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THESIS

FORECASTING THE MARINE CORPS' ENLISTED CLASSIFICATION PLAN: ASSESSMENT OF AN ALTERNATIVE MODEL

by

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March 2012

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In a given fiscal year, the United States Marine Corps accesses approximately 30,000 enlisted personnel into its ranks. This labor supply of recruits is classified into various Military Occupational Specialties (MOSs) according to the forecasted requirement for new personnel into a particular MOS. The Classification Plan is the primary initial training input into the Training Input Plan, which allocates all training resources for Training and Education Command. The current Classification Model is based on a steady-state Markov Model that estimates the first-term inventory of each initial training MOS inventory of personnel. A performance comparison was made against a transient Markov Model that solves for an optimal classification plan over the course of a four-year planning horizon. First, the validity of the steady-state assumption is tested and found to produce a variance of annual targets for each MOS throughout the Future Years Defense Plan that is prohibitively high. Next, a comparison of each models' ability to forecast annual attrition by MOS between the years 2001 and 2011 is tested. Results indicate that the transient model produced a more accurate forecast for 5,321 out of 7,379 design points (approximately 72% of the observations). The transient model achieved a Mean Absolute Proportional Error that was on average 14 percentage points smaller than that of the steady-state model. In over 25% of the cases, this difference exceeded 20 percentage points. Based upon this improved performance, it is recommended the Marine Corps adopt the enhanced transient Markov Model as the foundation for forecasting its annual Enlisted Classification Plan.

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ABSTRACT

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LIST OF ACRONYMS AND ABBREVIATIONS

CV	Coefficient of Variation
FY	Fiscal Year
FYDP	Future Years' Defense Plan
GAR	Grade Adjusted Recapitulation
KISS	Keep it Simple, Stupid
MAGTF	Marine Air-Ground Task Force
MAPE	Mean Absolute Percent Error
MCT	Marine Combat Training
MOE	Measure of Effectiveness
MOS	Military Occupational Specialty
NEAS	Non-End of Active Service
PMOS	Primary Military Occupational Specialty
TIG	Time in Grade
TIS	Time in Service
TOE	Term of Enlistment
TTT	Time to Train
YCS	Years Completed Service

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I. INTRODUCTION

A. BACKGROUND

As an organization of over 200,000 personnel, the Marine Corps recruits and brings into its workforce approximately 30,000 new personnel on an annual basis. This workforce is distributed across over 200 Military Occupational Specialties (MOSs). This distribution is a function of the total requirement for the MOS by rank, current MOS strength, new accessions to the MOS, and attrition from the MOS. Therefore, this labor supply of recruits is assigned into various MOSs due to the forecasted demand for new personnel into that particular MOS. The goal of this forecast is to ensure an enlisted force structure exists to meet manpower resource requirements.

The demand for new accessions per Fiscal Year (FY) is tied to forecasting attrition behavior. The plan that determines the number of Marines to assign to each MOS is referred to as the Enlisted Classification Plan. This classifications plan then serves as an input to a number of successive plans. From the classification plan, the Marine Corps develops requirements for its Recruiting Command's accession and initial training (recruit training) requirements, and its MOS training requirements for its multiple MOS-producing schools.

B. OBJECTIVES

Because of the sheer magnitude and impact that a classification plan has to the subsequent planning and the long-term health of an MOS, the importance of an accurate classification plan cannot be overemphasized. Further, in this era of fiscal austerity and future downsizing, the efficiency and precision of any forecasted number is worthy of analysis and scrutiny.

Given that desired endstrength is a function of beginning (current) endstrength + (plus) accessions – (minus) attritions, the number of personnel attritions must be forecasted to the highest degree of accuracy possible. In this formula, the desired and current personnel endstrengths are known quantities. The accessions required in a future fiscal year are predicated upon the attritions. Since the actual level of attrition is an

unknown variable, it must be forecasted. The current model used to predict attrition is based upon a steady-state inventory of personnel. However, it is believed that an enhanced, transient model could not only reduce misclassifications of MOSs, but also better account for dynamic changes to desired endstrength.

