aircraft, and 23 weeks for Armament. On completion of IET, members wear the rank of E02 (AC/W) and are posted to a unit to undertake routine aircraft maintenance and complete competency logbooks.

Generally, once a member posts to a Unit after IET, they will be supervised by a member of the next highest rank. An aviation technician E02 can expect to spend 12 months at a Unit before attaining the rank of E03 (LAC/W). Once promoted, an E03 may be required to undertake supervisory roles, depending on the unit and position (RAAF, 2021). A new regulatory framework for Defence Aviation, the Defence Aviation Safety Regulations (DASRs), has involved some significant changes to the licensing arrangements for aviation technicians. Previously, licensing and the ability to supervise were tied to rank, however, this is no longer the case (D. Silverwood, email to author, September 06, 2021). Under the DASRs, senior E03s are now performing supervisory roles but do not receive any reward by being promoted to E05 (CPL). Further, as the licensing is now tied to platform type, E05s who are targeted for posting to another location are moved and then must spend approximately six months to gain the new platform-specific qualifications (D. Silverwood, email to author, September 06, 2021). This leaves a gap at squadrons that E03s who hold the qualifications must fill; they are required to do what was traditionally a E05 job, but without recognition via promotion. The new licensing system is based on the system developed by the European Aviation Safety Authority (EASA), which means that technicians are more easily able to take jobs in civilian airlines both in Australia and in Europe (Hampson et al., 2015; D. Silverwood, email to author, September

06, 2021). It also means that E05s and E03s are more attractive to the civilian aviation industry, as they have the experience and knowledge that are required to certify aircraft as serviceable to fly, and do not require training. Table 1 explains the rank structure for the RAAF's enlisted workforce.

Table 1. RAAF Enlisted Ranks Structure

Enlisted	Rank Name	Rank Code
Junior Enlisted	Aircraftman/woman Recruit (AC/W REC)	E00
	Aircraftman/woman Trainee (AC/W TRN)	E01
	Aircraftman/woman (AC/W)	E02
	Leading Aircraftman/woman (LAC/W)	E03
Non-Commissioned Officers	Corporal (CPL)	E05
Senior Non-Commissioned Officers	Sergeant (SGT)	E06
	Flight Sergeant (FSGT)	E08
	Warrant Officer (WOFF)	E09

Between 2018 and 2019, the average time in rank for an E03 Aircraft, Avionics and Armament technician was six, five and four years, respectively (DWP-AF, personal communication, August 12, 2021). Promotion to E05 is merit-based where members are presented to a Career Management Board (CMB) and compete for a capped number of promotion targets with all others at their rank level. All promotions above E05 are also competitive through CMBs and each rank has a promotion target that must be filled. These targets are modeled and set by Directorate of Workforce Planning (DWP-AF) and are based on various factors such as organizational need, separation rates and recruiting targets. At the E05 rank, members hold the maintenance authority of a Trade Supervisor, although

Armament technicians may also be an independent maintenance inspector (IMI) or Maintenance Manager (MM) (RAAF, 2013a, 2013b, 2019). Further, an Armament technician who has completed their aerospace training can work in ground roles as Demolition Operators (DEMOP), Explosive Ordnance Disposal Reconnaissance (EODR), and Explosive Ordnance Disposal Technicians (EODT).

At the rank of E06, aviation technicians will hold the maintenance authority of IMI, MM, Line Safety Controller (LSC) and will normally hold a delegated Engineering Authority (Technical Assessor or LOGENG) (RAAF, 2013a, 2013b, 2019). An E08 will hold further delegations such as authority for finances in procurement, logistics management and, for Armament technicians, may be a Base Armament Management Authority (BAM) (RAAF, 2013a, 2013b, 2019). At the most senior rank of E09, members may hold the approval to carry forward unserviceabilities and may be required to supervise a large number of personnel.

3. Workforce Establishment Changes and Recruiting Practices

Over the last 10 years there have been several programs aimed at productivity improvements that have resulted in restructuring the enlisted aviation maintenance workforce. The most significant of these is the Maintenance Productivity Improvement Program (MPIP), which was initiated in 2012. At the time, there was pressure on the RAAF to rebalance its workforce to stay within the Average Funded Strength (AFS) cap of around 14,000 uniformed personnel. AFS is the measure used by government to determine the total number of personnel that will be funded in each service and is based on the average number of full-time equivalent salaries paid each year. MPIP was targeted at air trades and aimed to identify 350 maintenance positions that could be reinvested elsewhere in the RAAF (SRG, 2016). While not all the 350 positions were realized for investment, there was still a significant impact to the technical workforce as the total establishment was reduced by year 2017.

As a result of MPIP, there was a significant reduction in technician recruiting targets that was then followed by an increase to compensate for separations and recognition that it takes time to develop a fully qualified technician. This pulling and pushing on recruiting levers has subsequently affected promotion targets and the flow rates of personnel through the ranks. The Armament category has also been subject to changes in recruiting practices; for some time, recruiting ceased altogether because the RAAF felt that the functions could be performed by Avionics and Aircraft technicians. In 2009, the Armament trade was stood up again, as the RAAF realized that a specialist weapon category was still necessary (S. Hume, personal communication, September 4, 2021). Consequently, the demand has changed against a fairly fixed supply of personnel with these skills.

4. Separation Rates

Given that aviation maintenance categories have been the subject of a recent, large-scale review and restructure, it is assumed that the RAAF now has the number and structure of positions that it requires to meet future capability requirements. Therefore, any shortage of personnel to meet this demand is problematic and, as such, it is the scale of the gap that should be of specific concern. Previously the RAAF has focused on separation rates as an indicator of workforce health, citing seven percent as a healthy separation rate. There are issues with this measure, however, as it does not capture any granularity in separation behavior by rank or time, it does not address quality of personnel separating, and it is not contextualized with other workforce issues such as meeting recruiting targets. The problem needs to be better defined. For example, if separation rates are increasing, how much or how little is bad? This is where my research can provide more thorough analysis of observed separation behavior over time and the impacts on meeting future demand if separation rates change.

Figure 1 is the graph of separation rates for the aviation technician workforce, which encapsulates those members who have left the RAAF. The rates do not include those who have left the category to commission or to remuster. This figure demonstrates the issue of simply taking separation rates and presenting them without any context of other workforce behaviors. While the graph in Figure 1 shows general separation rates over time which, incidentally, hover around six percent, there is no insight into when these technicians are leaving in terms of their experience levels or talent nor any context about what else is happening in the workforce such as establishment changes and recruiting success.

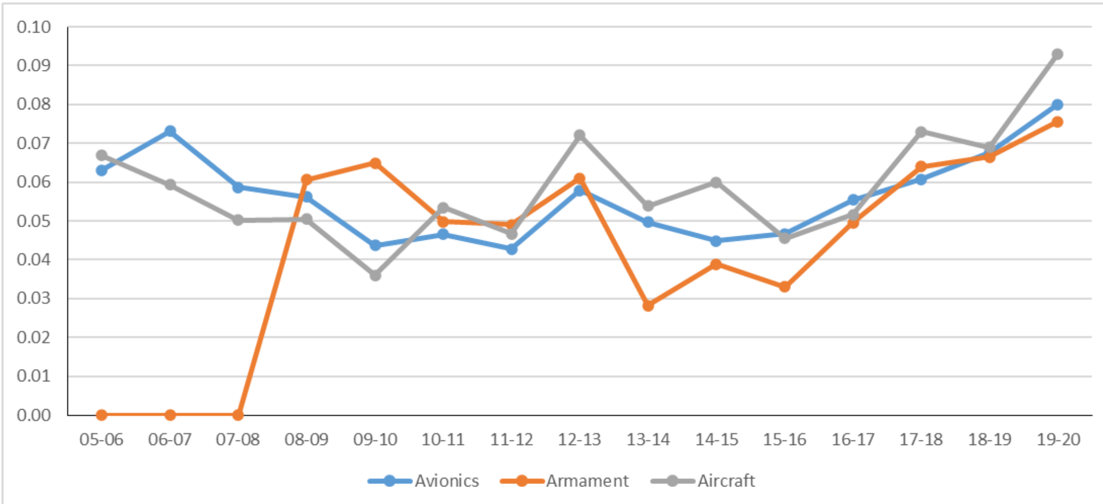

Figure 1. Aviation Technician Separation Rates 2005–2020

As the literature review reveals, there are increasing concerns about the retention of global aviation maintenance technicians, particularly those with experience, including within militaries. This thesis aims to determine if the RAAF is losing its technicians at higher rates and earlier in their careers and, if so, what the impact is on meeting future demand with a given establishment structure.

5. Superannuation and Retention Bonuses

The ADF has introduced differing conditions of service over the last few decades in response to various initiatives, such as increasing diversity or retention. For example, some cohorts are bound to a four-year initial minimum period of service (IMPS) while others must give six years. Older cohorts are under different superannuation schemes than newer members, which differ in the conditions by which members can access retirement bonuses and a pension. In 1972, the Defence Forces Retirement and Death Benefits (DFRDB) plan was introduced, which entitled a member who had served 20 years full-time access to a pension as soon as they discharged (Crockett, 2014). In the 1980s, the Australian government conducted a review of superannuation schemes and one of the outcomes was to replace the DRFDB with a new scheme (Crockett, 2014). The Military Superannuation and Benefits Scheme (MSBS) was introduced in 1991 and incorporated a retention bonus, as there were concerns that the military would lose members due to changes in the benefits under the new scheme (Crockett, 2014). The retention benefit was aimed at encouraging members to complete 20 years of service and offered a year's salary to members who had completed 15 years and who opted to stay another five. Access to the retention benefit ceased for those members who joined on or after 6 October 2005.

The data set for my thesis includes aviation technicians who fall under all these varying conditions of service. This is relevant because changes to conditions of service have been shown to correlate to changes in separation behavior. Crockett's (2014) thesis found that changes to the ADF retirement schemes produced considerable effects on separation behavior and smoothed out any spikes in the separation profile at 20 years of service. The limitation of the paper is that there was no indication of the impact of the quality of people who continued to serve when the retirement schemes changed (Crockett, 2014). While my thesis is not focused on the impact of retirement scheme changes to separation behavior, it is an important variable to consider alongside other factors that may impact separation rates.

C. ORGANIZATION OF STUDY

This chapter is introductory in nature, providing the objectives, background, and organization of the study. Chapter II reviews the literature on current global and military issues surrounding aviation maintenance technician shortages and the use of Markov models in manpower planning within the U.S. and Australian militaries. Chapter III provides a description of the data and the methodology used for this research. Chapter IV provides the results and application of the Markov models. Chapter V presents concluding remarks and recommendations for the RAAF to manage the enlisted aviation maintenance workforce.

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II. LITERATURE REVIEW

Currently, there is a significant amount of attention on the impacts to the global aviation industry of a shortage in qualified aviation maintenance personnel. This shortage is further complicated by the COVID-19 pandemic, which has resulted in significant numbers of aviation maintainers quitting and being laid-off (ARSA, 2021b; National Business Aviation Association, 2022; Satair, 2021). With predictions that air travel will return to some sort of normalcy in the next 12–18 months, coupled with a growing demand in the Maintenance Repair and Overhaul (MRO) industry, job losses, an aging workforce and demand for more complex skills, the pressures on the aviation sector are ever-increasing (ARSA, 2021b; Cooper et al., 2021).

While there is attention on the civilian aviation sector, little has been written on retention issues of aviation maintenance professionals in militaries. One comprehensive report by the U.S. Government Accountability Office GAO (2019) evaluates aircraft maintainer gaps in the U.S. Air Force. A recent article from the U.S. Naval Institute cites an association between declining experience of aviation maintainers and mishaps and readiness levels in the U.S. Navy (Eckstein, 2018). A report on the retention of ADF aviation maintainers cites the same issue whereby reduced skills and experience is accompanied by increased maintenance safety breaches, increased times for fault diagnosis, and declining workmanship standards (Xinos, 2001). The Xinos (2001) report is largely qualitative in nature and the extent to which he quantifies the retention problem is a statement that "the majority of aviation technicians leave the ADF after 10 or 12 years of service" (Xinos, 2001). It does not provide any empirical analysis of the extent of the problem. Furthermore, whilst Xinos's (2001) report is thorough in its analysis of the necessity for a uniformed ADF aviation maintenance workforce, and the reasons for separation, it is now 20 years old and there is no such work that focuses on the RAAF's aviation maintenance workforce.

