Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

EXPERIENCE ACCUMULATION IN MILITARY WORKFORCE PLANNING

Jillian Anne Henderson[1], Cameron Pike[2], Slawomir Wesolkowski[3], and René Séguin[1]

[1] Defence Research and Development Canada, Department of National Defence, Ottawa, ON, CANADA
[2] Defence Science and Technology Group, Department of Defence, Melbourne, VIC, AUSTRALIA
[3] Royal Canadian Air Force, Department of National Defence, Ottawa, ON, CANADA

ABSTRACT

Workforce planning is at the core of military strategic planning. We focus on a critical aspect of many occupations in military workforces: the on-the-job training received by an inexperienced mentee under the supervision of an experienced mentor. We introduce the Experience Accumulation Module to allow the Athena Lite workforce modelling software to consider experience gained through on-the-job training. We compare four models and illustrate their differences with detailed results and analysis: (a) promotion requires minimum time in level; (b) promotion requires upgrade gained through physical resource usage; (c) promotion requires physical resource usage and Mentors; and (d) promotion through physical resource-constrained upgrade. We verify model implementation in Athena Lite by comparing our results from (a) through (c) with a well-known continuous workforce model. We then increase the complexity of our model in (d) and study the impact of resource levels on the upgrade process and the health of the population.

1 INTRODUCTION

Workforce planning is at the core of military strategic planning. Maintaining a well-trained military workforce is of critical importance for armed forces worldwide to ensure that personnel are ready when needed by their respective governments. Armed Forces are large, complicated systems with many constraints, interdependencies and complex interactions among people, resources, schools, and units. Managing these workforces is complex because many military workforces are comprised of hundreds of occupations requiring different degrees of specialization (e.g., consider the differences between a soldier in the Land Forces and one in the Special Forces; while both need to know how to fight, the Special Forces soldier will be trained through a more rigorous and longer process due to the missions she may undertake).

These challenges are exacerbated by the military workforce's unique closed nature and strict rank hierarchy. Thus, armed forces primarily recruit externally into the lowest ranks, while higher ranks are typically filled exclusively via internal promotions with notable exceptions to this such as medical doctors, dentists, and lawyers. In rare cases, military personnel have been hired from allied countries. In other cases, foreign units like France's Foreign Legion have been organized in modern times. Armed forces are also unusual in taking nearly full responsibility for the trade-specific training of its workforce and unique proficiencies required for critical roles. This imposes a considerable time, resource and monetary cost on the armed forces given required platforms (e.g., airplanes), operating costs (e.g., fuel), and people (e.g., instructor pilots). In some specialized military trades, a recruit will not be deemed fully employable until up to seven years of training have been completed successfully (Allison 2022). Thus, unlike industry where personnel are trained through external organizations (universities and technical colleges), soldier production is bounded from both ends: a shortfall and a surplus of skilled staff can be costly and inefficient.

The level of experience of each soldier plays a critical part in how effectively the assets and infrastructure will be used and how effectively junior personnel will be trained. To achieve a high degree of experience, this closed loop system must be managed effectively to efficiently develop personnel at every stage of their military career. As budgets are restricted and efficiencies are found, the career pipelines are

979-8-3315-3420-2/24/$31.00 ©2024 European Union

also vulnerable to disruptions (e.g., COVID-19 pandemic). Given that decisions affecting the military workforce may have significant long-term ramifications such as their ability to respond to crises, armed forces are continuously assessing their needs and identifying gaps between estimated available supply sources (e.g., external recruits and internal personnel pools) and current and future workforce demand. To assess these gaps, defense departments have used a mix of quantitative and qualitative analytical methods to inform the workforce decision-making process (Bastian and Hall 2020; Jnitova et al. 2017). The use of analytical methods and tools to understand the decision space becomes more important for countries with a limited number of military personnel or for highly specialized occupations that require years of training, and experience building, as well as significant effort to maintain that experience. One such decision-support tool is Athena Lite: a discrete event-based simulation tool specifically designed for military workforce forecasting, planning, and analysis (Mortimer et al. 2023). The version of Athena Lite described by Mortimer et al. can estimate future military workforce size, conduct what-if analysis to examine the effects of changes in policies and planning, and help determine recruitment and promotion requirements.

In this paper, we focus on a critical aspect of many occupations in military workforces: the on-the-job training received by an inexperienced mentee under the supervision of an experienced mentor. We introduce the Experience Accumulation Module to allow Athena Lite to take into account experience gained with on-the-job training. In the Canadian context, personnel progress through various proficiency phases. For simplicity, we will focus on personnel entering the system as mentees (e.g., inexperienced pilots) who receive training under the supervision of mentors (e.g., experienced pilots), before becoming mentors themselves (Schaffel et al. 2021). In the context of pilot training, we refer to the production of new pilots, and their absorption in operational units where they become experienced operators (Séguin 2015; Taylor et al. 2002). We will compare four model scenarios and illustrate their similarities and differences with detailed results and analysis:

A. Promotion requires minimum time in level (assuming that the upgrade for promotion will be done in that time).
B. Promotion requires upgrade gained through physical resource usage.
C. Promotion requires upgrade gained through physical resource usage and requires Mentors.
D. Same as C with increasingly constrained physical resource availability for upgrade.

We show that when considering mentors and constraining physical resources, occupations can struggle to maintain a healthy population level.

The paper is organized as follows. Section 2 gives a brief overview of the research into workforce models, and specifically models that consider on-the-job training under supervision. Section 3 describes the mentor-mentee concept, a deterministic continuous model, a Discrete Event Simulation (DES) implementation of the concept in Athena Lite and the Athena Lite experience accumulation module. Section 4 presents results and a brief discussion. Section 5 concludes the paper.