C. RESEARCH QUESTION AND METHODOLOGY

The Marine Corps currently uses a steady-state Markov model to forecast the first-term inventory of each unique initial training MOS and subsequent accession requirement. As previously stated, accurate and precise forecasting is always important; however, the degree of required accuracy and resulting efficiency required of manpower planners will be ever increasing in the Marine Corps' drawdown and future Department of Defense's fiscally constrained environment. The purpose of this thesis is to assess the validity of a Classification Plan derived from a transient Markov Model.

Primary Research Question: Would a transient Markov Model serve as a more accurate forecasting tool to support the development of the Marine Corps' Enlisted Classification Plan? If more accurate, what is the relative magnitude in the difference in accuracy (i.e., how much better of a predictor is the transient model)?

Through simulation, a comparison of the current attrition model and a proposed enhanced attrition model is conducted. This comparison includes a review of each models' predicted attrition behavior.

D. SCOPE AND LIMITATIONS

The enlisted manpower and personnel analysts and planners make career force decisions (promotion, retention, training, etc.) based upon existing and forecasted personnel resources by specific MOS. These career force decisions are driven from the requirements by grade and specific MOS as outlined in the Grade Adjusted Recapitulation (GAR). As previously noted, the variable of attrition must be forecasted as a basis for these career force decisions. Therefore, the more accurately forecasted the level of attrition is as an input to this decision system, the less variability the system as a whole. Further, a forecast model that supports the ability to account for changes in

desired endstrength would not only prove useful in the short-term and future draw down of personnel endstrength, but also be flexible enough to support any future changes to desired endstrength.

Although Marine Corps' future endstrength requirements are not conclusively known, it is generally accepted that its endstrength will be no greater than 182,200 in the upcoming years (Amos, 2012). This roughly 10% decrease in overall personnel end-strength and subsequent reshaping of its force will have an effect across all MOSs. Additionally, technological advances, equipment changes, and unforeseen operational requirements contribute to the management of manpower and the subsequent personnel effects inherent in the Marine Corps' manpower and personnel system.

E. ORGANIZATION OF THESIS

Chapter II of this thesis consists of a literature review and commentary on those works that have previously looked at (either directly or indirectly) elements of the Marine Corps' Enlisted Classification Plan. Chapter III presents an overview of the current steady state Markov Model that is used by HQMC planners and introduces an enhanced Markov Model. Chapter IV presents an analysis and comparison of the current and transient models. Lastly, Chapter V presents a summary, conclusions, and recommendations for the developers of the Marine Corps' Enlisted Classification Plan.

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II. LITERATURE REVIEW

A. INTRODUCTION OF PREVIOUS STUDIES

Previous studies and papers discuss attrition and retention in the military as a binary (yes or no) outcome. This literature typically looks at various demographic and other observable variables (test scores, physical fitness scores, etc.) and attempts to predict behavior through multivariate regression analysis.

B. PAST NAVAL POSTGRADUATE SCHOOL THESIS

1. Forecasting Enlisted Attrition in the United States Marine Corps by Grade and Years of Service

In his thesis, Tamayo (2011) set out to analyze enlisted attrition behavior through various time series forecasting techniques. Comparing the results of both moving average and weighted moving average models, Tamayo then applied the two relative measures of effectiveness (MOE). Specifically, Tamayo analyzed the Mean Square Error and the Mean Absolute Percent Error of the various models to serve as his MOEs. Tamayo's modeling determined that the optimal weights associated with using a weighted-moving average model was nearly equivalent to that of a one-year moving average model.