A 2015 report published by the Australian Research Council (ARC) presents a review of the future of aircraft maintenance in Australia and makes mention of ADF training establishments as an important contributor in the supply of new technicians

(Hampson et al., 2015). However, there has been no recent analysis of retention issues or separation behavior in either the ADF or RAAF aviation maintenance workforce.

Despite the lack of any analysis into the separation behavior of the aviation maintenance workforce, the health of these categories is of concern to the RAAF. Even during the writing of this thesis, the RAAF released an update that it is going to adjust the establishment in the aviation maintenance workforce in January 2022 to try and alleviate some of the pressures on junior members who are undertaking supervisory roles but who have not been recognized either by rank or remuneration (RAAF, 2021). My thesis proposes to help better inform such workforce changes by analyzing the separation behavior of the RAAF enlisted aviation technical workforce and providing recommendations on how workforce behaviors may need to be adjusted to meet the future demand.

This chapter presents a literature review on the current global and military issues of aviation maintenance workforce shortages and retention, as well as the use of Markov modeling as a manpower planning tool. Section A discusses the growing issue of a global shortage in aviation maintenance professionals. Section B focuses on the retention of military aviation maintenance technicians. Section C discusses the use of Markov models to address questions of military manpower behavior. Finally, Section D provides an overview of the chapter.

A. GLOBAL AVIATION TECHNICAL WORKFORCE SHORTAGE

Two studies were published in 2014 to address concerns about a growing shortage of aviation maintenance professionals (ARSA, 2014; GAO, 2014). Both analyses provided mixed evidence of any shortage, and for aircraft mechanics, the GAO report suggested that demand was not outstripping supply as neither employment nor earnings had increased between 2000 and 2012 (GAO, 2014). Importantly, both reports cited difficulties in defining labor shortage (ARSA, 2014; GAO, 2014). The GAO (2014) report concluded that low unemployment rates mean that there is a small pool of people with specific skill sets, certifications and work experiences (GAO, 2014). The ARSA (2014) report echoed this conclusion, stating that there is greater competition among non-aviation industries for maintenance and electronic skills and that a large share of the aviation maintenance workforce is retiring with insufficient replacement rates. The opening paragraph of the proceedings of the Global Aerospace Summit in 2014 cited that the industry is facing unprecedented retirement, there is less interest in the aviation sector, and fewer students are excelling in math and science (Murray, 2014).

More recently, the picture is clearer and there is significant concern both by industry and authoritative international sources such as IATA, ICAO, and Boeing about a worldwide shortage of aircraft maintenance professionals (Hampson et al., 2015). The ARC produced an extensive report in 2015 looking at the future of aircraft maintenance in Australia and estimated a 30% global workforce shortfall by 2025 (Hampson et al., 2015). This shortfall is being felt in Australia, where chief engineers almost exclusively cite that their main challenge is skills shortages (Thorn, 2021). A shortage of aviation maintenance personnel creates pressure on global aircraft fleets and means that it is very difficult to keep up maintenance standards. A report to the U.S. congress on the aviation workforce shortage (Committee on Small Business, 2018) states that the aviation industry is facing a shortage of both pilots and mechanics at a time when there is increasing demand and modernizing of fleets. An estimated $333 to $643 million in foregone revenue was calculated in 2018 as a result of over 1000 aviation technician vacancies in the U.S. (ARSA, 2018). Additionally, 30% of those who complete aviation maintenance courses end up in other industries (Committee on Small Business, 2018). The aging workforce issue is also a concern; in 2017, the median age of aviation mechanics in the U.S. was 52, nine years older than the wider U.S. workforce (Wyman, 2017).

In the last two years, COVID-19 has further exacerbated the aviation maintenance workforce shortage issues. As of October 2020, it was estimated that the U.S. aviation maintenance industry had lost over 50,000 jobs (a quarter of the workforce) since the beginning of COVID (ARSA, 2020). The importance of aviation technical skills is evident from the announcement in September 2021 that the U.S. Department of Transportation will offer $482.3 million in funding to businesses under the Aviation Manufacturing Jobs Protection Program (ARSA, 2021a). Recent predictions of the global aviation MRO industry indicate that, while the future demand for MRO has been impacted by COVID, the sector will return to stable growth (see Figure 2; Cooper et al., 2021). This growth is going to place even greater pressure on the global demand for qualified aviation technicians.

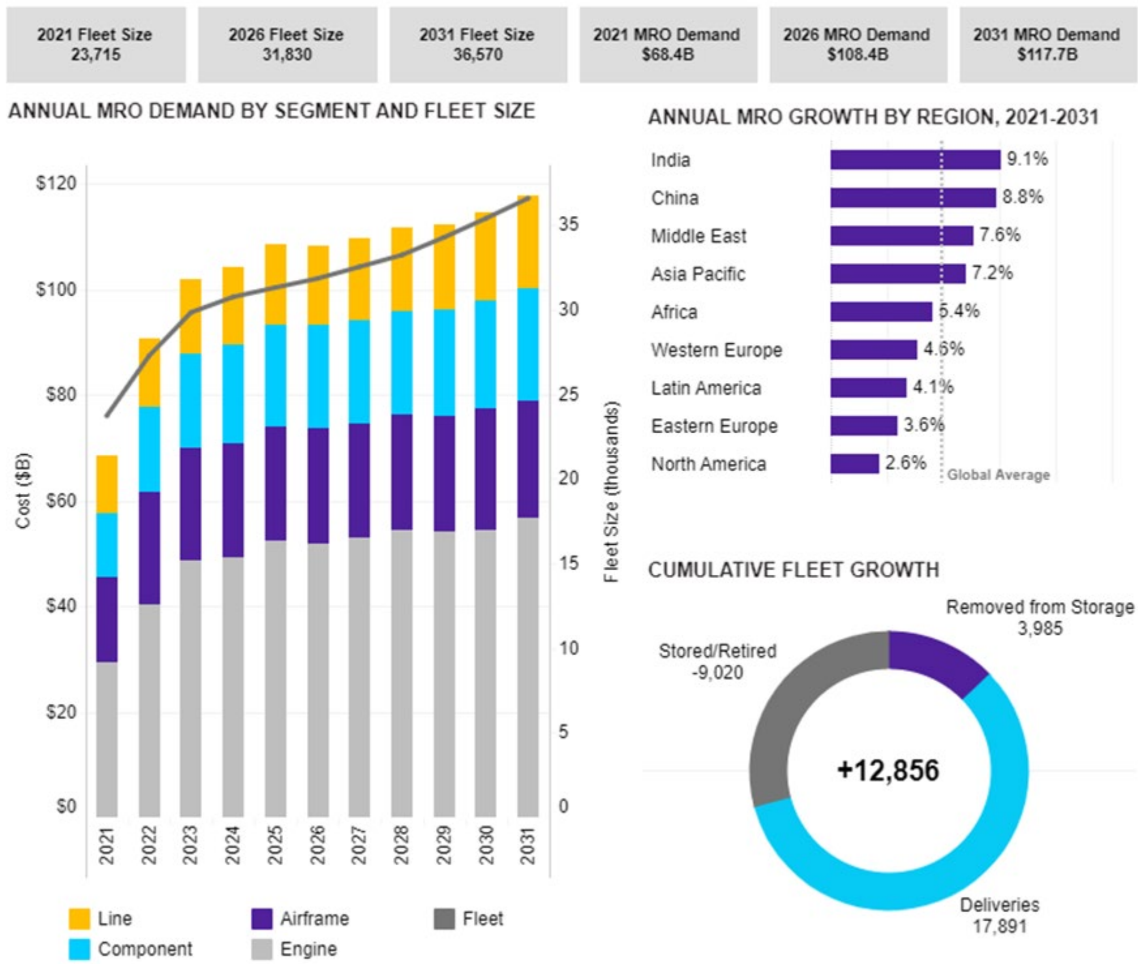


Figure 2. Forecast MRO Demand. Source: Cooper et al. (2021).

B. MILITARY AVIATION TECHNICIAN RETENTION

The global shortage of aviation technicians is not solely an issue for the civilian sector, but also for militaries. The issue of pilot attrition has been a focus for both the Australian and foreign military forces, as reflected in the literature (Cohen, 2021; Leroux-Parra, 2019; Maulsby, 2019; Thatcher, 2019). However, relatively little has been written on attrition in military enlisted aviation maintenance workforces. A 2013 paper by Mafini and Dubihlela investigated factors of turnover for aircraft technicians in a South African air force organization, as there had been a significant increase in separations to the civilian sector. This paper used several statistical tests such as exploratory factor analysis and regression analysis and determined that factors such as job satisfaction, job content, and economic and employment opportunities were significant in explaining turnover (Mafini & Dubihlela, 2013). My analysis, however, is not concerned with the factors driving retention but is concerned with changes in retention behavior and how future demand can be de-risked to accommodate such changes.

One significant contribution to understanding retention of Air Force aircraft maintainers is a 2019 GAO report, which assessed the extent of any staffing gaps in the U.S. Air Force aircraft maintainer workforce and attrition of experienced members, using data from 2010–2017. The report found that the U.S. Air Force is continuing to lose its more experienced maintainers and that there is no strategy to improve retention (GAO, 2019). Specifically, there are gaps at the 5- and 7-level, which represent maintainers around the senior airman and master sergeant ranks who are fully qualified and are able to supervise other maintainers (GAO, 2019). The RAAF equivalent of technicians at these levels is E05 to E08. The U.S. Navy is also experiencing a declining average age in its aviation technician specialists (Hatzung & Welborn, 2020). These findings are relevant to my research as I hypothesize that the RAAF is also losing members at the supervisory levels and there is no substitute for experience.

The GAO report cites that part of the gap in Air Force 5- and 7-level maintainers is due to reduced accessions in 2015 and 2016; these personnel would have grown into experienced maintainers (GAO, 2019). As discussed in the overview, the RAAF has tended to turn on and off the recruiting pipelines in the aviation maintenance workforce, which has downstream impacts on the levels of experience in the workforce. Experienced maintainers are required in squadrons to supervise more junior members, as well as provide critical skills that ensure aircraft are serviceable for operational duties.

Lempe's (1989) thesis analyzed the factors affecting retention of first- and second-term Air Force enlisted members. This thesis, however, did not focus on aviation technicians but rather on the wider enlisted workforce. The results of Lempe's logit model identified that reelinstment for electronics technicians increased with retention bonuses, suggesting that there were lucrative civilian opportunities (Lempe, 1989). This finding is consistent with the situation faced by the RAAF, whereby the civilian sector can offer attractive alternative employment, particularly to avionics and aircraft technicians. Australia is attracting more business in offshore maintenance for other countries, drawing more technicians away from Defence (Hampson et al., 2015). Further, the civilian sector offers other benefits such as locational stability, whereas the military cannot guarantee that members can remain in a location long-term.

The loss of qualified technicians is of interest in my research, as it is expensive to recruit and train aviation maintenance personnel. The loss of a senior enlisted Armament technician, for example, is significant as they undergo additional training to qualify in ground roles such as an EODT (T. Duke, personal communication, December 16, 2021). The costs to the services of losing a technically qualified specialist are much more than losing a trainee (Buddin, 1981). The RAAF has a mixture of legacy and next generation aircraft and, therefore, requires maintainers with a mixture of skills. Not only is it important to retain longer-serving maintenance technicians who have the knowledge and skills relevant to legacy frames, but it is vital to retain newer personnel beyond a first or second term as they have specialized skills to work on the newer, advanced aircraft. Additionally, research shows an increase in aviation mishaps in the Navy and Marine Corps due to less experience in their aviation maintenance crews (Eckstein, 2018).

C. MARKOV MODELS IN MILITARY MANPOWER PLANNING

Both foreign militaries and the Australian military have used Markov models for manpower planning issues. Several studies have been conducted that utilize Markov models to address U.S. military manpower problems (Schmidt & Colvin, 2012; Taylor, 2020). Taylor (2020) addresses the issue of building a cyber community within the United States Marine Corps (USMC) by building Markov models that compare the regular accessions method with direct accessions where officers join at the O4 and O5 levels. He uses eight years of data from the UAV community as a proxy for cyber accessions, and one year from the cyber community, to create a two-year aggregated transition matrix to forecast future cyber officer inventory for three years. The analysis also involves applying high and low attrition rates to the transition matrix to determine the impacts on reaching a mature state for a future cyber community. Taylor's analysis involves modifying attrition rates, but my analysis will involve varying promotion rates as the RAAF conditions of service currently do not allow for manpower control via setting attrition rates.