2 LITERATURE REVIEW

There is a variety of workforce planning models that have been developed to support military workforce decision-making (Bastian and Hall 2020; Jnitova et al. 2017). Differential equation models (Bryce and Henderson 2020; Doumic et al. 2016; Vincent and Okazawa 2019) and Markov chain models (Zais and Zhang 2015; Skulj et al. 2008, Filinkov et al. 2011) have both been used to mathematically describe military workforce characteristics and dynamics. In these models, population variables are often continuous given the computational efficiency of modelling in the continuous domain. However, they often lose accuracy for small populations and are limited in capturing feedback mechanisms and performing "what-if" analysis (Wang 2005; Nguyen et al. 2017).

Simulation-based approaches have also been used, including system dynamics (SD) (Thomas et al. 1997; Séguin 2015; Armenia et al. 2012) which can examine the interaction among organizational structure, policies, and decisions by modelling flows between population "stocks" as continuous variables (flows can result in feedback loops). One of the benefits of SD models is that simulations can be run quickly. Turan et al. (2019) developed an SD model to test 23040 experiments of distinct workforce supply and demand parameters within the Royal Australian Navy. But despite their speed, SD models often aggregate information and use simpler representations for complex interactions – compared to other simulation paradigms such as discrete event simulations – within the modelled population (Heath et al. 2011).

Discrete event simulation is a commonly applied simulation paradigm with systems being modelled as sequences of discrete events. It has been employed in many military workforce planning models (Scales et al. 2011; Novak et al. 2015; Henderson and Bryce 2019; Bastian et al. 2019), including by Davenport et al. (2007) to examine United States Marine Corps training and by Moorhead et al. (2008) to identify potential shortfalls of personnel in operations by the Canadian Forces. Heath et al. (2011) argued that compared to system dynamics, DES is more flexible and can capture more detailed characteristics of modelled systems. This is at the cost of greater data requirements and being more time-consuming to develop and run.

Many workforce models focus on the flow of personnel based on rank progression and usually ignore experience accumulation whether linked to resource use (e.g., aircraft or simulator) or mentor-mentee dynamics (e.g., an experienced pilot flying with an inexperienced co-pilot). However, there are some notable exceptions. Séguin (2015) implemented a systems dynamics model to examine the absorption of trainee pilots within operational squadrons by examining the effect of the number of experienced pilots (mentors) on training inexperienced pilots (mentees or trainees). The author examined the impact of increased pilot production (from increased trainee intakes) and reduced budget on the occupation.

Schaffel et al. (2021) built a two-level mentor-mentee model based on a "predator-prey" model (Swift 2002). Since individual mentees cannot be distinguished from one another in this differential equation model, some mentees may become mentors with a small amount of time spent carrying out on-the-job-training. To allow the predator-prey-based model to represent a more realistic scenario, Lahteenmaa-Swerdlyk et al. (2023) introduced experience accumulation tracking for each mentee in the system through the creation of many levels, each corresponding to a different training period. Although an improvement on the two-level model, the multi-level mentor-mentee model does not allow the modelling of complex workforce policies.

In this work, we employ the military workforce planning tool Athena Lite (Mortimer et al. 2023). Athena Lite is a discrete-event simulation and optimization web-based software tool used to estimate future military workforce size and experience, conduct what-if analysis to examine the effects of changes in policies and planning, and determine recruitment and promotion requirements. It was developed by the Australian Defence and Science Technology Group in 2019 as one of two successors to the similarly purposed simulation tool Athena Aircrew (Nguyen et al. 2017). Athena Aircrew was developed to identify potential issues in the Australian Defence Force aviation workforce training system, and Athena Lite expanded on this by capturing not only aviation and training systems, but also other military occupations as well as dynamics within the career phases of service.

Athena Lite has been used to model workforces of up to one hundred thousand personnel over a forty-year period. In the tool, the workforce is divided into a series of workgroups (career specializations), levels (ranks or skill grades) and units (groups of related positions) which personnel can be allocated to. Personnel are modelled as individuals with attributes which can change over the course of the simulation. Advantageously, this allows dynamics such as attrition, qualifications, and promotion to be based on these attributes, providing the opportunity for a more realistic model that does not aggregate out such factors. These dynamics are also modelled probabilistically, with historical or predicted probability distributions input into the software and Monte Carlo methods are used to sample from these distributions over several repetitions to provide estimates of the variance of the forecasted results. Athena Lite is used extensively by the Australian Defence Force, such as in analyzing helicopter platform transition plans for the Australian Army (Mortimer et al. 2023). The experience accumulation model described in Section 3 has been recently implemented in Athena Lite and the work presented here serves as a proof of concept.

3 MODEL DESCRIPTION

Pilots are one of the military occupations where on-the-job training is important (Séguin 2015). First, we describe a simplified pilot career flow model incorporating experience accumulation and upgrading concepts as a career progression from inexperienced (mentee) to experienced (mentor) pilot on an operational squadron. Lastly, we describe the experience accumulation modelling components in Athena Lite and the discrete event simulation model of the mentor-mentee concept implemented in the software.

3.1 Mentee-Mentor Concept

An important aspect of military workforce training is on-the-job-training. Inexperienced members of the armed forces, the mentees, are required to train under the supervision of experienced members, the mentors. This training often requires a ratio of one mentor to one mentee but can vary from occupation to occupation and for specific training tasks.

Referring to Figure 1, mentees enter the system via armed forces training. For mentees to become mentors, they require a certain amount of training hours under the supervision of a mentor. For pilots, this on-the-job training is usually understood to be flying hours (Séguin 2015). This training may require use of physical resources such as aircraft or aircraft simulators. Military training systems can include tasks that are carried out over a fixed amount of time (e.g., courses) and over ad hoc periods of time depending on mentor availability, physical resources, and other factors such as weather (e.g., flight training). Mentees are considered inexperienced until they have reached a pre-determined amount of experience on different resources, at which point, they upgrade and become mentors. In military parlance, the mentees are absorbed in operational squadrons (e.g., they can train others or perform complex missions on their own).

