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Forecasting Demand for Air National Guard Enlisted Training

WEAI Presentation

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Executive Summary

The Air National Guard (ANG) relies on the U.S. Air Force to provide enlisted entrants with basic and technical skills training. This enlisted training pipeline begins with Basic Military Training (BMT), which lasts approximately 8 weeks and provides individuals with basic skills to become airmen. Afterwards, individuals complete career-specific technical training at one of 210 different Tech Schools, which are tightly coupled with airmen's eventual occupation: their Air Force Specialty Code (AFSC).

Because BMT and Tech Schools are operated by the Air Force, the ANG must reserve training slots for these schools in advance, typically forecasting school slot demand up to 36 months in the future and budgeting for training costs 5 years in advance. Currently, 150 individual ANG Career Field Managers (CFMs) collect data through various methods to forecast school slot demand to replace airmen that exit the ANG, to fill vacancies created by airmen switching to another AFSC, and to upside/downsize particular AFSCs. While reserving BMT slots is typically unproblematic, ANG experiences long delays (up to a year) for critical technical schools due to inaccurate or incomplete school slot forecasts. These training delays harm unit readiness and contribute to inefficient resource expenditure while airmen await training, to the overall detriment of the ANG.

Using the Retention Prediction Model (RPM), a Machine Learning (ML) package developed by the Institute for Defense Analyses (IDA), this analysis provides the ANG with enhanced training demand forecasts. Given that training demand is filtered through AFSCs, we provide the ANG with the expected number of exits at the detailed (3-digit) AFSC-level, 5 years into the future. Our forecast model uses Defense Manpower Data Center (DMDC) personnel data, combined with ANG training data, spanning 2005–2020. These data comprise about 1.4 million person-years, and about 215,000 unique enlisted airmen.

Using a 5-year test set, interim results suggest that the model correctly classifies about 71% of service exits and about 79% of service retentions across the period. On balance, our model achieves about 77% accuracy and performs about 19 percentage points better than a naïve model that uses historical average AFSC exit rates.

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Forecasting Demand for Air National Guard Enlisted Training

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30 June 2021

The Air National Guard (ANG) faces inefficiencies in forecasting training school slot demand

ANG asked IDA to develop and apply a person-level Retention Prediction Model (RPM)

Forecasting enlisted school demand is just one application

Approach: We use a gradient-boosted tree model to forecast individual retention/exit probabilities

Performance: Using a 2005–2015 training set to forecast exits/stays in 2016–2020, we

Correctly predict 76.7% of all exit-survival observations,

Achieve **51.8%** precision and **70.6%** recall, and

Produce predictions with ~20% less error than average historical rate

Environment

The Air National Guard (ANG) is one of seven reserve components with both federal and state missions

On average, ANG annually has 20,000 officers 90,000 enlisted airmen

ANG offers careers to Non-prior service and prior service Full-time and part-time personnel

Most airmen are part time and maintain a regular civilian job



National Guard Bureau - New Jersey Army National Guard, http://www.njarmyguard.com/organization/

Technical school training programs for ANG airmen are run by the active Air Force

Technical school training corresponds to an Air Force Specialty Code (AFSC), a person's occupation

The most common enlisted AFSCs include aircraft maintenance, security, and cyber

ANG requests its expected number of school slots from the Air Force up to **36 months** in advance

ANG budgets for training costs over a **5-year** period

Existing ANG forecast model is inaccurate, leading to significant delays for technical schools

Research Question:

How can we better forecast demand for <u>technical school slots</u> using individual ANG retention prediction?



What drives AFSC demand?



AFSC tech school demand equals the number of billets to be filled by untrained individuals

Training demand depends on how the AFSC demand is filled

Source	Requires Basic Training?	Requires Tech School?
Non-prior military service entrants		
ANG AFSC transfers without required occupation training	×	
ANG AFSC transfers with required occupation training	X	X
Prior military service entrants without required occupation training	X	
Prior military service entrants with required occupation training	X	X

AFSC tech school demand equals the number of billets to be filled by untrained individuals





ANG seeks to forecast net demand for school slots $(D_{j,t})$ for AFSC j in year t

$$\Delta_{j,t} + \varphi_{j,t} + \lambda_{j,t} = \gamma_{j,t} + \theta_{j,t} \tag{1}$$

$$\gamma_{j,t} = \Delta_{j,t} + \varphi_{j,t} + \lambda_{j,t} - \theta_{j,t}$$
(2)

$$D_{j,t} = \max(0, \Delta_{j,t} + \varphi_{j,t} + \lambda_{j,t} - \theta_{j,t})$$
(3)

Where

 $\Delta_{j,t} =$ **ANG structural adjustment** in AFSC *j* desired headcount $\varphi_{j,t} =$ **Exits from service** from AFSC *j* between *t*-1 and *t* $\lambda_{j,t} =$ **Switch-outs** to other AFSCs between *t*-1 and *t* $\gamma_{j,t} =$ **Non-trained new entrants** to AFSC *j* between *t*-1 and *t* $\theta_{j,t} =$ **Pre-trained new entrants** to AFSC *j* between *t*-1 and *t*