The 2013 thesis by Schmidt and Colvin assesses the adequacy of current accession plans on the retention of Navy Medical Corps officers. In this study, Markov models were created to predict the survivability of various accession programs. The retention probabilities were derived from the authors' probit model and a separate dataset was used to provide the continuation rates (Schmidt & Colvin, 2012). Another study that applied Markov models to questions of retention is that by Zais and Zhang (2015). They constructed a Markov chain model to help address the question of the impact of monetary incentives on retention in the U.S. Army. Their justification for using a Markov model was that it allowed them to study military personnel dynamics over time, unlike traditional classification approaches such as logistics regression models (Zais & Zhang, 2016). Similarly, my analysis uses Markov models to investigate the separation behavior of the aviation maintenance workforce over a long period of time.

Markov models have also been applied to workforce planning problems in the Australian military (Clark, 2020; Powell, 2016; Wang, 2005). Wang's (2005) paper investigates the use of four different operations research (OR) techniques in workforce modeling, including Markov chain models. The purpose of his paper is to assist the Australian Army's Training Command in building a model that can help in future training planning. Wang (2005) describes some limitations of Markov models, namely that they cannot be used for optimizing costs or maximizing productivity, they are linear and cannot incorporate feedback, and a small sample size will render the transition estimates unstable (Wang, 2005). The results of my thesis adds to this body of work by providing an application of Markov models to a workforce planning issue in the RAAF, demonstrating the utility of the approach despite the limitations outlined by Wang (2005).

Two previous RAAF Naval Postgraduate School (NPS) students utilized Markov modelling in their research (Clark, 2020; Powell, 2016). In his thesis on Military Working

Dogs (MWD), Powell (2016) developed a fixed inventory Markov model to determine how many MWDs need to be recruited to meet an increased quota. His results provided the RAAF with the total number of dogs (282) that needed to be recruited to meet the demand by the end of year 2023 (Powell, 2016).

A second thesis by Vivienne Clark (2020) developed a Markov model to forecast the number of Air Intelligence Analysts needed to meet the future demand in the RAAF until 2030. The model was also used to provide a measure of the expected time in rank for promotion (Clark, 2020). Similarly to Powell's (2016) work, the outcome was a recommendation for the total number of personnel, or dogs in Powell's case, required through fiscal year 2030. Powell (2016) and Clark's (2020) work is highly relevant to my research as I will also be building a Markov model to investigate changes in separation behavior and impacts to future demand for the aviation maintenance workforce. My research will also add further weight to the utility of Markov modelling for workforce planning in the RAAF, a recommendation from both prior studies.

D. CHAPTER SUMMARY

This chapter summarizes the literature that is relevant to my thesis study. I provide an overview of the broader issue of retention in the global aviation maintenance workforce, then narrow the focus to explore literature on foreign military retention issues for aviation technicians. I highlight the gap in work done to look at separation behavior of aviation maintainers in the ADF. Finally, I discuss the use of Markov models in manpower planning both in foreign militaries and in Australia.

III. DATA AND METHODOLOGY

This chapter describes the data that I use in my thesis and how I utilize it to build the Markov models. Section A outlines the source of the data and the nature of the data set including the variables used. Section B offers a theoretical description of Markov models. Section C explains the methodology of how I use Markov models to determine the separation behavior of the RAAF's aviation maintenance workforce and the impact on future demand with changing separation rates. Section D summarizes the chapter.

A. DATA

DWP-AF provides the data for my thesis via queries from the ADF's HR Data Warehouse. Each query extracts an observation of every member in the Avionics, Aircraft, and Armament workforces for each fiscal year from 2005 to 2020. There are three sets of data that capture the total population, promotions, and separations. The number of observations in the data set is 49,025. Individual members are de-identified and given a new identification number (New ID).

1. Data Set Variables

The Markov models in my thesis utilize the following variables. There are more variables in the original data set but these are unnecessary for my analysis.

a. New ID

The New ID variable is created to replace the individual members' PMKey or Service number. It is a 10-digit alpha-numeric code that has been randomly assigned to each member so that their identity cannot be determined. In the original data set for separations, there were 44 observations that did not have a unique ID. These rows were manually coded with a New ID in the separation file and these members were then also added to the population file for the relevant previous fiscal year. As it was unknown how long these members had been in service, they could not be added to additional fiscal years.

b. Rank Code

The Rank Code variable is an alpha-numeric code that identifies the current rank of the member with "E" representing an enlisted rank. The ranks E00, E01 represent members who are in recruit training or IET. E02 is a newly trained member on time-based promotion to E03. The ranks E03 and E05 are referred to as Non-Commissioned Officers (NCOs). Senior Non-Commissioned Officers (SNCOs) are the ranks E06, E08 and E09. Table 1 (page 5) provides a full list of the Rank Codes and corresponding rank description. Figure 3 is the rank break down of the aviation maintenance workforce in the data set by fiscal year. The ranks E00, E01 and E02 are combined as these represent those technicians who are under-training (E00 and E01), and E02 who are fully trained but are on time-based promotion.

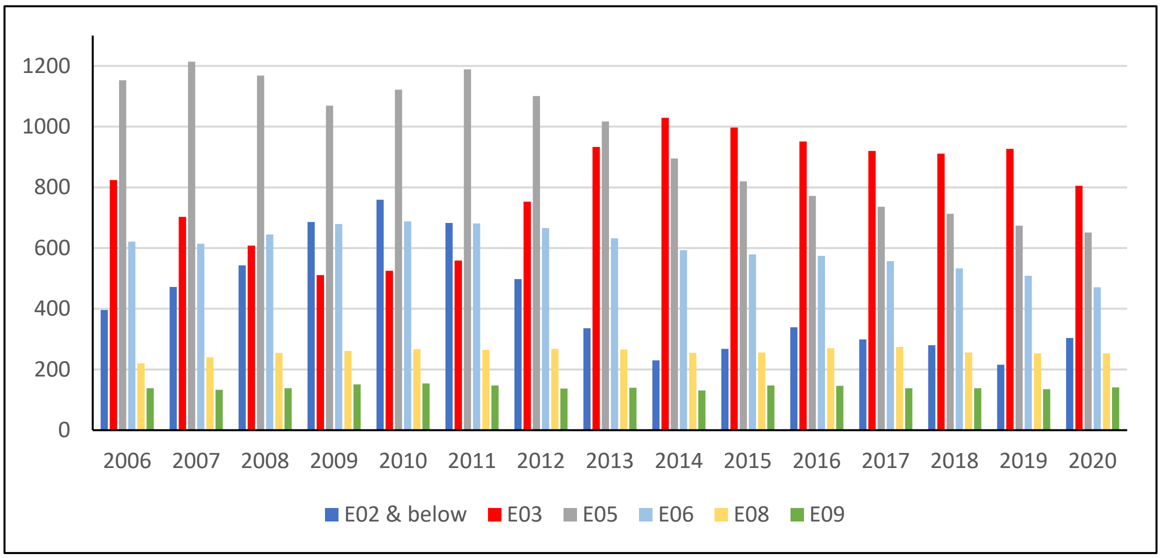


Figure 3. Distribution of Ranks in the RAAF Aviation Technical Workforce

c. Fiscal Year

The fiscal year (FY) in Australia runs from 01 July until 30 June the following year. So, for example, FY 2019–2020 represents all observations between 01 July 2019 and 30 June 2020. The data covers each FY from 2005–2020.

d. Category Short Description

Category Short Description is the abbreviated name for each aviation maintenance category. Avionics is for Avionics Technicians, Aircraft is for Aircraft Technicians, and Armament is for Armament Technicians.

e. Length of Service

This variable is an integer identifying the years of completed service at the time the data was pulled.

f. Time in Rank

This variable is an integer that represents time in rank at the time of the observation, with each year of completed service in rank as the unit of measurement.

2. Data Manipulation

Snapshots of the population for each year in the data set provide the flows of personnel into the states of promotion, continue in rank, recruitment (accession), and attrition. So, for example a person is counted as an attrite where they do not appear from one snapshot to the next. This method highlighted a discrepancy in the wastage data where 2938 individuals had separated based on a comparison of snapshots of the population but are not all captured in the separation and movement data from DWP-AF. Finally, attrition rates are based on those who have a separation count, not a movement count.

B. MARKOV MODEL DESCRIPTION

Markov models are a valuable tool for manpower planning in large organizations such as the RAAF, as they allow you to describe how a complex system behaves. A Markov model is a quantitative method that uses the probabilities of transitioning between different states to generate predictions of future states such as total end strength. They are also used to model categories of a system such as promotion rates, job communities, and time in rank. Transition matrices are built based on state spaces where a state is a particular category, such as rank or time in service, in which a person may reside for a period of time that is exclusive of other states.

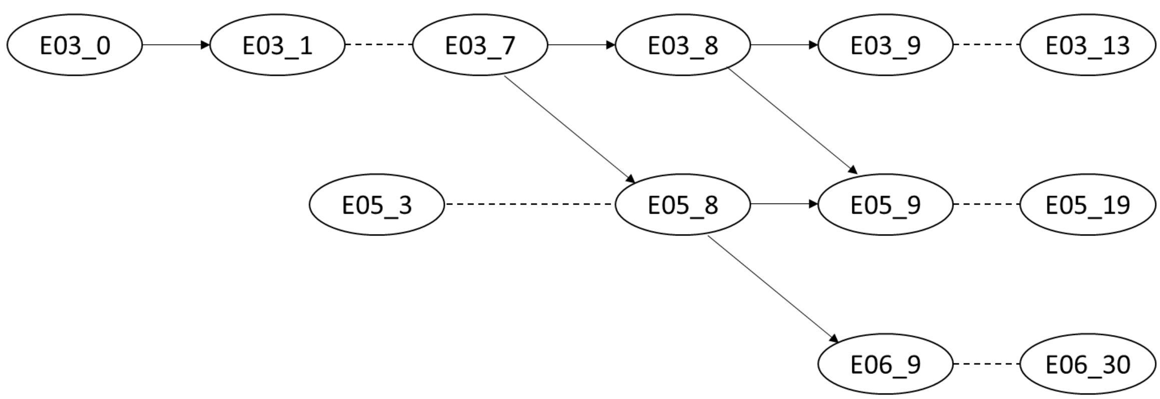
The three fundamental assumptions of Markov models are:

1. The system has a finite number of states.

2. The Markovian Property.

3. Stationary Transition Probabilities (Seagren, 2021).

The state-spaces in the Markov models in my thesis are years in service and years in rank, both of which have a set number of states. The conceptual model of the time in service model is shown in Figure 4. The individual states are time in service by rank, as represented in the circles, and the yearly transition probabilities p_{ij} are the arrows. In the time in service model, the p_{ij} is the probability that an aviation maintenance technician with transition from state *i* to state *j*. So, for example, p_{11} is the probability that an E03 with zero years in service will continue in rank to become an E03 with one year in service. Transition p_{22} is the probability that an E05 with eight years in service promotes to E06 with nine years in service and p_{12} is the probability that an E03_1 attrites and leaves the system.



Only the ranks of E03 to E06 are shown in the figure due to space limitations. Solid arrows represent transition to the next state, which includes continue in rank, promote, and attrite. All states have the potential to flow into the attrite state. Hashed lines represent that some states are not shown in the figure but are included in the model.

Figure 4. Conceptual Markov Model of Time in Service

The Markovian property states that the probability that a system will transition to the next state *j* depends on the current state *i* (Bartholomew, 1975). In the time in service model this means that, for example, the probability of an E03 with three years of service transitioning to the next space with four years of service only depends on the fact that they have done three years already. The time in rank model meets the Markovian property because transitioning to the next state, whether that is continuing in rank, promoting or attriting largely relies on the previous state.