To his credit, Tamayo included a sizable time horizon of study in his thesis (FY1987–2009). This timeline was significantly long enough to capture data prior to the personnel build up during Operation DESERT SHIELD/DESERT STORM and the accompanying personnel reductions, and the recent build up in endstrength in support of Operations ENDURING FREEDOM and IRAQI FREEDOM. Additionally, Tamayo acknowledges that the benefit and simplicity of using a one-year moving average model and its ability to support manpower planners' ability to quickly estimate forecasts by grade and MOS.

To be sure, the Marine Corps organizationally supports and endorses the KISS (keep it simple, stupid) Principle. However, there is a cost with too much simplicity. Tamayo's findings must be put into further context to gain a deeper appreciation for this cost-benefit analysis. Tamayo's findings are correct for the analyzed data set on the

aggregate. However, his recommendations are nearly completely counter to the rankings (Tamayo, 2011, Table 3, p. 23) in those FYs, which were subject to sizable changes in consecutive years. The relevance of point in today's environment is an understanding that the Marine Corps' enlisted endstrength is likely to decrease by approximately 20,000 personnel in coming five FYs. (Amos, 2012) This volatility in endstrength is not a particularly well suited environment for a forecasting model that essentially states that the current situation very much mirrors the last observed situation.

2. Analysis of the U.S. Marine Corps' Steady State Markov Model for Forecasting Annual First-Term Enlisted Classification Requirements

In his thesis, Nguyen (1997) proposed an alternative to the then-current method of forecasting continuation rates that were used by manpower planners as the basis for their forecasting. His claim stated that although the manpower planners were using equations in the steady state Markov Model properly, some components within the model needed to be reexamined.

Specifically, the manpower planners at the time were using a Markov Model that determined requirements using a weighted-average continuation rate. This weighted-average then assumed that the most recent attrition information was the most relevant and reliable, but it is also subject to greater relative over/under estimation due to this greater influence of the most recent years. In fact, Nguyen graphs continuation trends for PMOSs 0121 and 6521 (Cohorts 1986–94) to demonstrate this roller-coaster effect.

Nguyen's thesis proposes that a revised steady-state model which employees an average continuation rate versus the weighted-average continuation rate would produce calculations that are more accurate and better forecast classification requirements for each Primary MOS (PMOS). Additionally, proposed changes to the spreadsheet formulations would lead to more precise (admittedly minor) results due to the effect of eliminating rounding errors that would otherwise be compounded with successive calculations.

The shortcoming to Nguyen's model is that it assumes a constant total Grade Adjusted Recapitulation (GAR) requirement. This assumption is not a problem so long as total billets required for a given PMOS remains constant from year to year. However, in those scenarios that a GAR requirement changes from year to year in a particular PMOS and/or when overall endstrength results in changes to nearly all PMOSs, this model may not accurately account for such variations while still producing precise forecasts.

3. Forecasting Marine Corps Enlisted Attrition Through Parametric Modeling

In his thesis, Hall's (2009) purpose was to apply a parametric modeling (specifically survival analysis) of historical data sets of enlisted personnel to develop a more efficient forecasting tool for manpower planners. Further, Hall's intent was to tease out those variables that effect attrition behavior and focus on those contributing factors that lead to non-end of active service attrition (those Marines who did not complete their contracted term of enlistment).

Hall's thesis specifically researched those contributing factors that influenced non-end of active service (NEAS) attrition. This NEAS attrition is an important element of the overall losses to the manpower system within a given FY. As Hall points out, personnel end strength is calculated at the end of each FY as:

Endstrength = FY beginning strength – (minus) losses + (plus) gains.