Our mentee-mentor model assumes some simplifications to allow comparison with the continuous mathematical model which follows. These include the assumption that attrition only occurs in the mentor population and that there is no limit on the number of people who can exist in the system.

3.2 Continuous Model

Previously, the mentee-mentor flow model for on-the-job training in Figure 1 was implemented as a deterministic continuous model (Schaffel et al. 2021). We briefly summarize this model and the useful properties investigated so we may use it as a verification case for our DES implementation that follows.

Mentee (m) and mentor (M) population dynamics are defined by the following non-linear differential equations:

$$dm/dt = a - b\,\min(m, rM) \tag{1}$$

$$dM/dt = b\,\min(m, rM) - cM \tag{2}$$

The change in mentee population over time, dm/dt, is given by the intake rate, a (people over time), minus the absorption rate of people into the mentor population, $b\,\min(m, rM)$. The absorption rate is a non-linear term with a constant upgrade frequency, b, and driven by whichever population is smaller: either the mentee population or the mentor population times the latent absorption capacity, r (i.e., the mentee-mentor ratio required for the upgrade process). The change in mentor population over time, dM/dt, is given by the upgrade rate minus attrition, where attrition is a constant rate of leaving, c , of the mentor population, cM.

The continuous model has two regimes of interest:

1. "Unsaturated" or mentee-limited when $m < rM$. There are enough mentors to train all mentees and m determines the upgrade rate. The time to upgrade is given by $t_{upgrade} = 1/b$.
2. "Saturated" or mentor-limited when $m > rM$. The mentor's availability for upgrading is evenly distributed to all mentees, extending the time it takes for each to upgrade ($t_{upgrade} > 1/b$).

The time to upgrade directly affects the capacity of the system to support the generation of experienced personnel and this will be revisited in Section 4.

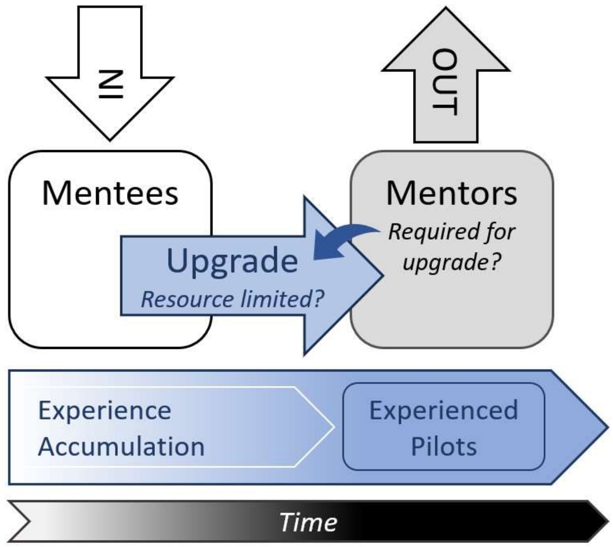

Figure 1: Mentee-mentor model for pilot career flow.

3.3 Discrete Model

To compare the continuous model with a discrete event simulation version, the mentor-mentee concept was modelled in the Athena Lite workforce tool. An integrated module within Athena Lite provides modelling components for this purpose, where multiple resource entities such as aircraft and simulators can be established. Each resource can have a defined average availability over some period of time. They can also have a normally distributed availability which captures the potential for resources not to have constant availability due to factors such as unscheduled maintenance and weather conditions. In the mentor-mentee model implemented here, only constant usage of a single aircraft resource was modelled.

Levels of proficiency are modelled as a sequential progression of experience grades. Each grade has a defined total amount of experience (defined in generic units, but often represented as hours) required to progress to the next grade, as well as specific minimum amounts of experience required from each resource. For example, to progress from a trainee pilot to an experienced pilot, a trainee may require 1000 hours of flying time, 600 hours of which must be on actual aircraft, while the remainder may be acquired by training on simulators. For the mentor-mentee model, there are only two experience grades: mentee and mentor.

Personnel with specified experience grades – the mentors – can be defined to train personnel with lower experience grades – the mentees. Members can be further restricted to only groups of personnel in particular postings in the workforce, i.e., to be a mentor, personnel may need the appropriate experience grade and be in an instructing role. Each person has a total availability as well as a specific maximum mentoring availability and mentee availability.

Experience acquisition is modelled via user-defined *experience allocation events*. An event specifies the planned amount of usage of a single resource by the personnel in a single experience grade at a particular time. Multiple allocation events may occur at a single time. Constraints may also be applied to limit the total or per person amount of experience that may be distributed. Furthermore, an availability-experience ratio may be applied to indicate how many units of mentor or mentee availability are consumed per unit of resource usage. This allows additional, non-resource time expenditure such as preparation time and debriefing time to be considered. For simplicity, we exclude these ratios from the process description below, noting that they act as proportionality constants for calculating mentor and mentee availability.

For each event, the resource usage is first calculated as shown in the "Resource Usage" subprocess in Figure 2. The planned resource usage defined in the event may not be achievable due to resource availability, mentor availability, and mentee availability constraints. Therefore, the resource usage is calculated as the minimum of these values. This amount is then subtracted from the remaining resource availability.

Next, the reduction in mentor availability is calculated. The total resource usage is divided by the number of mentors to obtain the average time commitment per mentor. This loss of availability is continuously and equally distributed across the mentors, with any remainders (due to an individual mentor not having sufficient availability) being equally redistributed to the other mentors. This process is performed in the "determine availability used for individual mentor" step in Figure 2.