The last assumption for a valid Markov model states that the transition probabilities stay the same over time. An inspection of the raw data (see areas circled in red in Figure 5) immediately highlights that the system is changing over time and is not stationary. A pattern emerges over the years where larger numbers of technicians are found in the states of more years in service. Consequently, a proof of stationarity is not carried out, but cross validation is undertaken to determine the adequacy of the models and is described in section C.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
2		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
66	E03_35	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
67	E03_36	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0
68	E03_37	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0
69	E03_38	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
70	E05_0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
71	E05_1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0
72	E05_2	0	6	1	0	0	0	2	2	2	1	0	0	0	0	0	0
73	E05_3	0	12	5	1	1	0	1	3	6	1	1	0	0	0	0	0
74	E05_4	0	87	119	47	58	55	42	1	3	6	2	1	0	0	0	0
75	E05_5	0	177	241	260	94	177	134	54	1	3	6	6	1	0	0	0
76	E05_6	0	117	171	227	269	97	180	133	55	3	8	10	9	4	1	1
77	E05_7	0	85	108	151	197	261	91	169	126	64	19	25	19	16	9	8
78	E05_8	0	61	76	89	129	182	248	82	161	116	86	48	36	28	26	22
79	E05_9	0	99	59	70	74	103	170	231	77	148	110	104	68	46	44	37
80	E05_10	0	114	81	42	47	60	94	146	209	66	135	102	99	87	61	59
81	E05_11	0	30	89	56	22	31	54	78	126	176	55	109	90	95	86	70
82	E05_12	0	35	21	62	33	17	28	47	67	98	147	49	99	80	82	81
83	E05_13	0	56	27	10	42	24	13	27	39	58	75	120	43	80	67	72
84	E05_14	0	89	36	17	7	31	24	11	26	36	45	59	107	35	62	55
85	E05_15	0	54	50	23	10	7	31	22	11	22	29	36	49	91	28	44
86	E05_16	0	42	35	30	15	9	7	28	19	10	20	19	28	44	77	25
87	E05_17	0	21	29	22	17	11	9	6	25	15	8	14	11	26	40	59
88	E05_18	0	21	16	18	12	14	10	9	6	21	12	5	13	8	22	36
89	E05_19	0	10	16	13	10	8	12	10	9	7	19	12	4	13	7	18
90	E05_20	0	7	7	9	8	7	7	10	10	8	6	17	11	4	13	7
91	E05_21	0	2	5	6	9	8	7	6	9	9	5	6	17	11	4	13
92	E05_22	0	4	1	2	5	7	5	7	6	6	7	4	4	14	9	3
93	E05_23	0	10	2	1	2	5	6	3	7	5	5	6	3	4	10	7
94	E05_24	0	7	8	1	1	1	4	5	3	5	5	4	6	3	3	10
95	E05_25	0	1	6	5	0	1	1	4	5	2	5	4	4	4	3	3
96	E05_26	0	3	1	2	3	0	1	0	4	4	1	4	3	4	3	3
97	E05_27	0	2	3	1	2	2	0	1	0	2	3	0	4	3	3	3
98	E05_28	0	0	2	3	0	2	2	0	1	0	2	3	0	3	3	2
99	E05_29	0	0	0	2	3	0	2	1	0	1	0	2	3	0	2	3
100	E05_30	0	0	0	0	0	3	0	2	1	0	1	0	2	4	0	1
101	E05_31	0	0	0	0	0	0	3	0	1	1	0	1	0	2	3	0
102	E05_32	0	0	0	0	0	0	0	2	0	1	1	0	1	0	2	3
103	E05_33	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	2

Figure 5. Selection of Data for Raw Flows, Time in Service Model

C. MARKOV MODEL DEVELOPMENT

1. Building the Transition Matrices

A snapshot method is used to provide the flows for every year of data for both time in service by rank and time in rank. As the data set starts at the end of fiscal year 2005–06, the end of fiscal year 2006–07 is the first occurrence when transition probabilities are calculated. For the time in service model, the matrix of raw flows is 97 by 97 states and 67 by 67 states for time in rank. The state spaces for each model are shown in Tables 2 and 3 and describe the boundaries of each model. For example, the time in service model starts at E06 with nine years in service as this is when, on average, most members start to appear in this state.

The state of E02 includes all members in the rank of E02 and below. While E02 is part of the trained workforce and the RAAF aggregates positions at E02 and E03 for workforce planning, I have aggregated E02 and below to capture the behavior of those junior technicians who are in the first two years of their career and still under an IMPS. My models, therefore, have separate states for E02 and E03. Once I have inventory predictions for each state, I then aggregate E02 with E03 but exclude the state of E02_0 to better match the future demand provided. In the time in rank model, all ranks start at zero years because, on promotion, a member has not had any prior time in that rank.

The tables are not all the possible available states and I have chosen them according to the raw data and whether there are sufficient (generally greater than 10) numbers in each space over the years as derived from the snapshot method. I do not include years where there are no or low numbers in a state, as they do not add value to the Markov models in describing the system; these transition rates are zero or very close to zero. Figure 5 (page 22) shows how I have chosen the state space for E05 in the time of service model; only the highlighted data is selected for the model.

Table 2. State Space for Time in Service Model

	Min years of service	Max years of service
E02	0	4
E03	0	13
E05	3	19
E06	9	30
E08	16	34
E09	21	38

Table 3. State Space for Time in Rank Model

	Min years in rank	Max years in rank
E02	0	2
E03	0	10
E05	0	15
E06	0	13
E08	0	10
E09	0	11

I build the annual transition matrices for the entire aviation maintenance population using the flows of people who continue in rank, promote or attrite. The transition probabilities matrix for each year is calculated using the flows for each transition divided by the total number in the population for that rank and time in service or time in rank. The sum of all transition probabilities in each row is one. The calculation for the transition rates

(p_{ij}) is in Equation 1 where f_{ij} is the number of people who flowed from state i to state j in that year, and n_i is the total number of people who started in state i.

$$\hat{\boldsymbol{p}}_{\boldsymbol{ij}} = \frac{\boldsymbol{f_{ij}}}{\boldsymbol{n_i}} \tag{1}$$

Figure 6 shows some of the transition probabilities for the time in service model for the year 2019. As an example, the red circle highlights the probability of an E08 technician with 30 years of service transitioning to an E09 with 31 years of service is 0.117. Figure 7 shows part of the transition matrix for the time in rank model for 2019. The red circle shows that an E03 with five years in rank has a 0.108 probability of promoting to an E05 with zero years in rank.

2019 column:	E09_23	E09_24	E09_25	E09_26	E09_27	E09_28	E09_29	E09_30	E09_31	E09_32	E09_33	E09_34	E09_35	E09_36	E09_37	E09_38	Attrite	Sum
E06_30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1
E08_19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1
E08_22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.111111	1
E08_23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.058824	1
E08_26	0	0	0	0	0.064516	0	0	0	0	0	0	0	0	0	0	0	0.096774	1
E08_27	0	0	0	0	0	0.04	0	0	0	0	0	0	0	0	0	0	0.12	1
E08_28	0	0	0	0	0	0	0.045455	0	0	0	0	0	0	0	0	0	0.045455	1
E08_29	0	0	0	0	0	0	0	0.045455	0	0	0	0	0	0	0	0	0.136364	1
E08_30	0	0	0	0	0	0	0	0	0.117647	0	0	0	0	0	0	0	0	1
E08_31	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	1
E08_32	0	0	0	0	0	0	0	0	0	0	0.066667	0	0	0	0	0	0.2	1
E08_33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E08_34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E09_21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E09_22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E09_23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E09_24	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
E09_25	0	0	0	0.888889	0	0	0	0	0	0	0	0	0	0	0	0	0.111111	1
E09_26	0	0	0	0	0.875	0	0	0	0	0	0	0	0	0	0	0	0.125	1
E09_27	0	0	0	0	0	0.833333	0	0	0	0	0	0	0	0	0	0	0.166667	1
E09_28	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
E09_29	0	0	0	0	0	0	0	0.923077	0	0	0	0	0	0	0	0	0.076923	1
E09_30	0	0	0	0	0	0	0	0	0.857143	0	0	0	0	0	0	0	0.142857	1
E09_31	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
E09_32	0	0	0	0	0	0	0	0	0	0	0.928571	0	0	0	0	0	0.071429	1
E09_33	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
E09_34	0	0	0	0	0	0	0	0	0	0	0	0	0.8	0	0	0	0.2	1
E09_35	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
E09_36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.857143	0	0.142857	1
E09_37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1

totals | attrites | accessions | promote | same | 2007 | 2007 T | 2008 | 2008 T | 2009 | 2009 T | 2010 | 2010 T | 2011 | 2011 T | 2012 | 2012 T | 2013 | 2013 T | 2014 | 2014 T | 2015 | 2015 T | 2016 | 2016 T | 2017 | 2017 T | 20

Figure 6. Transition Matrix for Time in Service Model 2019

2019	E03_9	E03_10	E05_0	E05_1	E05_2	E05_3	E05_4	E05_5	E05_6	E05_7	E05_8	E05_9	E05_10	E05_11	E05_12	E05_13	E05_14	E05_15	E06_0	E06_1	Attrite	Sum
E02_0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.036364	1
E02_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	1
E02_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E03_0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.018692	1
E03_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.034091	1
E03_2	0	0	0.010753	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.010753	1
E03_3	0	0	0.030769	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.061538	1
E03_4	0	0	[illegible]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.082707	1
E03_5	0		0.108108	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.074324	1
E03_6	0	0	[illegible]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.071942	1
E03_7	0	0	0.125	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.113636	1
E03_8	0.756757	0	0.162162	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.081081	1
E03_9	0	0.75	0.166667	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.083333	1
E03_10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E05_0	0	0	0	0.9375	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0625	1
E05_1	0	0	0	0	0.88	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.12	1
E05_2	0	0	0	0	0	0.888889	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.111111	1
E05_3	0	0	0	0	0	0	0.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	1
E05_4	0	0	0	0	0	0	0	0.692308	0	0	0	0	0	0	0	0	0	0	0	0	0.307692	1
E05_5	0	0	0	0	0	0	0	0	0.894737	0	0	0	0	0	0	0	0	0	0	0	0.105263	1
E05_6	0	0	0	0	0	0	0	0	0	0.863636	0	0	0	0	0	0	0	0	0	0	0.136364	1
E05_7	0	0	0	0	0	0	0	0	0	0	0.789474	0	0	0	0	0	0	0	0.065789	0	0.144737	1
E05_8	0	0	0	0	0	0	0	0	0	0	0	0.816092	0	0	0	0	0	0	0.057471	0	0.126437	1
E05_9	0	0	0	0	0	0	0	0	0	0	0	0	0.8	0	0	0	0	0	0.138462	0	0.061538	1
E05_10	0	0	0	0	0	0	0	0	0	0	0	0	0	0.807018	0	0	0	0	0.087719	0	0.105263	1
E05_11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.84	0	0	0	0.12	0	0.04	1
E05_12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.882353	0	0	0.029412	0	0.088235	1
E05_13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.92	0	0.04	0	0.04	1
E05_14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.818182	0	0	0.181818	1
E05_15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1

Figure 7. Transition Matrix for Time in Rank Model 2019

2. Fixed Recruiting and Fixed Inventory

I use both a fixed recruiting and fixed inventory approach to predict future inventory by applying Bartholomew's inventory equation (see Equation 2). This equation takes the inventory of the previous time step and multiplies it with the transition matrix and then adds the new recruitment with the ascribed distribution to produce the inventory for the next time step. The lowercase **n** is the vector for timestep *t* and **P** is my transition matrix. *R* denotes the total recruitment in that year and *r* denotes how the new recruits are distributed in each time step.

$$\mathbf{n}(\boldsymbol{t}) = \mathbf{n}(\boldsymbol{t}-\mathbf{1}) \cdot \mathbf{P} + \boldsymbol{R} \cdot \mathbf{r} \qquad (2)$$

Initially, I use Barthomolew's equation in a fixed recruiting model. The fixed recruiting model shows how the system is expected to behave if recruiting is fixed over time where the recruitment numbers are set before running the model. Fixed or steady-state recruiting is an approach that the RAAF tends to take to reduce fluctuations in separations when members complete their IMPS. Steady recruitment allows for better planning in training units and posting plots. Also, constraints on training units, such as instructor to student ratios, generally mean that recruitment figures for technicians do not fluctuate much between years.

The fixed inventory model also applies Bartholomew's equation to derive the future years' predictions but then I use Excel's Solver to adjust *R* to minimize errors each year, as described in part 4 on Future Inventory.

3. Cross-validation

Initially, I choose a one-year approach to cross validate both the time in service and time in rank models. I predict the most recent three years based on the prior year's transition matrix; 2017 to predict 2018, 2018 to predict 2019, and 2019 to predict 2020. For the time in service model, I also choose the 2007 and 2014 matrices to predict the 2020 inventory to see how the predictions vary using historical behavior. To find the best performing model, I also use a two-year aggregated model for the last four years in the data set. I apply this to both the time in service and time in rank models to determine the best performing predictions. I cross-validate with both a one-year and two-year model to determine whether an aggregated model provides better predictions. An aggregated model may better capture the behavior of a population and is worth investigating to ensure that future predictions are as accurate as possible.