"New entrants" are non-prior service entrants, prior service entrants, and transfers

This research phase focuses on exits from service

$$\Delta_{j,t} + \boldsymbol{\varphi}_{j,t} + \lambda_{j,t} = \gamma_{j,t} + \theta_{j,t}$$
(1)

$$\gamma_{j,t} = \Delta_{j,t} + \boldsymbol{\varphi}_{j,t} + \lambda_{j,t} - \theta_{j,t}$$
(2)

$$D_{j,t} = \max(0, \Delta_{j,t} + \boldsymbol{\varphi}_{j,t} + \lambda_{j,t} - \theta_{j,t})$$
(3)

Where

 $\Delta_{j,t} = \text{ANG structural adjustment in AFSC } j \text{ desired headcount}$ $\varphi_{j,t} = \text{Exits from service from AFSC } j \text{ between } t-1 \text{ and } t$ $\lambda_{j,t} = \text{Switch-outs to other AFSCs between } t-1 \text{ and } t$ $\gamma_{j,t} = \text{Non-trained new entrants to AFSC } j \text{ between } t-1 \text{ and } t$ $\theta_{j,t} = \text{Pre-trained new entrants to AFSC } j \text{ between } t-1 \text{ and } t$

"New entrants" are non-prior service entrants, prior service entrants, and transfers

Share of enlisted ANG personnel remaining by year of service



Note: 2005–2020 data. Kaplan-Meier estimates with 95% confidence intervals shown



Methodology

The Finite Interval Forecasting Engine (FIFE) is a survival analysis tool

Free, open-source Python package offering an array of Machine Learning (ML) and other models for discrete-time survival analysis

Designed by the Institute for Defense Analyses (IDA) and sponsored by the Office of the Undersecretary of Defense for Personnel and Readiness (OUSD(P&R))

We use a Light Gradient Boosting Machine (LightGBM) survival model



FIFE estimates individual survival (or retention) probabilities for each person and period

Estimates probability of individuals in period t remaining in service τ periods into future, conditional on prior survival

Survival probabilities τ periods into future defined as

$$\hat{y}_{x,\tau} = Pr(T_{x,t} \ge \tau | F_{x,t}) \tag{4}$$

Where

 $x = \operatorname{Person} x$

 $F_{x,t}$ = vector of feature values for individual x at time t

 $T_{x,t}$ = number of consecutive future periods x remains after time t

We sum individual exit/retention probabilities by AFSC to obtain the expected number of exits per AFSC

Recall

 $\varphi_{j,t+\tau} = \text{Exits from service from AFSC } j,$ between $t + \tau - 1$ and $t + \tau$ We estimate $\tilde{\varphi}_{j,t+\tau} = \text{Exits from service of those in AFSC } j$ in t, between $t + \tau - 1$ and $t + \tau$ $= \sum_{x \in X_{j,t}} \hat{y}_{x,t+\tau}$

(5)

Where

 $X_{j,t}$ = Individuals in AFSC *j* in period *t*

 $\hat{y}_{x,t+\tau}$ = Exit probability for individual x in period $t + \tau$

ANG exit forecasting for school slot forecasting requires adjusting for AFSC transfers and new entrants



There are several ways an airman can leave AFSC j





FIFE survival forecasts are one part of the exit component in the demand equation

$$\varphi_{j,t+\tau} = \sum_{\forall x \in X_{j,t}} E_{t+\tau}(x) - \sum_{\forall x \in X_{j,t}} E_{t+\tau}(x) * (1 - I_{j,t+\tau-1}(x)) + \sum_{\forall y \in Y_{j,t}} E_{t+\tau}(y) * I_{j,t+\tau-1}(y) + \sum_{\forall n \in N_{j,t+\tau}} E_{t+\tau}(n) * I_{j,t+\tau-1}(n)$$
(6)

Where

 $X_{j,t+\tau}$ = individuals in AFSC j in t+ τ $Y_{j,t+\tau}$ = individuals in service but not in AFSC j in t+ τ $N_{j,t+\tau}$ = New entrants to AFSC j after t but before t+ τ $I_{j,t+\tau}$ (person p) = 1 if p is in AFSC j in t+ τ $E_{t+\tau}$ (person p) = 1 if p exited service between t+ τ -1 and t+ τ

Note: We estimate the part in red

We train using all years of data <u>except</u> the last few and then use these as a performance test

We construct a panel dataset (individual, year)

Using last few years as test set most closely emulates real-world performance in period of interest (2022–2026)

<u>Training set</u>: 2005–2015

<u>Test set</u>: 2016–2020

Hyper-optimized model (200 trials, 25% validation share)

Scope and data

Analytic set for modeling: all enlisted ANG personnel serving between June 2005 and June 2020