Lastly, availability of mentees is consumed, and they are allocated experience as shown in the bottom subprocess of Figure 2. The same availability consumption process applied to mentors is also applied to mentees. The total experience gained is equivalent to the resource usage and this amount is continuously distributed across the mentees. The amount each mentee receives is equal to the amount of their availability that was consumed. After experience is allocated, the experience of the mentee is then checked (the "required experience achieved" decision in Figure 2) to determine if they have acquired the required total amount of experience, as well as the minimum experience required for each resource. If they have met these requirements, then the mentee will upgrade to the next experience grade.

Athena Lite also considers other workforce dynamics such as attrition, promotion, and posting, but these occur independently of the experience accumulation module and are not the focus for this paper. However, an attrition rate was applied in the implemented mentor-mentee model. Finally, Athena Lite utilizes Monte Carlo methods to run multiple repetitions to examine the resultant variance produced by random sampling of stochastic elements such as attrition and resource availability.

4 RESULTS AND DISCUSSION

An experimental set-up and results for the model and simulation are presented in this section.

4.1 Experimental Set Up for Discrete Model Verification

We reproduce scenarios A, B and C described in Section 1 using the same initial conditions and experimental set up for a population growth scenario of the deterministic continuous model of (Schaffel et al. 2021). Scenario D will be examined in a later subsection. An initial population of mentees ($m_i = 25$) and mentors ($M_i = 100$) is grown to a final population ($m_f = 50$ and $M_f = 200$, respectively). This is implemented in the continuous model (see Equations 1 and 2) by setting the attrition rate parameter ($c = 5\%$ per year) and mentee-to-mentor ratio ($r = 1$) then calculating the steady state values of the intake rate ($a = cM_f = 10$ people per year) and the upgrade frequency ($1/b = m_f/a = 5$ years). Note that the mentee-to-mentor ratio ($r = 1$) differs from (Schaffel et al., 2021) which used an $r = 1/3$, but is more realistic for the pilot model we consider here.

In Athena Lite, population growth is achieved by setting a position requirement on the mentee and mentor levels to the target populations m_f and M_f. Annual intake is set to 10 people per year who enter at the same time. The discrete intake spike mimics a cohort of pilots being posted to an operational flying squadron from a training unit.

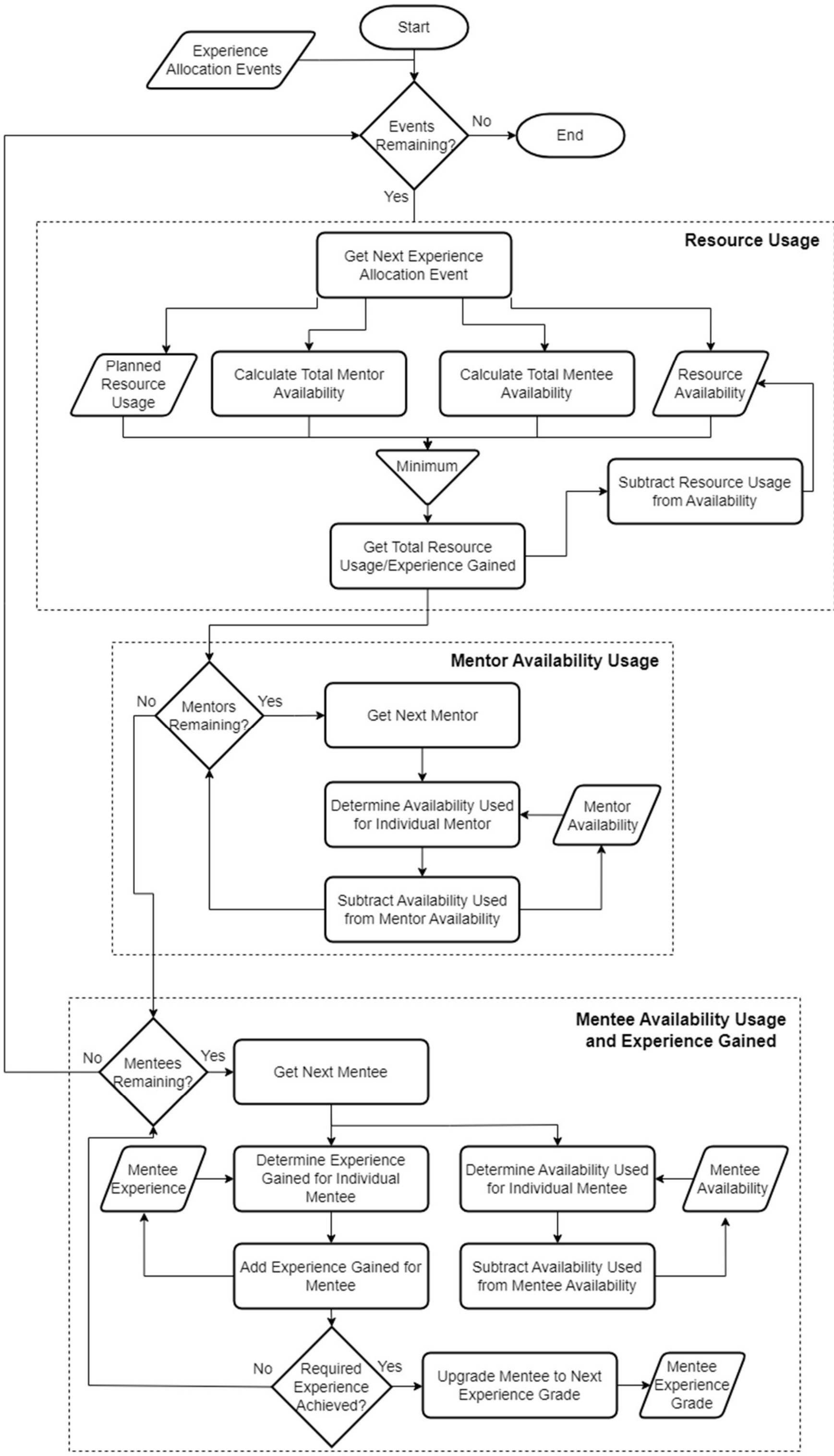

Figure 2: A process diagram of the resource usage and experience allocation procedure in Athena Lite. The process is divided into three main subprocesses: determining the amount of resource used, determining the availability consumed for mentors, and determining the experience gained and availability consumed for mentees.