4. Future inventory

I use the best performing models from the cross-validation exercise to predict future inventory. Initially, I base future inventory predictions on a fixed *R* amount for the last year of data (2020). The distribution of recruitment is based on all recruits entering the first time step, which is an E02 with zero years of service remembering that E02 in these models represents all ranks between E00 and E02. There are circumstances where personnel enter different states through lateral recruitment and return to service, but these numbers are so low that it is safe to set them at zero. I aggregate the predictions of future inventory for each state into rank so that I can compare them with the provided future demand. I calculate the mean absolute proportional error (MAPE) and sum of squared errors (SSE) between each year of inventory predictions, aggregated by rank, against the future demand targets.

The fixed recruiting approach shows what will happen to the future demand if there is no change to recruitment figures.

Then I also apply the fixed inventory approach using Solver in Excel to derive a feasible solution that minimizes each of the following objectives: minimize SSE across all ranks, minimize SSE for E05 and E06, minimize MAPE for all ranks, and minimize MAPE for E05 and E06, by adjusting R for every year of future predictions.

D. CHAPTER SUMMARY

This chapter describes the data used in the model and the theory on Markov models. I explain the conceptual model and how I apply Markov models in my thesis to predict future inventory of aviation maintenance technicians in the RAAF using a time in service and time in rank approach. I provide an explanation of how the transition matrices are built and how I apply Bartholomew's equation in a fixed recruiting and fixed inventory approach.

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IV. MODEL PERFORMANCE AND RESULTS

This chapter outlines the performance of the models and the results of the predictions against the future demand. Section A outlines the trends in the data from the raw flows. Section B discusses the results of the cross validation of the time in service and time in rank models. I discuss the predictions from the preferred models and the impact on future demand in Section C. Section D highlights the separation behavior in the aviation maintenance population. Section E includes a discussion of the model limitations and the chapter ends with a summary in Section F.

A. TRENDS IN THE DATA

Initial observations of the raw data highlights some trends that do not require any modeling or data manipulation. Figure 5 (see page 22) shows that for all ranks over the years of the data set, larger numbers of personnel are found in later years of service. The pattern is less obvious in the time in rank data but still shows a greater variance in more recent years compared to earlier in the data set. For example, in Figure 8 the spread of personnel in the E06 rank is changing over time with a greater spread across time in rank in more recent years.

1			05-06	06-07	07-08	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20
2		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
50	E06_0	0	67	104	153	142	72	35	51	37	41	58	75	35	20	26	37
51	E06_1	0	157	78	92	133	151	70	29	43	41	31	51	78	33	22	22
52	E06_2	0	142	143	73	85	125	148	70	27	37	40	28	47	74	34	21
53	E06_3	0	117	122	127	69	79	121	139	69	22	38	37	25	45	70	33
54	E06_4	0	33	88	102	110	68	73	114	132	66	21	35	35	25	43	67
55	E06_5	0	25	17	50	76	94	60	66	101	118	61	18	30	33	23	40
56	E06_6	0	9	16	10	31	53	88	52	58	91	108	56	18	26	33	19
57	E06_7	0	21	3	6	8	19	46	73	47	51	78	98	52	18	24	30
58	E06_8	0	16	13	2	2	6	18	38	63	36	46	68	88	49	17	21
59	E06_9	0	13	10	8	1	2	4	15	30	49	30	37	55	82	40	13
60	E06_10	0	5	8	5	6	1	2	4	11	22	38	18	33	47	69	29
61	E06_11	0	4	3	7	4	3	0	2	3	8	15	29	16	29	36	53
62	E06_12	0	0	2	3	4	4	3	0	2	2	8	12	23	14	24	29
63	E06_13	0	3	0	1	1	4	4	2	0	2	2	5	12	18	13	19
64	E06_14	0	1	1	0	1	1	4	3	1	0	1	2	4	11	17	8
65	E06_15	0	5	0	1	0	1	0	4	2	1	0	1	2	3	9	14
66	E06_16	0	1	3	0	1	0	1	0	3	2	1	0	1	2	3	8
67	E06_17	0	0	1	2	0	0	0	1	0	2	1	1	0	1	2	3
68	E06_18	0	1	0	1	2	0	0	0	1	0	2	1	1	0	1	1
69	E06_19	0	0	1	0	1	2	0	0	0	0	0	2	1	1	0	1
70	E06_20	0	1	0	1	0	1	2	0	0	0	0	0	1	1	1	0

Figure 8. E06 Time in Rank Raw Data

This could suggest that members who joined near the start of the data set are choosing to stay in service longer than those who have joined more recently. It may also suggest a lack of promotion targets and personnel are pooling in rank for longer periods of time. I calculate weighted averages from the raw data of time in service to determine changes in time to promote. I calculate average time to promote for the last five years for E03, E05, and E06. I also calculate the average for 2007 to provide a comparison with average time to promote from earlier in the data set. It is important to note that, in 2007, promotion was time-based and, therefore, was not linked to addressing supply and demand imbalances. After this time, promotions became merit-based and, combined with the reduction in positions through MPIP, there is now a pooling in the lower ranks due to less demand at the higher ranks. The results in Table 4 show that the time to promote is increasing over the period of the data and, for E03, has more than doubled since 2007.

Table 4. Average Time in Years to Promote

	2007	2016	2017	2018	2019	2020
E03	4.7	7.8	8.4	8.8	8.9	9.6
E05	13.7	13.8	14.3	13.6	14.9	15.5
E06	18.1	21.5	21.7	21.9	22.9	22.4

B. VALIDATION

The results of the cross validation show that, in terms of the total difference between predicted and actual numbers, the time in service model tends to perform slightly better than time in grade model. For the time in service model both a one-year and two-year model performed very well in predicting the last three years, but the one-year model was slightly more accurate. For time in rank, a one-year model did best at predicting the last three years. Table 5 shows all of the cross validations that I attempted. *R* for each validation is the average of two- or three-years recruitment, including the year of the prediction. So, for example, the 2018–19 model uses the average recruitment of years 2018 to 2020. The distribution of *R* is set up so that every member enters the system at zero years in service or zero years in rank. The predictions for each time step are aggregated by rank so that they can be compared with the future demand.

Table 5. Cross-validations for Time in Service and Time in Rank

Note: Difference is the overall difference between predicted and actual inventory for all ranks

Matrix Used for Prediction	**Year Predicted**	**Time in Service**		**Time in Rank**	
		Difference	**MAPE**	**Difference**	**MAPE**
One-year models					
2007	2020	648	0.424		
2014	2020	454	0.141		
2017	2018	12	0.018	20	0.013
2018	2019	-22	0.014	-10	0.007
2019	2020	-3	0.012	19	0.024
Two-year models					
2016-17	2018	14	0.029	21	0.017
2017-18	2019	-19	0.024	30	0.027
2018-19	2020	1	0.034	28	0.051

Based on the cross-validation results, I choose the one-year time in service model to forecast future inventory. The one-year model that uses 2019 to predict 2020 performs the best in terms of the lowest MAPE and the overall difference in inventory with an under-estimate of only three members (see Table 5). I calculate the proportion of deviation for each rank and the one-year model produces very accurate predictions across all ranks (see Table 6). I calculate the MAPE for all ranks as 0.012. The accuracy of the inventory prediction overall and the low MAPE suggests that this model performs well. Also, the predictions are accurate across each state for all years of service.

The two-year model using 2018–19 to predict 2020 also performs very well, however, the one-year model performs better at the individual rank level, and I choose this for the predictions of future inventory. Intuitively, a two-year aggregated model seems appropriate for manpower planning as it may better capture personnel behavior than relying on only one year. Therefore, I also perform future inventory predictions using the two-year model and include the results in Appendix 1.

Table 6. Prediction of 2020 Inventory Using 2019 Time in Service Model

	E02	E03	E05	E06	E08	E09	Total	
End 2019	275	894	640	499	228	131	2667	
Predicted 2020	231	909	610	473	229	129	2581	
Actual 2020	222	912	612	476	232	130	2584	
Difference	9	-3	-2	-3	-3	-1	-3	MAPE
Prop Deviation	0.041	0.003	0.003	0.006	0.013	0.008	0.001	0.012

The best predictor for time in rank was a one-year model using 2018 to predict the 2019 inventory and the results are in Table 7. While this model under-predicts by 10 people compared to the one-year time in service model that under-predicts by three, it is a better predictor at the ranks of E03 to E09. The deviation at the E02 rank is very similar to the time in service model with a difference of 0.039, and the MAPE is 0.007. Based on these results the models perform very well, and I use both to make inventory predictions to compare with the future demand provided.

Table 7. Prediction of 2019 Inventory Using 2018 Time in Rank Model

	E02	E03	E05	E06	E08	E09	Total	
End 2018	299	919	703	536	244	121	2822	
Predicted 2019	269	910	684	513	230	125	2731	
Actual 2019	280	910	683	513	230	125	2741	
Difference	-11	0	1	0	0	0	-10	MAPE
Prop Deviation	0.0393	0.0000	0.0015	0.0000	0.0000	0.0000	0.0036	0.007

I predict the inventory of the aviation technician workforce until fiscal year 2030–31 using the one-year time in service model and the one-year time in rank model. I compare each year of predictions to the fictitious demand provided by DWP-AF in Table 8. The provided future demand aggregates the lower ranks E02 and E03 but does not include positions for E00 and E01, as these are training positions and not trained establishment. Given that my Markov models are based on grouping E00, E01, and E02 into the first time step, I adjust the predictions to exclude the E02_0 figures as personnel would not reach the rank of E02 with zero years of time in service.

Table 8. Future RAAF Demand for Aviation Maintenance Technicians

		20-21	21-22	22-23	23-24	24-25	25-26	26-27	27-28	28-29	29-30	30-31
AIRCRAFT	E0203_AC_LACW	300	303	303	305	305	306	313	318	321	323	325
	E05_CPL	255	255	255	254	253	253	256	259	263	263	263
	E06_SGT	157	157	156	156	156	157	159	159	160	160	160
	E08_FSGT	79	79	80	79	79	79	79	79	79	79	79
	E09_WOFF	53	53	53	52	52	52	52	52	52	52	52
	Total	**843**	**846**	**846**	**845**	**844**	**846**	**858**	**866**	**874**	**876**	**878**
ARMAMENT	E0203_AC_LACW	116	118	118	120	123	125	135	137	140	140	144
	E05_CPL	107	107	106	108	108	109	109	109	109	109	109
	E06_SGT	81	81	82	82	83	83	83	83	83	83	83
	E08_FSGT	49	49	51	51	51	51	51	51	51	51	51
	E09_WOFF	20	20	18	19	19	19	19	19	19	19	19
	Total	**374**	**377**	**376**	**381**	**385**	**388**	**397**	**399**	**402**	**402**	**406**
AVIONICS	E0203_AC_LACW	305	305	305	308	309	310	316	321	325	327	329
	E05_CPL	300	303	301	301	301	302	305	306	311	311	311
	E06_SGT	222	222	219	218	218	219	222	223	224	224	224
	E08_FSGT	114	114	115	116	116	118	119	120	121	121	121
	E09_WOFF	63	63	62	61	61	61	61	61	61	61	61
	Total	**1,003**	**1,006**	**1,002**	**1,003**	**1,004**	**1,009**	**1,022**	**1,031**	**1,042**	**1,044**	**1,046**

C. FUTURE INVENTORY PREDICTIONS

1. Fixed Recruiting

Initially I use a fixed recruiting scenario for both the time in service and time in rank models. I do this as the RAAF tends to lean towards consistent recruiting, as members have indefinite tenure, and it is better to minimize fluctuations between years. The fixed recruiting approach shows how the population fares against the future demand if there are no changes to recruiting practices. I aggregate every time step of year in service into each rank to allow for meaningful comparison with the provided demand. The future demand provided by DWP-AF aggregates E02 and E03, whereas my model aggregates the ranks E02 and below. I exclude the prediction for the time step of E02_0 and aggregate all other E02 partitions with E03 to better match the aggregated demand provided by DWP-AF.

The inventory predictions for time in service are based on a one-year model. The recruiting figure, R, is based on 2020 and is set at 136. The results of the predictions, based on a fixed R, are in Table 9. The predictions show that, over the next ten years, the inventory for E05, E06, and to a lesser extent, E08 and E09 cannot keep up with the demand. By 2030–31 there is an overall deficit of 836 personnel, and this is largely borne by the E05 and E06 ranks. Further, personnel are pooling at the E03 rank and are not flowing through the system at a rate that is sufficient to fill the higher ranks.