Although Hall's end strength equation is generically correct, it is missing a key element that makes the equation more significant to manpower planners. The variable of capturing the net change to endstrength between consecutive FYs adds a depth and richness to the equation that is missing without its inclusion. Perhaps a more meaningful equation would include:

Endstrength = Beginning Strength – losses + accessions +/- net change in FYs

C. CENTER FOR NAVAL ANALYSIS REPORT

1. Endstrength: Forecasting Marine Corps Losses Final Report

The purpose of this study is stated as a "recognition of the importance of correctly forecasting endstrength losses and gains and the severe consequences of incorrect estimates" (Hattiangadi, Kimble, Lambert, & Quester, 2005). Further, deviation from endstrength requirements results in one of two negative consequences for the service. First, carrying too many personnel into a future FY (over endstrength) constitutes an over expenditure in the MPMC account that must then come out of the O&M account. Second, carrying too few personnel forward may have impacts upon the operational readiness of units should they have fewer assigned personnel then necessary to properly execute their assigned missions. Citing a specific example, the authors note that, "The endstrength planners finished FY04 with an enlisted endstrength of 2,040 Marines above target."

The authors state that at the beginning of their study the Marine Corps had "no institutionalized and document methodology for forecasting losses, (that) no one had made a systematic attempt to determine whether the (then) current combinations of methods could be improved, (and) no structured capability existed to run loss scenarios".

The authors present two alternatives to aid planners in their task of forecasting. The first alternative presented is an optimization tool based upon the methodology that enlisted planners in the Air Force use to determine weighting of historical data to forecast future personnel predictions. The second alternative presented is exponential smoothing. The technique of using exponential smoothing assigns the greatest weight to the most recent observation and relatively less weight to older observations. Additionally, the authors note that exponential smoothing can be adapted to account for seasonality and trend patterns within historical data observations.

III. MODEL OVERVIEW

A. INTRODUCTION

The foundations for the transition models analyzed in this thesis are based upon the Markov Chain model structure. The following is a brief discussion of the principles and notation associated with these models. Fundamentally, the purpose of these models is to "Serve in a practical manpower planning situation, (and to answer the question of) what should the recruitment numbers be in order to achieve a desired structure in a specified time?" (Bartholomew, Forbes, & McClean, 1991)

B. PRINCIPLES AND ASSUMPTIONS IN THE MARKOV CHAIN

1. States

The system consists of states. That is to say that the model is partitioned into defined locations within the system. Examples of states include paygrade, time in grade, years of service, etc. The states of interest in this research is years of completed service (YCS).

2. Markovian Property

Although the notation for this assumption follows in upcoming paragraphs, this property essentially states that the probability that the system transitions to a state *j* depends ONLY upon current state. This "memory-less" property lends itself to transitioning to the next state only depends upon current state location.

3. Stationary Transition Probabilities

The probability of transitioning between states is constant over time. Although the probability of transitioning from state to state is likely to experience some variation over time, these probabilities must be treated as constant to provide a baseline for comparison and to keep our models relatively simple and manageable to use by planners.

C. NOTATION

The following notation conventions are drawn from academic literature (Bartholomew, Forbes, & McClean, 1991).

Let i = some initial state (years of service) and j = some subsequent state, then

p_{ij} = Pr(an element transitions from i to j in one timestep)

We define $\mathbf{P}=\{p_{ij}\}$ as the matrix of transition probabilities. For four-year Terms of Enlistments (TOE), a Marine can be in one of four states {0, 1, 2, or 3} YCS during his or her first term. Therefore, their associated **P** is a 4x4 matrix. MOSs with five-year TOEs require an additional state and thus require a 5x5 transition matrix.

D. CURRENT STEADY-STATE MODEL

A steady-state model is currently used by manpower planners to determine the number of new accessions required to match long-term population requirements. The following figure graphically represents the transition probabilities between the various states of potential YCS. In this simple model, personnel either transition to the next state or attrite out of the system when YCS changes. In this model (depicting a four year TOE), Marines with fewer than 12 months of service are partitioned into state 0, those with more than 12 months but less than 24 months are in state 1, and so on. Since most enlistment periods are for a period of 48 months, the final state in this system is 3 (greater than 36 months of service, but less than 48 months). Upon completing 48 months of service, all personnel in state 3 transition into the attrition state.