Under unconstrained upgrading conditions intake cohorts promote at the same time resulting in corresponding discrete promotion events into the mentor population with a delay equal to the upgrade time. The continuous attrition rate was transformed to the equivalent discrete rate ($c_{discrete} = 1 - e^{-c}$). Promotion from mentee to mentor levels is only achieved after the full experience grade is awarded, the details for which depend on the scenario:

A. The minimum time in level before a promotion is set to 5 years.
B. The upgrade required for promotion is set to take $t_{upgrade} = 5\,years$ under unconstrained conditions: 60 resource hours are required for each mentee to upgrade; mentees are available for 12 hours a year for upgrading; mentors are not required; and the total physical resource cap per year is $R = 10000$ hours (effectively unlimited).
C. The upgrade required for promotion additionally requires mentors (i.e., people who have achieved the upgrade and have been promoted to the mentor level). Mentors are available 12 hours per year for upgrading.

The initial population of 25 mentees is modelled as five cohorts each with a time in level (Scenario A) or time of resource usage (Scenarios B and C) equal to 5 years for the most experienced cohort to 1 year for the least experienced. Experience allocation events were set to occur weekly with 2% of the annual resource cap available for distribution. The simulation was run for 150 years to give time to reach and run at steady state. Mean results are averaged over 100 simulation runs. Where stated, steady state means ($\overline{m}_{SS}, \overline{M}_{SS}$), standard deviation (σ), and standard error of the mean (SEM) were calculated over 20 years (simulation years 120 to 140). The steady state period was carefully determined to include a whole number of intake/promotion spike periods such that the means presented here are *true* population means over the entire simulation period.

We expect that all three scenarios of the discrete model under unconstrained resource conditions and a one-to-one mentee-mentor relationship will behave similarly to the continuous model during the population growth phase and match in steady state.

4.2 Results for Scenarios A, B, and C

Simulation results for the mean mentee and mentor counts from scenarios A, B and C are shown as solid curves in Figure 3 (left hand side for mentors, right hand side for mentees) compared to the continuous model (dashed curve) and the position requirement (dotted curve). Annual averages have been plotted to ease comparison, but they have the effect of smoothing the discrete intake and promotion event spikes. As expected, under unconstrained resources all three simulation scenarios give the same results (curves exactly overlap). The simulated populations follow their continuous model counterparts and reach steady state values ($\overline{m}_{SS} = 50.153 \pm 0.004$, $\overline{M}_{SS} = 199.93 \pm 0.04$, and $t_{upgrade} = 5.0118 \pm 0.0001\,years$). The simulation is primarily in an unsaturated or mentee-driven regime. The exception is in the initial growth phase when the first intake spikes enter the mentee population, but their subsequent promotion event will not occur until the upgrade time of $t_{upgrade} = 5\,years$ has passed. This results in the rapid growth of the mentees to m_f in Athena Lite. Meanwhile, the initial population is undergoing upgrade and contributes to the mentor population at a slower rate than the continuous model.

4.3 Results for Scenario D: Constrained Physical Resources

We now examine a parameter of the simulation model that will constrain the upgrading process and challenge the growth of the population: the annual physical resource cap. Figure 4 shows the simulation results as the annual resource cap, R, is lowered from an adequate 600 hours per year (the amount required for an intake of 10 mentees per year) to 60 hours per year. In contrast to Figure 3, weekly average populations are plotted to highlight the intake, upgrade and promotion event frequency followed by periods of attrition in the case of the mentor population. As resources are constrained, the frequency of upgrades and corresponding promotions decrease, eventually failing to offset attrition in the mentor population resulting in the inability to meet the position requirements (left hand side of Figure 4). Meanwhile, intake has remained constant, and mentees build up beyond the position requirements (right hand side of Figure 4). The scenario enters a saturated or mentor-limited regime throughout which the time to upgrade is extended beyond the 5 years it takes in the unconstrained cases (Scenarios A, B and C).