Table 9. One-Year Time in Service Model, Fixed R

Predictions Fixed Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Fixed R
20-21	960	585	425	229	138	2,337	136
21-22	924	545	371	231	134	2,204	136
22-23	896	484	328	233	133	2,073	136
23-24	877	414	277	227	141	1,936	136
24-25	868	375	241	219	141	1,843	136
25-26	876	331	220	198	137	1,762	136
26-27	890	299	197	177	138	1,700	136
27-28	905	273	170	159	130	1,638	136
28-29	918	255	147	146	116	1,582	136
29-30	929	243	129	135	102	1,538	136
30-31	933	236	112	126	87	1,494	136
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	116
21-22	726	665	460	242	136	2,229	-24
22-23	726	662	458	245	132	2,223	-150
23-24	733	663	457	245	131	2,229	-293
24-25	737	662	458	245	131	2,233	-390
25-26	741	664	460	247	131	2,243	-481
26-27	763	670	464	248	131	2,277	-577
27-28	776	674	465	249	131	2,296	-658
28-29	786	683	467	250	131	2,318	-736
29-30	790	683	467	250	131	2,322	-784
30-31	798	683	467	250	131	2,330	-836

Inventory predictions for time in rank are based on a one-year model using the 2020 recruitment figure of 139. The results are in Table 10.

Table 10. One-Year Time in Rank Model, Fixed R

Predictions Fixed Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Fixed R
20-21	961	611	430	228	124	2,354	139
21-22	919	560	394	232	131	2,235	139
22-23	890	507	357	246	133	2,133	139
23-24	871	465	317	253	147	2,053	139
24-25	866	415	294	246	154	1,976	139
25-26	881	369	277	237	154	1,916	139
26-27	906	326	260	225	155	1,872	139
27-28	920	298	243	212	156	1,830	139
28-29	931	287	230	201	161	1,810	139
29-30	941	280	214	193	165	1,793	139
30-31	946	276	195	183	168	1,769	139
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	134
21-22	726	665	460	242	136	2,229	7
22-23	726	662	458	245	132	2,223	-91
23-24	733	663	457	245	131	2,229	-177
24-25	737	662	458	245	131	2,233	-258
25-26	741	664	460	247	131	2,243	-327
26-27	763	670	464	248	131	2,277	-405
27-28	776	674	465	249	131	2,296	-466
28-29	786	683	467	250	131	2,318	-508
29-30	790	683	467	250	131	2,322	-529
30-31	798	683	467	250	131	2,330	-561

The results of the one-year time in rank model show the same excess in inventory at the E02/E03 rank as in the time in service model. However, the one-year time in rank model provides a better solution from a management perspective due to the better predictions across the ranks and a lower overall difference by the year 2030–31. However, there is still a significant under-supply particularly at the E05 and E06 ranks. Also, there is a predicted over-supply at the E09 rank, which is more acceptable than an under-supply as predicted by the one-year time in service model. An over-supply at the E09 rank is more acceptable as it provides a small management margin. The predictions produce an overall deficit of 561 personnel, which is closer to the future demand than the time in service model.

2. Fixed Inventory

I also apply a fixed inventory approach using the same one-year models for time in service and time in rank. I forecast the next 10 years of inventory and then I use Solver to minimize the SSE and MAPE by varying *R*. I add constraints to Solver to ensure that *R* does not vary by more than 20% from one year to the next, which forces a managerially relevant solution. I solve for the values of *R(t)* that minimize SSE and MAPE across all ranks and then again just for the ranks E05 and E06. The optimal solutions from each approach, including the fixed recruiting scenarios, are in Table 11 (page 36). The fixed inventory one-year time in rank model, when optimized for minimum SSE across all ranks, performs the best across all measures of fit and is bolded in Table 11. The yearly inventory predictions for this model are in Table 12 (page 37) and show that there is a deficit across all ranks except for E09 and an overall deficit by 2030–31 of 734 personnel. Further, the largest deficit is in the E05 and E06 ranks with the predicted inventory being less than 50% of the required demand by 2030–31.

The model that is closest in terms of overall difference with the future demand is the one-year time in service model that minimizes MAPE for E05 and E06 (see Table 13). I include this to show that, while the deficit is only 15 personnel, the solution is managerially infeasible due to the extreme pooling in the lower ranks and *R* values that the

RAAF would not be able to meet due to the yearly fluctuations and difficulty in recruiting such high numbers of new technicians.

Regardless of how *R* is set, the same issues are observed for all solutions that were in the fixed recruiting model where, particularly, the E05 and E06 inventory cannot meet future demand. The consistent under-achievement in these ranks highlights that simply adjusting *R* will not solve the problem. The results show that there is also pooling of E03 members, which suggests that not enough are flowing through to fill the higher ranks. The bottleneck at E03 and under-supply at the higher ranks suggests that there are issues in retention behavior at the E05 and E06 ranks.

Table 11. Model Performance When Optimized for SSE and MAPE

	SSE all ranks	SSE E05 & E06	MAPE all ranks	MAPE E05 & E06
Time in Service Models				
Fixed Recruiting one-year TIS	197,970	168,044	0.291	0.467
Fixed Inventory one-year TIS min SSE all ranks	186,388	172,796	0.268	0.471
Fixed Inventory one-year TIS min SSE E05 & E06	671,566	162,687	0.414	0.463
Fixed Inventory one-year TIS min MAPE all ranks	186,793	173,883	0.266	0.472
Fixed Inventory one-year TIS min MAPE E05 & E06	774,118	160,872	0.419	0.448
Time in Rank Models				
Fixed Recruiting one-year TIR	150,363	122,849	0.247	0.385
Fixed Inventory one-year TIR min SSE all ranks	**136,517**	**126,099**	**0.221**	**0.388**
Fixed Inventory one-year TIR min SSE E05 & E06	980,264	116,223	0.408	0.378
Fixed Inventory one-year TIR min MAPE all ranks	140,629	125,714	0.231	0.387
Fixed Inventory one-year TIR min MAPE E05 & E06	980,265	116,223	0.408	0.387

[a] TIS is Time in Service Model and TIR is Time in Rank Model

Table 12. One-Year TIR Model, Fixed Inventory, Minimize SSE All Ranks

Predictions Vary Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Vary R
20-21	961	611	430	228	124	2,354	108.3
21-22	889	560	394	232	131	2,206	90.3
22-23	816	507	357	246	133	2,058	112.8
23-24	776	465	317	253	147	1,957	128.2
24-25	765	415	294	246	154	1,874	106.8
25-26	754	369	277	237	154	1,789	116.1
26-27	767	325	260	225	155	1,732	120.1
27-28	775	294	243	212	156	1,681	118.5
28-29	782	279	230	201	161	1,653	127.8
29-30	800	266	214	193	165	1,638	106.5
30-31	792	257	195	183	168	1,596	133.1
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	134
21-22	726	665	460	242	136	2,229	-23
22-23	726	662	458	245	132	2,223	-165
23-24	733	663	457	245	131	2,229	-272
24-25	737	662	458	245	131	2,233	-359
25-26	741	664	460	247	131	2,243	-454
26-27	763	670	464	248	131	2,277	-545
27-28	776	674	465	249	131	2,296	-614
28-29	786	683	467	250	131	2,318	-665
29-30	790	683	467	250	131	2,322	-684
30-31	798	683	467	250	131	2,330	-734
					Min SSE all ranks		136535.01

Table 13. One-year TIS Model, Fixed Inventory, Minimize SSE for CPL and SGT

Predictions Vary Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Vary R
20-21	943	585	425	229	138	2,320	162.5
21-22	935	545	371	231	134	2,215	203.1
22-23	972	484	328	233	133	2,149	253.9
23-24	1065	414	277	227	141	2,124	317.4
24-25	1226	373	241	219	141	2,199	396.7
25-26	1470	329	220	198	137	2,354	330.6
26-27	1642	296	197	177	138	2,449	275.5
27-28	1749	272	170	159	130	2,480	229.6
28-29	1786	261	147	146	116	2,457	191.3
29-30	1771	265	129	135	102	2,401	159.4
30-31	1705	285	112	126	87	2,314	132.9
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	99
21-22	726	665	460	242	136	2,229	-13
22-23	726	662	458	245	132	2,223	-74
23-24	733	663	457	245	131	2,229	-105
24-25	737	662	458	245	131	2,233	-34
25-26	741	664	460	247	131	2,243	110
26-27	763	670	464	248	131	2,277	172
27-28	776	674	465	249	131	2,296	184
28-29	786	683	467	250	131	2,318	139
29-30	790	683	467	250	131	2,322	80
30-31	798	683	467	250	131	2,330	-15
					Min SSE CPL and SGT		162687.30

3. Interpretation of Results

The results from the predictions by both models suggest that behaviors in the workforce are driving an under-supply of technicians in the future. It appears that not enough personnel in the E03 ranks are staying to fill the next ranks, and those that are staying are spending too much time in rank. It is also possible that retention and promotion rates for E05, E06 and, to a lesser extent, E08 is an issue and is not sufficient to meet the provided future demand. Simply increasing the *R* value is not going to achieve a sustainable future inventory as it does not address the issues of the current behavior in these ranks.

4. Time-based Promotion Model

As there are so many states in each model, it is difficult to adjust the probabilities for continue in rank, promotion, and attrition to derive a set of behaviors that are feasible to meet the future demand. However, in an attempt to determine the impacts of changing some of the behavior in the system, I change the transition rates for E03 promotion in the time in rank model. I set the transition rates to simulate a time-based promotion system for E03 such that the probability of promoting to E05 is 0.9 after four years in rank. The timing of four years in rank is based on the six-year IMPS where a member can leave the RAAF without penalty at this point in their career. If a member does not promote after four years in rank they attrite. This simulates the "up or out" system in the USMC. The results for a fixed *R* approach and a Solver approach varying *R* to minimize MAPE across all ranks are shown in Tables 14 and 15 (page 39). The better prediction is from the model where *R* is varied (see Table 15), which results in an overall deficit of 483 personnel.

A time-based promotion system that allows the majority of E03 to promote after four years in rank, significantly improves the ability to match demand at the E05 rank compared to the previous models. The inventory is still unable to meet demand, however, at E06 and E08. Adjusting promotion rates and moving to an "up or out" approach is only one lever available to the RAAF and would require significant policy changes, given the current merit-based promotion system based and a lack of appetite for forcing people out of the service. Additionally, there are still issues with the behavior at, particularly, the E05 and E06 ranks that requires further modeling to ascertain how the future demand for these ranks can be met. Other considerations for the RAAF are investigating retention behaviors at key exit points in a member's career.

Table 14. E03 Time-based Promotion Model, Fixed *R*

Predictions Fixed Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Fixed R
20-21	599	590	430	228	124	1,971	139
21-22	610	551	394	232	131	1,917	139
22-23	640	508	357	246	133	1,884	139
23-24	661	491	317	253	147	1,869	139
24-25	658	493	294	246	154	1,846	139
25-26	721	436	276	237	154	1,823	139
26-27	773	388	256	225	155	1,797	139
27-28	747	421	241	212	156	1,777	139
28-29	747	439	231	201	161	1,778	139
29-30	747	455	221	193	165	1,780	139
30-31	747	469	211	183	168	1,778	139
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	-249
21-22	726	665	460	242	136	2,229	-311
22-23	726	662	458	245	132	2,223	-339
23-24	733	663	457	245	131	2,229	-360
24-25	737	662	458	245	131	2,233	-388
25-26	741	664	460	247	131	2,243	-420
26-27	763	670	464	248	131	2,277	-480
27-28	776	674	465	249	131	2,296	-519
28-29	786	683	467	250	131	2,318	-540
29-30	790	683	467	250	131	2,322	-542
30-31	798	683	467	250	131	2,330	-552

Table 15. E03 Time-based Promotion Model, Fixed Inventory, Minimize MAPE

Predictions Min MAPE	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Vary R
20-21	599	590	430	228	124	1,971	117
21-22	588	551	394	232	131	1,896	146
22-23	627	508	357	246	133	1,871	182
23-24	689	491	317	253	147	1,897	152
24-25	696	493	294	246	154	1,884	127
25-26	748	436	276	237	154	1,849	125
26-27	788	385	256	225	155	1,809	156
27-28	775	419	241	212	156	1,804	149
28-29	786	433	231	201	161	1,811	142
29-30	781	455	221	193	165	1,814	177
30-31	798	487	211	183	168	1,847	222
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	-249
21-22	726	665	460	242	136	2,229	-333
22-23	726	662	458	245	132	2,223	-353
23-24	733	663	457	245	131	2,229	-332
24-25	737	662	458	245	131	2,233	-349
25-26	741	664	460	247	131	2,243	-394
26-27	763	670	464	248	131	2,277	-468
27-28	776	674	465	249	131	2,296	-492
28-29	786	683	467	250	131	2,318	-506
29-30	790	683	467	250	131	2,322	-508
30-31	798	683	467	250	131	2,330	-483
					Min MAPE all ranks		0.19

D. SEPARATION

Utilizing the raw data, I calculate separation probabilities by aggregating the figures for each rank by year of service over each year of data. Figure 9 shows the last five years of separation probabilities aggregated by rank. The results suggest that separation rates have increased in recent years particularly at the E03, E05, and E08 ranks. The probability of E03 separating increases by over three percentage points between 2019 and 2020. This means there are fewer technicians supplying the E05 rank. Separation probability for E09 is relatively stable over recent years.