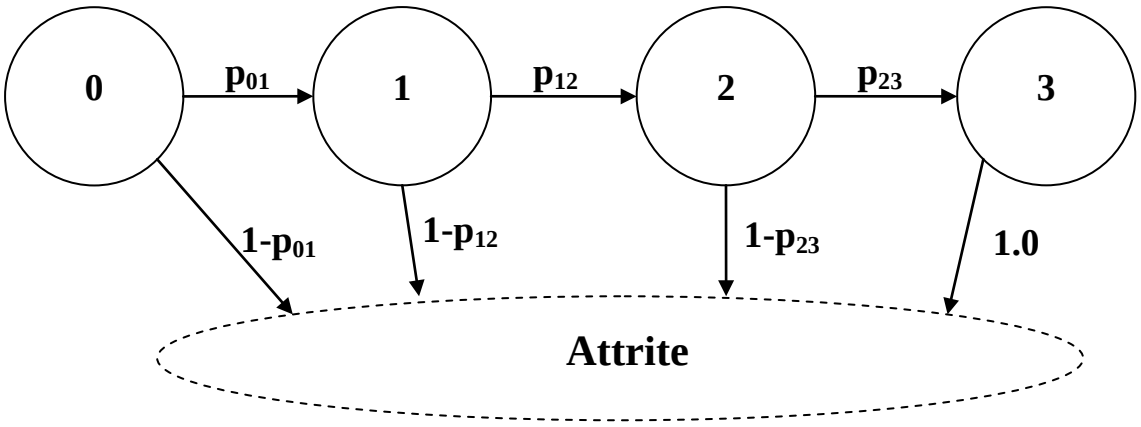

Figure 1. Transition Probabilities Between the Various States of Potential YCS

Keeping with notation convention, let *R* be the total number of new Marines assigned to an MOS. Further, **r** is the distribution vector associated with MOS assignment over the given states (YCS). Although most Marines obtain their MOS in state 0 or 1, there is a proportion of Marines (especially those with a five year TOE and long MOS producing schools) who do not attain their MOS until a later state. Therefore, our **r** vector tells us that some proportion of each assessed FY cohort enters the system in state 0 and others from their cohort in state 1 or later. Therefore, *R**r is our row vector that tells us the quantity of each assessed cohort that is assigned to a given state.

Irrespective of initial beginning inventory of personnel, the current model produces a steady-state inventory of a constant number of personnel by state and required to be accessed (*R*) and distributed across states proportionality (**r***)* each FY is captured with the following:

$$\mathbf{n}^{*} = R\mathbf{r}\left(1-\mathbf{P}\right)^{-1}$$

The First-Term Inventory Planner must however plan for accessions that support the requirements stated in the GAR. Although the specifics of determining the target (*T*) are discussed in additional detail in the next chapter, the underlying goal of the planners is to minimize the difference in the number of Marines accessed and the target. Mathematically, this goal is represented with:

$$\min \sum_{j=0}^{J=TOE} \left(n_j^*\right) - T$$

$$s.t.: R > 0$$

where $\mathbf{n}^* = Rr\left(1-\mathbf{P}\right)^{-1}$.

The model manager typically selects some future year GAR value for the target, usually the third out year. The rationale is that since the model assumes the system is in steady-state, that to the extent that the system is not in steady-state, then building to a year in the future provides the best chance of driving the system to steady state most effectively.