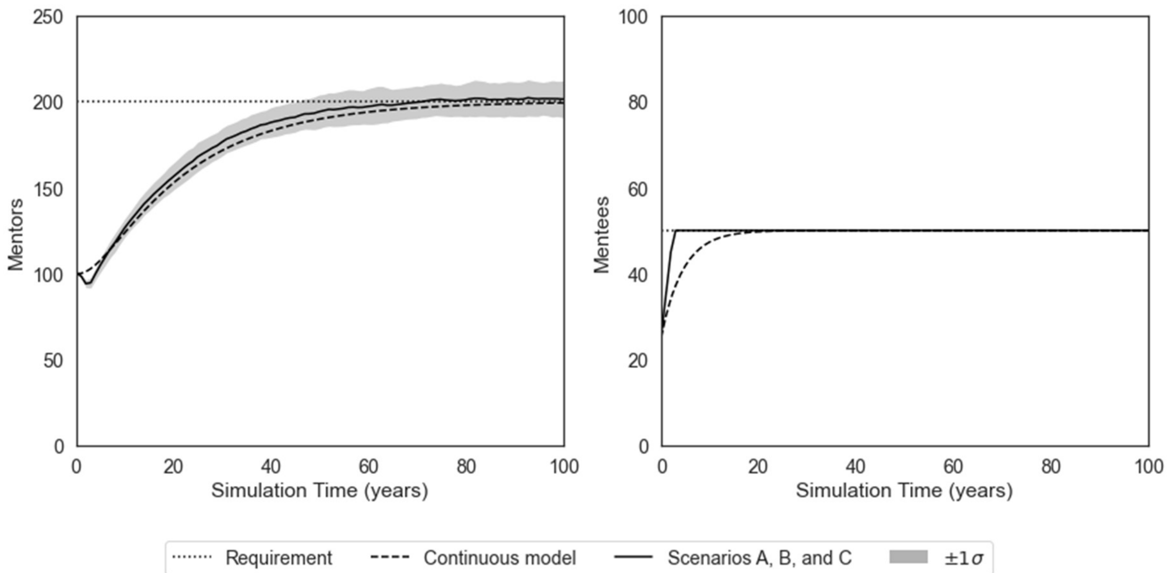

Figure 3: Discrete simulation results for Scenarios A, B and C (solid curve, results overlap) against the continuous model (dashed curve) and the position requirement (dotted curve). The spread of simulation results is illustrated by the shaded region +/- 1σ.

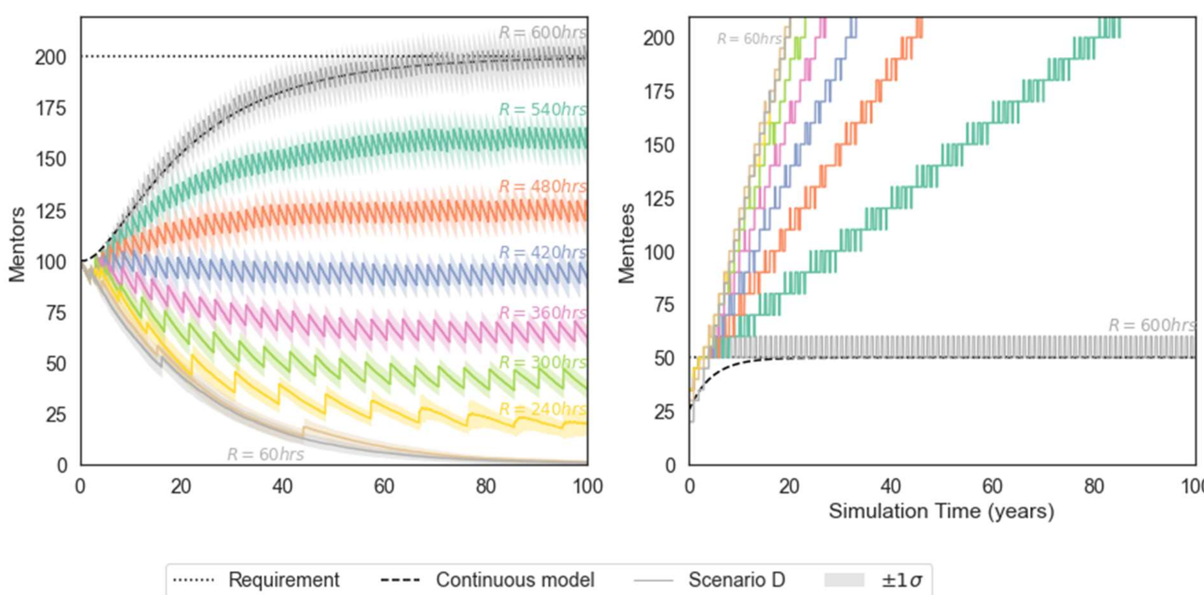

Figure 4: Discrete simulation results for Scenario D with the annual resource cap decreasing from 600 to 60 hours (coloured curves). Results are contrasted against the continuous model (dashed curve) and the position requirement (dotted curve). The spread of simulation results is illustrated by the shaded region +/- 1σ.

The times to upgrade for Scenario D simulation results are shown in Figure 5. As resources become more constrained (R decreases), the mentee population requiring upgrading increases over time (lower panel of Figure 4) which increases the time to upgrade for each cohort. In the cases of $R = 120hrs$ and $R = 60hrs$ the time to upgrade is greater than the simulation period and so these cases do not appear in Figure 5. In the continuous model, the upgrade frequency, b, is independent of time. The modeller would have to determine the benefit over time trade-off of including a time-dependent $b(t)$ term in the continuous model to encapsulate the effects of constraining the system through resource caps or other effects. This level of complexity is arguably more appropriately captured in the DES model.

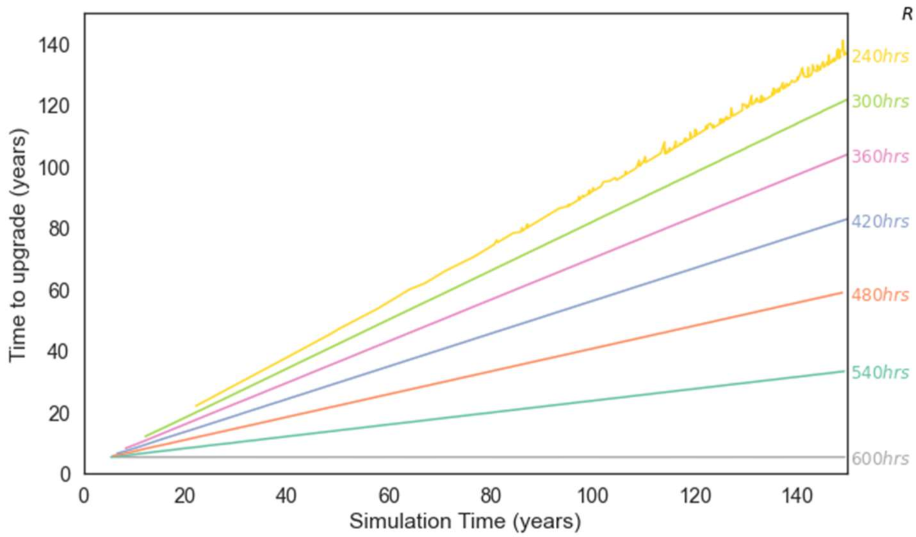

Figure 5: Discrete simulation results for Scenario D showing upgrade time.