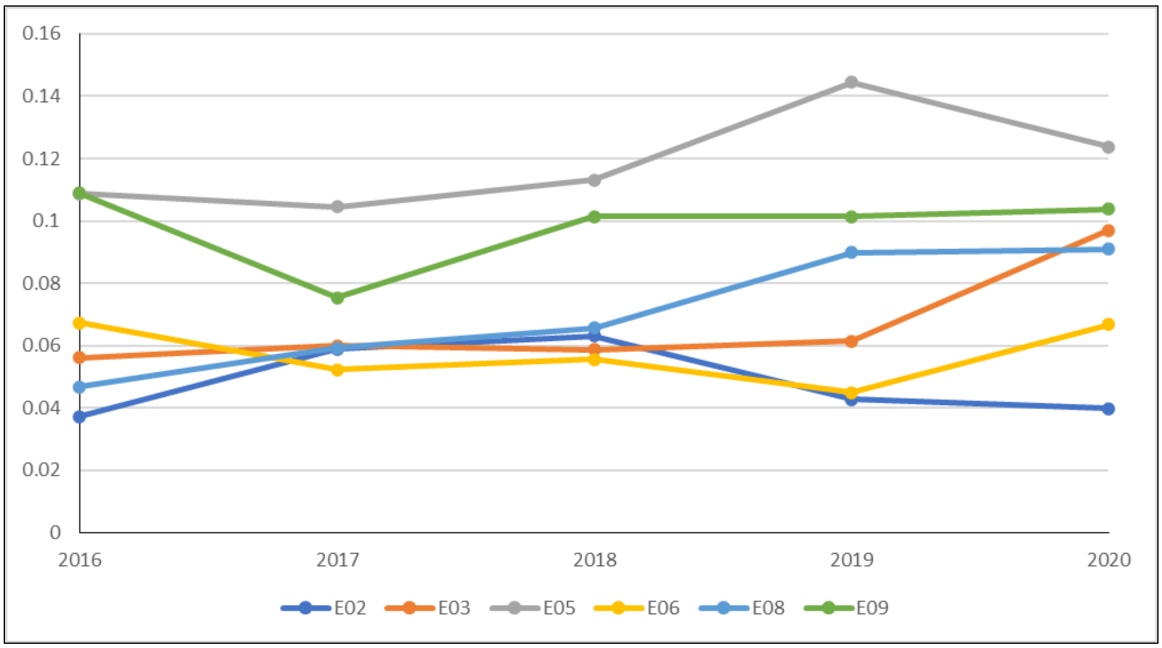

Figure 9. Separation Probabilities by Rank

Then I use a weighted average to calculate separation probabilities by time in rank. The results in Figure 10 (page 42) suggest that, for E03, the probability of separating is occurring earlier in a members' time in rank as seen in the figures for 2020 where separation rates between one and five years in rank has increased compared to earlier years. The graphs show that, around four years in rank, there is a higher probability in recent years that an E03 will separate. Around four years in rank as an E03 is when a technician completes their IMPS and can leave the RAAF.

The results for E05 in Figure 11 (page 42) show that, in 2019 and 2020, by the time someone has spent one to three years in rank and again at seven and 10 years, there is greater probability of separating. The increase in separation probability for an E05 around three years in rank is problematic, as this is when a technician has gained significant experience performing maintenance tasks as well as supervising junior members. Earlier separation also helps explain why the predictions of future inventories cannot match the required demand at this rank. When compared to the results for the promotion rates, members may not be staying in service because it is taking longer to promote.

While there is an increase in 2020 of the probability of separating for E06s who have just promoted, there are no obvious trends in the data and separation behavior seems to be fairly random (see Figure 12 page 43). In general, it seems that personnel at the E06 rank have a slightly lower probability of separating in the first three years in rank in more recent years compared to 2016 and 2017. Interestingly, at seven years in rank, there is a fairly consistent probability over the years of separating at around 0.04.

At the E08 rank there is an increase in 2019 and 2020 of the probability of separating for those who have had one year, three, and four years in rank (see Figure 13 page 43). In general, there is a trend in recent years for a higher probability of separating sooner in a member's time in rank. However, there seems to be a tendency for a lower probability of separating when a member has had more time in rank, around five to seven years. The higher separation probability earlier in years in rank means that there is more of a draw on the E06 population to fill promotions, which further exacerbates the inability to meet future demand as seen in the modeling. Higher separations at E08 are identifiable in the modeling of future predictions for time in rank where the inventory in future years drops well below the starting point, particularly at three and four years in rank.

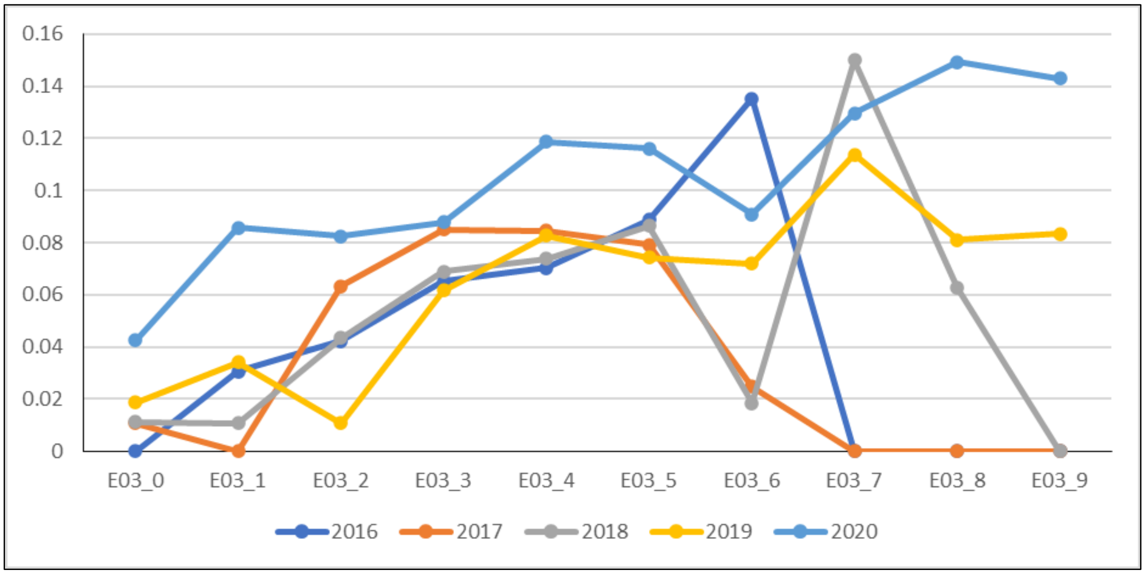

Figure 10. LAC Weighted Average of Separations by Time in Rank

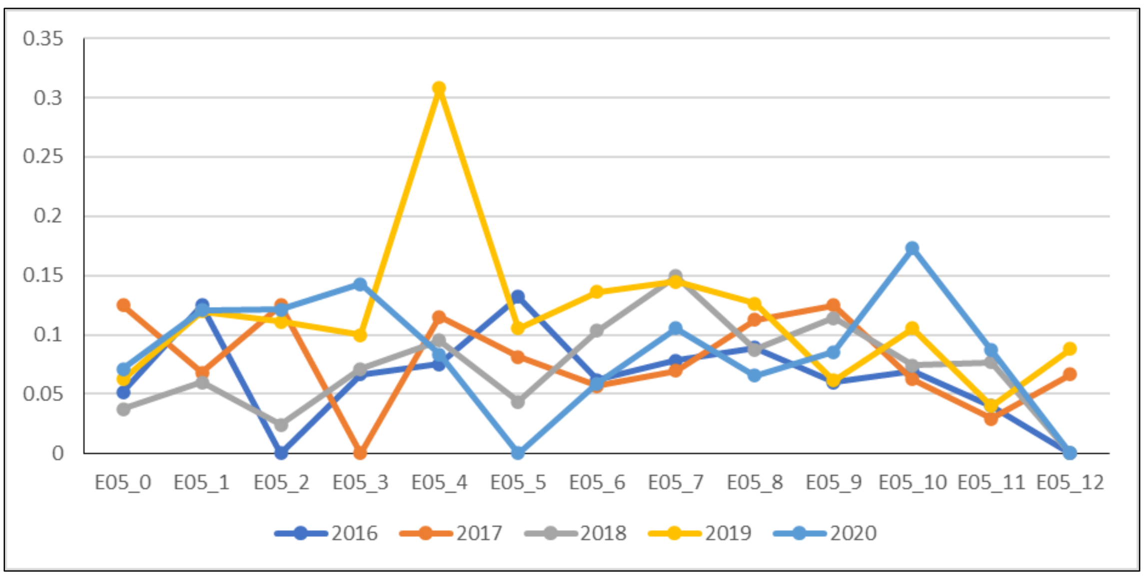

Figure 11. CPL Weighted Average of Separations by Time in Rank

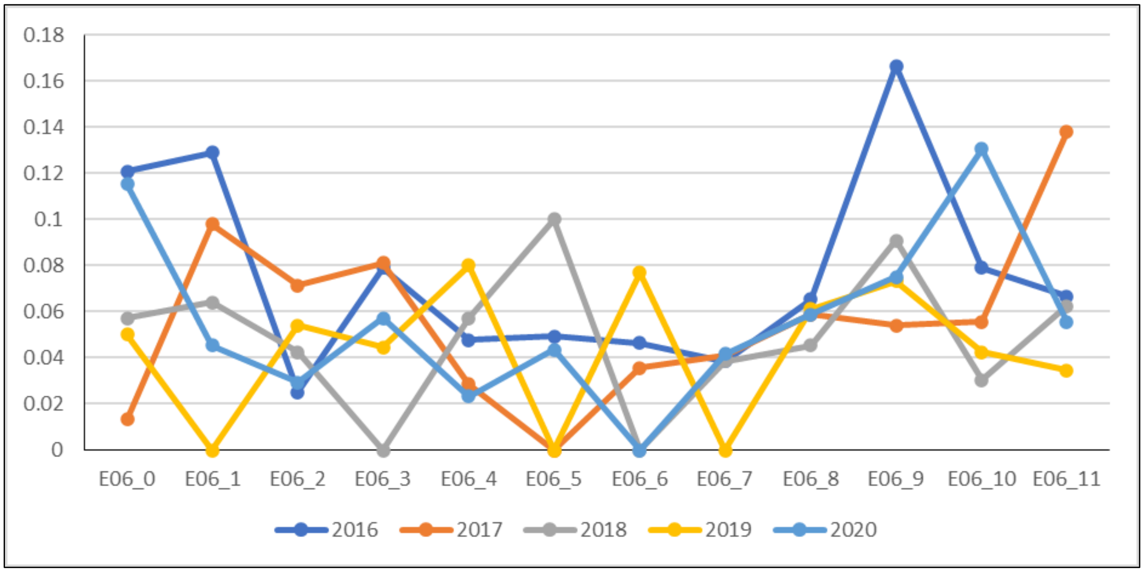

Figure 12. SGT Weighted Average of Separations by Time in Rank

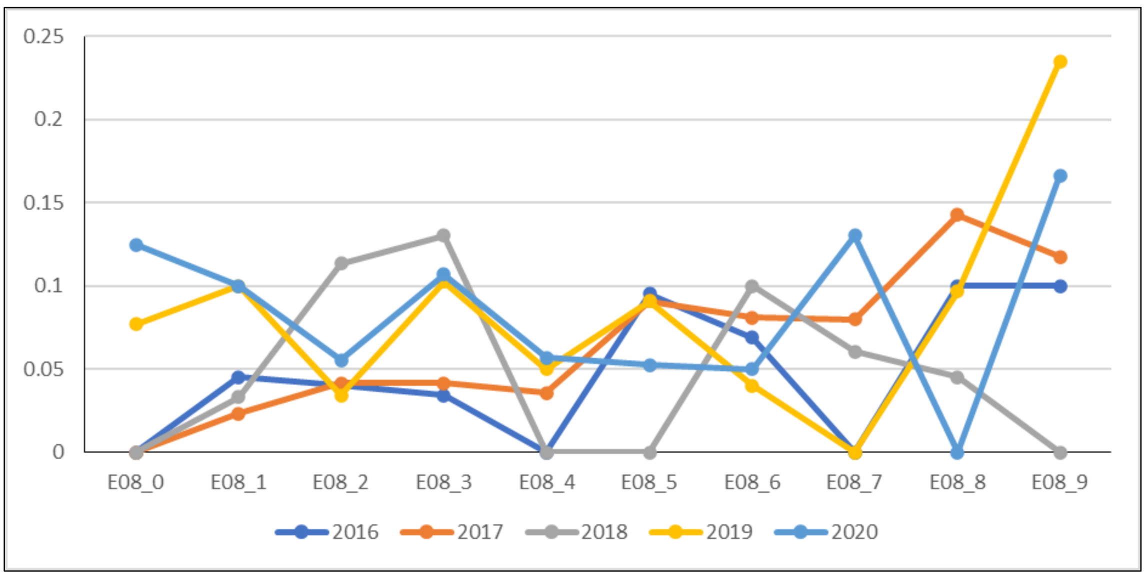

Figure 13. FSGT Weighted Average of Separations by Time in Rank

E. MODEL LIMITATIONS

Due to the unwieldy nature of the large matrices, managerial interpretation of these models is limited. Consequently, I aggregate the inventory predictions of each state for years of service and years in rank back to individual ranks, to compare with the future demand. Further, due to the large number of states it is difficult to make changes to transition probabilities such as promotion and separation rates.