Before modeling, we exclude

Direct commissioned officers and any post-commission observations Post-ANG observations (e.g., move other service/component) Observations before year 2005 due to poor data quality

Observations occur each June (annual frequency)

Results presented today use full population of ANG personnel who meet these criteria

Our dataset comprises DMDC, CPS, and ANG data

Dataset	Source	Description	
Master	Defense Manpower Data Center (DMDC)	Demographics, career history	
Pay	DMDC	Various pay fields	
Deployments	DMDC	Deployment history	
Family/Defense Enrollment Eligibility Reporting System (DEERS)	DMDC	Family and dependents	
Activations file	DMDC	Title 10 federal activations	
Casualties file	DMDC	Personal injuries, fatalities in unit	
Civilian labor market data	Current Population Survey (June)	External labor market conditions	
Supplementary ANG training data	ANG	ANG training	

Total columns: 638

Results:

How would we have done if you asked us 5 years ago?



We accurately predict 70.6% of exits and 78.7% of retentions between 2016 and 2020



Note: Full ANG population meeting analytic restrictions (test: N=90,805). DMDC annual (June) data, 2005–2015. Estimates based on FIFE LightGBM model. The confusion matrix was produced with a threshold of **0.685** (i.e., PR(Y) > 0.685 classified as remain, else exit)

Predicting stays is easier than predicting exits



How well can our prototype forecast exits within AFSCs? Forecasted vs. observed ANG exits for select AFSCs, 2016–2020



Forecast errors among 20 largest AFSCs Covering 69% of enlisted personnel, 2016–2020



Note: Twenty largest AFSCs according to total personnel in (June) 2015

RPM-ANG performs 19% better than a model using average AFSC exit rate in 2005–2015

Mean Absolute Error						
Year	Forecast Horizon	FIFE	AFSC Average	% Improvement Using FIFE		
2016	<i>†</i> +1	0.042	0.031	-35.5%		
2017	<i>t</i> +2	0.027	0.031	12.9%		
2018	<i>†</i> +3	0.051	0.033	-54.5%		
2019	†+ 4	0.041	0.068	39.7%		
2020	<i>†</i> +5	0.031	0.066	53.0%		
Overall		0.029	0.046	19.3%		

Note: Outcome is the share of exits per AFSC-year. Both models trained using 2005–2015, using 2016-2020 as test set. Baseline model uses average AFSC exit rate in 2005–2015. FIFE model sums individual exit forecasts by AFSC-year and error per AFSC-year

Discussion and conclusion

<u>Accomplished</u>

- Modeled one component of demand equation (exits from service)
- Successfully created model that outperforms existing methods used by the ANG
- Developed aggregate prediction method using expected values



- Model other components of demand equation (switching, new entrants)
- Make post-modeling forecast adjustments to further improve proposed method
- Compare other regression and time-series models on an AFSC level





Backup

Net personnel changes across AFSC-years



Note: Changes calculated as AFSC switch-outs minus switch-ins. We exclude recoded or disbanded AFSCs by restricted to AFSC-years in which the number of remaining individuals in an AFSC >1 and the number of stayers is >1 (1535/1668). Mean=1.66, std=324

Enlisted ANG personnel in analytic set in 2005–2020



215,879 unique persons observed over 1,463,343 person-years

Retention among enlisted direct entrants vs. enlisted prior service individuals



Note: 2005–2020 data. Kaplan-Meier estimates with 95% confidence intervals shown

Share of females among ANG enlisted stock and new ANG entrants



Note: 2005–2020 data, own analyses. New entrants defined as persons not present in previous period(s)

Share of prior service (any service/component) among ANG stock and new ANG entrants



Note: 2005–2020 data, own analyses. New entrants defined as persons not present in previous period(s)

Median age among ANG stock and new ANG entrants



Note: 2005–2020 data, own analyses. New entrants defined as persons not present in previous period(s)

Precision-recall curve

Depicts tradeoff between precision and recall for various probabilistic thresholds

Positive class = exit

Precision: share of true exiters correctly identified

True Positives

True Positives + False Positives

Recall: Share of true exiters identified of all exiters

True Positives True Positives + False Negatives



Credit: https://en.wikipedia.org/wiki/Precision_and_recall



Precision-recall gain curve for 2016–2020 test



Note: Full ANG population meeting analytic restrictions (test: N=90,805). DMDC annual (June) data, 2005–2015. Baseline rate is observed attrition rate (i.e., when precision-recall curve threshold is zero)

Option 1: Directly exit service from AFSC $\boldsymbol{\alpha}$





Option 2: Start in AFSC α , switch to another AFSC, then exit service



Option 3: Start in another AFSC, switch to AFSC α , then exit service



Option 4: Start in another AFSC, switch to AFSC α , switch to another AFSC, then exit service



Option 5: Start in AFSC α , switch to another AFSC, return to AFSC α , then exit service



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