In practice, the mentee oversupply is effectively comprised of pilots waiting to start on-the-job-training. Significant mentee population growth would be untenable over too many years; however, this simple simulation highlights the sensitivity of a system that relies on resources, experience accumulation and experience transfer (mentoring). The assumption that all necessary training will be accomplished in a constant specified amount of time is too optimistic.

5 CONCLUSION

In this paper we showed a proof of concept of experience accumulation in a workforce flow model implemented as a DES (Athena Lite). The discrete model implementation was verified against a deterministic continuous model with a non-linear experience accumulation upgrade term under unconstrained resource conditions run to steady state. A more realistic scenario for the discrete model was then explored by increasingly constraining the physical resources required for the upgrade process. In future work, the discrete model fidelity can be increased by addressing the simplifying assumptions taken here. In the case of a military pilot model, these could include modelling multiple upgrade levels, specifying upgrade requirements depending on individual attributes, or enforcing a fixed size for the mentee-mentor population such that mentors are pushed out when mentees are pushed in. In all these cases, the increase in complexity of the experience accumulation model will require a delicate balance between intake and the upgrade capacity of the system.

ACKNOWLEDGMENTS

We thank Melbourne eResearch Group for implementing the experience accumulation module.

REFERENCES

Allison, G. 2022. *How long does it take to train a British military pilot?* UK Defence Journal. https://ukdefencejournal.org.uk/how-long-does-it-take-to-train-a-british-military-pilot/, accessed 15th December 2023.

Armenia, S., A. Centra, V. Cesarotti, A. De Angelis, and C. Retrosi. 2012. "Military Workforce Dynamics and Planning in the Italian AirForce". In *Proceedings of the 30th International Conference of the System Dynamics Society*, edited by E. Husemann, and D. Lane, 123-160. Albany, New York: System Dynamics Society.

Bastian, N., C. Fisher, A. Hall, and B. Lunday. 2019. "Solving the Army's cyber workforce planning problem using stochastic optimisation and discrete-event simulation modelling". In *Proceedings of the 2019 Winter Simulation Conference,* edited by N. Mustafee, K. G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y. Son, 738–749. Piscataway, NJ: IEEE.

Bastian, N., and A. Hall. 2020. "Military Workforce Planning and Manpower Modeling". In *Handbook of Military and Defense Operations Research (1st ed.)*, edited by N.M. Scala, and J.P. Howard, 83-112. New York: CRC Press.

Bryce, R., and J. Henderson. 2020. "Workforce Populations: Empirical versus Markovian Dynamics". In *Proceedings of the 2020 Winter Simulation Conference,* edited by K. G. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, 1983–1993. Piscataway, New Jersey: IEEE.

Davenport, J., C. Neu, W. Smith, and S. Heath. 2007. "Using discrete event simulation to examine Marine training at the Marine Corps communication-electronics school". In *Proceedings of the 2007 Winter Simulation Conference,* edited by S. G. Henderson, B. Biller, M. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, 1387–1394. Piscataway, New Jersey: IEEE.

Doumic, M., B. Perthame, E. Ribes, and D. Salort. 2016. "Toward an integrated workforce planning framework using structured equations". *European Journal of Operational Research* 262(1): 217-230.

Filinkov, A., M. Richmond, R. Nicholson, M. Alshansky, and J. Stewien. 2011. "Modelling personnel sustainability: a tool for military force structure analysis". *The Journal of the Operational Research Society* 62(8):1485–1497.

Heath, S. K., S. C. Brailsford, A. Buss, and C. M. Macal. 2011. "Cross-paradigm simulation modeling: Challenges and successes". In *Proceedings of the 2011 Winter Simulation Conference,* edited by S. Jain, R. R. Creasey, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 2783-2797. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Henderson, J. A., and R. M. Bryce. 2019. "Verification methodology for discrete event simulation models of personnel in the Canadian Armed Forces". In *Proceedings of the 2019 Winter Simulation Conference,* edited by N. Mustafee, K. G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y. Son, 2479–2490. Piscataway, New Jersey: IEEE.

Jnitova, V., S. Elsawah, and M. Ryan. 2017. "Review of Simulation Models in Military Workforce Planning and Management Context". *The Journal of Defence Modelling and Simulation: Applications, Methodology, Technology* 14(4):447-463.

Lahteenmaa-Swerdlyk, T., F. Bourque, and S. Wesolkowski. 2023. "Workforce Modelling with Experience Accumulation". In *Proceedings of the 12th International Conference on Operations Research and Enterprise Systems (ICORES 2023)*, edited by F. Liberatore, S. Wesolkowski, M. Demange, and G. H. Parlier, 27-37. Setúbal, Portugal: SciTePress.

Moorhead, P., A. Wind, and M. Halborhr. 2008. "A discrete event simulation model for examining future sustainability of Canadian Forces operations". In *Proceedings of the 2008 Winter Simulation Conference,* edited by S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, and J. W. Fowler, 1164-1172. Piscataway, New Jersey: IEEE.

Mortimer, K., C. Pike, and V. Nguyen. 2023. "Defence Workforce Transition Simulation and Analysis". In *Proceedings of the 12th International Conference on Operations Research and Enterprise Systems (ICORES 2023)*, edited by F. Liberatore, S. Wesolkowski, M. Demange, and G. H. Parlier, 249-258. Setúbal, Portugal: SciTePress.