F. CHAPTER SUMMARY

The Markov models in my thesis, based on time in service and time in rank, show that the RAAF is not going to be able to meet future demand particularly at the E05 and E06 ranks. The best prediction, that is also managerially relevant, suggests an under-supply of 561 personnel by 2030–31 based on the one-year time in rank model with fixed recruiting. The models highlight that simply changing recruiting practices by varying *R* does not address the issue of under-supply, nor of the retention behavior in the junior and middle ranks. I attempt to improve the performance in the system by simulating a time-based promotion at the E03 rank using the time in rank model. This improves the ability to meet future demand, particularly for E05, but still results in an under-supply of 483 personnel by the end of FY2030-31. Inspection of separation shows that more personnel are separating earlier in their time in rank and the overall rates are increasing in recent years. Further, the time to promote is increasing for the ranks of E03 to E06. These two system behaviors may be linked and technicians are unwilling to wait longer to promote and choose to separate from the RAAF.

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V. CONCLUSION AND RECOMMENDATIONS

My thesis has aimed to investigate evidence for changes in behavior of the aviation technician population and whether the RAAF can meet future demand for this workforce based on the results of Markov modeling. I used a time in service and time in rank model to calculate transition probabilities for every year between 2005 and 2020. The results of the cross-validation show that a one-year time in service model and one-year time in rank model perform very well.

Based on the predictions in the models, the RAAF should expect that it will not meet future demand for the aviation maintenance workforce by 2030–31 without significant changes. The RAAF needs to address the behaviors in the workforce that are driving E03 personnel to leave sooner in their time in rank and to increase retention at the E05 and E06 ranks. I have attempted to apply one lever by adjusting promotion rates, however, another may be adjusting retention rates at key years in service. Further, the RAAF needs to reconsider the future demand and workforce structure to determine how these can be met given the changing behavior in the aviation technician workforce.

(1) Recommendations

The performance of the time in service and time in rank models show that Markov modeling is a valuable tool for predicting future inventory levels in a workforce. This adds further weight to the prior work that has been done using Markov models for RAAF workforce planning. Due to the unwieldy nature of the models used in my thesis, I recommended that the RAAF works on models that use rank as the states. Based on the results, the RAAF should consider policies that will improve retention and flow in the aviation maintenance workforce to meet future capability needs.

(2) Future Studies

I recommended that the RAAF conducts further Markov modeling to investigate changing behaviors such as retention and promotion rates, to derive a system that will meet future demand. Further, a model where rank is the state space is suggested, as well as modeling the aviation categories individually rather than as an entire aviation population.

It is also recommended that an alternate modelling approach such as survival analysis is conducted to determine separation behavior in cohorts either by year or by IET course. This would provide further granularity on when personnel are separating from the RAAF and help inform policy makers on what can be done to improve retention. If the RAAF is interested in why technicians are separating, then a survey of the population could be conducted that seeks to elicit responses about reasons for staying and reasons for separating from the RAAF.

APPENDIX: RESULTS OF A TWO-YEAR TIME IN SERVICE MODEL

I also apply a two-year time in service fixed recruiting and fixed inventory model to make predictions of future inventory. I investigate this approach as intuition suggests that a model that is based on aggregate behavior may do better at predicting future outcomes than a model that is based on one year of behavior. Tables A1 to A4 show the results of the fixed inventory approach when I optimize for different measures of fit between all ranks and for E05 and E06. The model that is closest in terms of the smallest difference in predictions and future demand, is minimizing MAPE across E05 and E06 (see Table A2). However, this solution is managerially infeasible due to the extreme pooling in the lower ranks and *R* values that the RAAF would not be able to meet due to the yearly fluctuations and difficulty in recruiting the higher numbers of new technicians. The solution that minimizes MAPE across all ranks (Table A1) is the most managerially relevant even though it results in a deficit of 937 personnel by 2030–31. The results of the fixed recruiting approach are in Table A5.

Regardless of how *R* is set, the same issues are observed across all the two-yar models as those that were observed with the one-year time in service results where, particularly, the E05 and E06 inventory cannot meet future demand. The consistent under-achievement in these ranks highlights that simply adjusting *R* will not solve the problem. The results show that there is also pooling of E03 members, which suggests that not enough are flowing through to fill the higher ranks. The bottleneck at E03 and under-supply at the higher ranks suggests that there are issues in retention behavior at the E05 and E06 ranks.

Table A1. Two-Year Time in Service Model, Varied *R* to Minimize MAPE all ranks

Predictions Vary Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Vary R
20-21	964	578	434	231	135	2,344	108.3
21-22	918	531	391	232	134	2,206	90.3
22-23	859	468	352	232	134	2,045	86.4
23-24	801	395	303	229	140	1,868	96.9
24-25	764	355	269	217	142	1,747	110.7
25-26	759	313	246	198	138	1,655	114.9
26-27	765	282	223	182	139	1,592	113.1
27-28	776	256	194	167	135	1,527	111.6
28-29	786	234	169	158	122	1,470	116.3
29-30	802	217	149	147	107	1,422	132.9
30-31	827	203	132	138	93	1,393	150.0
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	123
21-22	726	665	460	242	136	2,229	-22
22-23	726	662	458	245	132	2,223	-178
23-24	733	663	457	245	131	2,229	-362
24-25	737	662	458	245	131	2,233	-486
25-26	741	664	460	247	131	2,243	-588
26-27	763	670	464	248	131	2,277	-685
27-28	776	674	465	249	131	2,296	-768
28-29	786	683	467	250	131	2,318	-848
29-30	790	683	467	250	131	2,322	-900
30-31	798	683	467	250	131	2,330	-937
					Min MAPE all ranks		0.26

Table A2. Two-Year Time in Service Model, Varied *R* to Minimize MAPE for E05 and E06

Predictions Vary Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Vary R
20-21	964	578	434	231	135	2,344	162.5
21-22	969	531	391	232	134	2,257	203.1
22-23	1014	468	352	232	134	2,201	253.9
23-24	1110	395	303	229	140	2,177	317.4
24-25	1271	355	269	217	142	2,255	396.7
25-26	1518	313	246	198	138	2,414	330.6
26-27	1699	283	223	182	139	2,526	275.5
27-28	1822	260	194	167	135	2,578	229.6
28-29	1882	250	169	158	122	2,581	191.3
29-30	1888	254	149	147	107	2,546	159.4
30-31	1839	273	132	138	93	2,475	150.0
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	123
21-22	726	665	460	242	136	2,229	29
22-23	726	662	458	245	132	2,223	-23
23-24	733	663	457	245	131	2,229	-52
24-25	737	662	458	245	131	2,233	21
25-26	741	664	460	247	131	2,243	171
26-27	763	670	464	248	131	2,277	249
27-28	776	674	465	249	131	2,296	282
28-29	786	683	467	250	131	2,318	263
29-30	790	683	467	250	131	2,322	224
30-31	798	683	467	250	131	2,330	145
					Min MAPE CPL and SGT		0.45

Table A3. Two-Year Time in Service Model, Varied *R* to Minimize SSE all Ranks

Predictions Vary Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Vary R
20-21	964	578	434	231	135	2,344	108.3
21-22	918	531	391	232	134	2,206	90.3
22-23	859	468	352	232	134	2,045	83.2
23-24	798	395	303	229	140	1,865	102.5
24-25	766	355	269	217	142	1,750	97.5
25-26	749	313	246	198	138	1,645	121.9
26-27	762	282	223	182	139	1,589	116.6
27-28	776	256	194	167	135	1,527	110.6
28-29	786	234	169	158	122	1,469	103.9
29-30	790	217	149	147	107	1,410	113.7
30-31	798	203	132	138	93	1,363	127.2
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	123
21-22	726	665	460	242	136	2,229	-22
22-23	726	662	458	245	132	2,223	-178
23-24	733	663	457	245	131	2,229	-365
24-25	737	662	458	245	131	2,233	-484
25-26	741	664	460	247	131	2,243	-599
26-27	763	670	464	248	131	2,277	-688
27-28	776	674	465	249	131	2,296	-768
28-29	786	683	467	250	131	2,318	-849
29-30	790	683	467	250	131	2,322	-911
30-31	798	683	467	250	131	2,330	-967
					Min SSE all ranks		186445.36

Table A4. Two-Year Time in Service Model, Varied *R* to Minimize SSE for E05 and E06

Predictions Vary Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Vary R
20-21	964	578	434	231	135	2,344	162.5
21-22	969	531	391	232	134	2,257	203.1
22-23	1014	468	352	232	134	2,201	253.9
23-24	1110	395	303	229	140	2,177	317.4
24-25	1271	355	269	217	142	2,255	396.7
25-26	1518	313	246	198	138	2,414	330.6
26-27	1699	283	223	182	139	2,526	275.5
27-28	1822	260	194	167	135	2,578	229.6
28-29	1882	250	169	158	122	2,581	191.3
29-30	1888	254	149	147	107	2,546	159.4
30-31	1839	273	132	138	93	2,475	150.0
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	123
21-22	726	665	460	242	136	2,229	29
22-23	726	662	458	245	132	2,223	-23
23-24	733	663	457	245	131	2,229	-52
24-25	737	662	458	245	131	2,233	21
25-26	741	664	460	247	131	2,243	171
26-27	763	670	464	248	131	2,277	249
27-28	776	674	465	249	131	2,296	282
28-29	786	683	467	250	131	2,318	263
29-30	790	683	467	250	131	2,322	224
30-31	798	683	467	250	131	2,330	145
					Min SSE CPL and SGT		160871.75

Table A5. Two-Year Time in Service Model, Fixed *R*

Predictions Fixed Recruiting	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Fixed R
20-21	981	578	434	231	135	2,361	136
21-22	960	531	391	232	134	2,248	136
22-23	942	468	352	232	134	2,128	136
23-24	928	395	303	229	140	1,995	136
24-25	922	357	269	217	142	1,907	136
25-26	933	315	246	198	138	1,831	136
26-27	949	286	223	182	139	1,780	136
27-28	970	262	194	167	135	1,727	136
28-29	986	245	169	158	122	1,681	136
29-30	1000	236	149	147	107	1,639	136
30-31	1005	230	132	138	93	1,598	136
Future Demand	E0203_AC_LACW	E05_CPL	E06_SGT	E08_FSGT	E09_WOFF	Total	Difference
20-21	721	662	460	242	136	2,221	140
21-22	726	665	460	242	136	2,229	19
22-23	726	662	458	245	132	2,223	-95
23-24	733	663	457	245	131	2,229	-234
24-25	737	662	458	245	131	2,233	-327
25-26	741	664	460	247	131	2,243	-412
26-27	763	670	464	248	131	2,277	-497
27-28	776	674	465	249	131	2,296	-568
28-29	786	683	467	250	131	2,318	-637
29-30	790	683	467	250	131	2,322	-683
30-31	798	683	467	250	131	2,330	-732

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