Nguyen, V., A. Novak, M. Shokr, and K. Pash. 2017. "Aircrew manpower supply modeling under change: An agent-based discrete event simulation approach". In *Proceedings of the 2017 Winter Simulation Conference,* edited by V. W. K. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. H. Page, 4070–4081. Piscataway, New Jersey: IEEE.

Novak, A., L. Tracey, V. Nguyen, M. Johnstone., V. Le, and D. Creighton. 2015. "Evaluation of tender solutions for Aviation Training using discrete event simulation and best performance criteria". In *Proceedings of the 2015 Winter Simulation Conference,* edited by L. Yilmaz, V. W. K. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 2680–2691. Piscataway, New Jersey: IEEE.

Schaffel, S., F. Bourque, and S. Wesolkowski. 2021. "Modelling the Mentee-Mentor Population Dynamics: Continuous and Discrete Approaches". In *Proceedings of the 2021 Winter Simulation Conference*, edited by S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, 1-10. Piscataway, New Jersey: IEEE.

Scales, C., S. Okazawa, and M. Ormrod. 2011. "The Managed Readiness Simulator". In *Proceedings of the 2011 Winter Simulation Conference,* edited by S. Jain, R. R. Creasey, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 2514-2524. Piscataway, New Jersey: IEEE.

Séguin, R. 2015. "PARSim, a simulation model of the Royal Canadian Air Force (RCAF) pilot occupation - an assessment of the pilot occupation sustainability under high student production and reduced flying rates". In *Proceedings of the 2015 International Conference on Operations Research and Enterprise Systems*, edited by B. Vitoriano, and G. H. Parlier, 51-62. Setúbal, Portugal: SciTePress.

Skulj, D., V. Vehovar, and D. Stamfelj. 2008. "The modelling of manpower by Markov chains - a case study of the Slovenian armed forces". *Informatica (Slovenia)* 32:289–291.

Swift, R. J. 2002. "A Stochastic Predator-Prey Model". *Bulletin of the Irish Mathematical Society* 48:57-63.

Taylor, W. W., J. H. Bigelow, C. Moore, L. Wickman, B. Thomas, and R. S. Marken. 2002. "Absorbing Air Force Fighter Pilots: Parameters, Problems, and Policy Options". MR-1550-AF, RAND Corporation, Santa Monica, California.

Thomas, D., B. Kwinn, M. McGinnis, B. Bowman, and M. Entner. 1997. "The US Army enlisted personnel system: a system dynamics approach". In *Proceedings of the 1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*, edited by L. Leon, I. Cedo, M. E. Fullum, A. C. Brozowski, M. S. Wagner, 1263–1267. Piscataway, New Jersey: IEEE.

Turan, H., S. Elsawah, and M. Ryan. 2019. "Simulation-based Analysis of Military Workforce Planning Strategies". In *Proceedings of the 2019 International Conference on Management Science and Industrial Engineering*, edited by P. Chutima, and C. Chien, 68-75. New York: The Association for Computing Machinery.

Vincent, E., and S. Okazawa. 2019. "Determining Equilibrium Staffing Flows in the Canadian Department of National Defence Public Servant Workforce". In *Proceedings of the 8th International Conference on Operations Research and Enterprise Systems (ICORES 2019)*, edited by G. Parlier, F. Liberatore, and M. Demange, 205–212. Setúbal, Portugal: SciTePress.

Wang, J. 2005. "A review of operations research applications in workforce planning and potential modelling of military training". DSTO Technical Report DSTO-TR-1688, DSTO System Sciences Laboratory, Edinburgh, Australia.

Zais, M., and D. Zhang. 2015. "A Markov chain model of military personnel dynamics". *International Journal of Production Research* 54:1–23.

AUTHOR BIOGRAPHIES

JILLIAN ANNE HENDERSON is a Defence Scientist at the Defence Research and Development Canada (DRDC) Centre for Operational Research and Analysis (CORA). Her career in defence began in 2014 researching data analytics of human factors in Command and Control experiments. In 2016, she started in the field of military career pipeline modelling and simulation, bringing her experience to CORA in 2021 where she is a member of the Directorate Air Staff Operations Research (DASOR) Team. Dr. Henderson holds a doctorate in Science (Astronomy) from the Universidad Nacional Autónoma de México (UNAM). Her email address is jillian.henderson@forces.gc.ca.

CAMERON PIKE is an Operations Research Scientist at the Defence Science and Technology Group (DSTG) in Melbourne, Australia. He holds a BSc and MEng in Mechnical Engineering and during his time at DSTG he has primarily specialized in developing simulation and optimisation models for workforce modelling applications within the Australian Defence Force. His research interests include metaheuristic optimization, reinforcement learning, causal inference machine learning, and metamodelling. His email address is cameron.pike@defence.gov.au.

SLAWOMIR WESOLKOWSKI is a Senior Engineer in the Department of National Defence who provides analytics advice to the Government of Canada. Dr. Wesolkowski worked previously among others at Defence Research Development Canada – Centre for Operational Research and Analysis, and NCR Canada Ltd. He holds PhD, MASc and BASc degrees in Systems Design Engineering from the University of Waterloo. He is an INFORMS Certified Analytics Professional (CAP®) and the recipient of numerous awards for analytics including the 2018 Royal Canadian Air Force Commander Commendation.

RENÉ SÉGUIN holds a Ph.D. in Operations Research from the University of Montréal. Since 2002, he has been a Defence Scientist in the Centre for Operational Research and Analysis of Defence Research and Development Canada. He is currently working on readiness issues pertaining to the Canadian Armed Forces. His current research interests are resource allocation, scheduling and simulation. His email is rene.seguin@forces.gc.ca.