E. PROPOSED ENHANCED CLASSIFICATION PLAN MODEL

This volatility in the forecast thus lends itself to a transient, fixed inventory model that accounts for current inventory, annual accessions into the various states, and most importantly, allows for changes in accessions to meet changes in required endstrength. Building upon the notation previously discussed, the additional variable of year (y) is added to the equation. Solving for *R* in this formula then provides for the annual accession requirement (target).

$$\mathbf{n}(y) = \mathbf{n}(y\text{-}1)\mathbf{P} + R(y)\mathbf{r}$$

Within this model construct, planners aim to minimize the difference between the number of classified into a particular MOS's targeted requirement (n(y) and each of the build years of the FYDP that is associated with each GAR, given by T(y) (Seagren, (working draft)).

$$\min_R \sum_{y=1}^{4} \left(\left(\sum_{j=0}^{5} n_j(y) \right) - T(y) \right)^2$$

where: $\mathbf{n}(y) = \mathbf{n}(y-1)\mathbf{P} + R(y)\mathbf{r} \qquad y = 1,2,3,4$

In addition to allowing the accession quantity to change as endstrength (target) changes, the transient model can support additional constraints to limit the magnitude of change allowable to MOS target strengths in successive years. Although the tolerance levels on these constraints could be adjusted by the individual manpower planner, the intent of the constraints is to purposefully smooth out and limit variation in target requirements from year to year. The goal of minimizing these ebbs and flows is to create a manpower flow of personnel inside a system with reduced volatility. The effect of controlled builds and/or descents of personnel requirements aids in reducing or eliminating the proverbial "pig in the python" effect. Sharp increases and/or decreases in requirements have a detrimental effect on force shaping and both system effectiveness and efficiency.

F. SUMMARY

As discussed, both models share the common characteristics as described in common manpower planning models (Bartholomew). The current steady-state model provides planners with a generally "good enough" solution. However, the dynamic state of the Marine Corps manpower system layered with the current political and economic environment calls for systems that pursue continuous improvement. Once planners account for the current inventory and revise MOS distribution vectors ($R\mathbf{r}$) to account for the differing MOS' time-to-train (TTT), they employ a model that is more accurate and responsive to changes in the manpower system.

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IV. ANALYSIS OF MODELS

A. OVERVIEW OF THE ANALYSIS

1. Purpose of Analysis

Prior to diving into the analysis of the different outputs that the two models produced, it merits a moment to reflect on the purpose of this research. As introduced in the opening chapter, the purpose of this research is to address the following questions:

1. Primary Question: Would an enhanced attrition model serve as a more accurate forecasting tool to support the development of the Marine Corps' Enlisted Classification Plan?
2. Secondary Question: If more accurate, what is the relative magnitude in the difference in accuracy (i.e., how much better of a predictor is the enhanced model)?

At its heart, the purpose for this research and analysis is to serve as the foundation for model validation. Further, this analysis is intended to serve as an input to decision-makers as they consider potential changes to current processes.

2. Method of Analysis

First we assess GAR targets for each build year between FY2001 and FY2011 to determine the validity of the steady-state assumption. Next, we use historical data in that time period to build transition matrices and estimate attrition for each MOS and build year using both the steady-state model and the transient model.

3. Endstate of Analysis

The endstate to this analysis serves as an indication to the value of changing the methodology for developing the Classification Plan. The current model is less complex and there is certainly value to a process and system that is relatively simple to operated and execute. However, should additional complexity also produce additional clarity and more accurate estimations, then perhaps the "juice is worth the squeeze." Ultimately, should the hypothesis that a transient model performs better be valid, then this analysis provides justification for the Marine Corps' adoption of this transient Markov model.

B. STEADY-STATE ASSUMPTION

Fundamentally, the steady-state assumption asserts that the manpower system is static. Within the context of this analysis, this assumption translates to an environment in which annual accessions, individual MOS requirements, and overall endstrength remain constant over time, or at least sufficiently stable for the steady-state assumption to apply. Intuitively though, we understand that this environment is dynamic and subject to change as a result of any number of potential internal and/or external forces at work. Therefore, with the scenario in which either MOS targets and/or other inputs to the models changes, there is merit in questioning if the steady-state assumption is appropriate for planners. The following tables show the dynamic nature of both the number of accessions and the overall authorized endstrength from FY01–FY11.

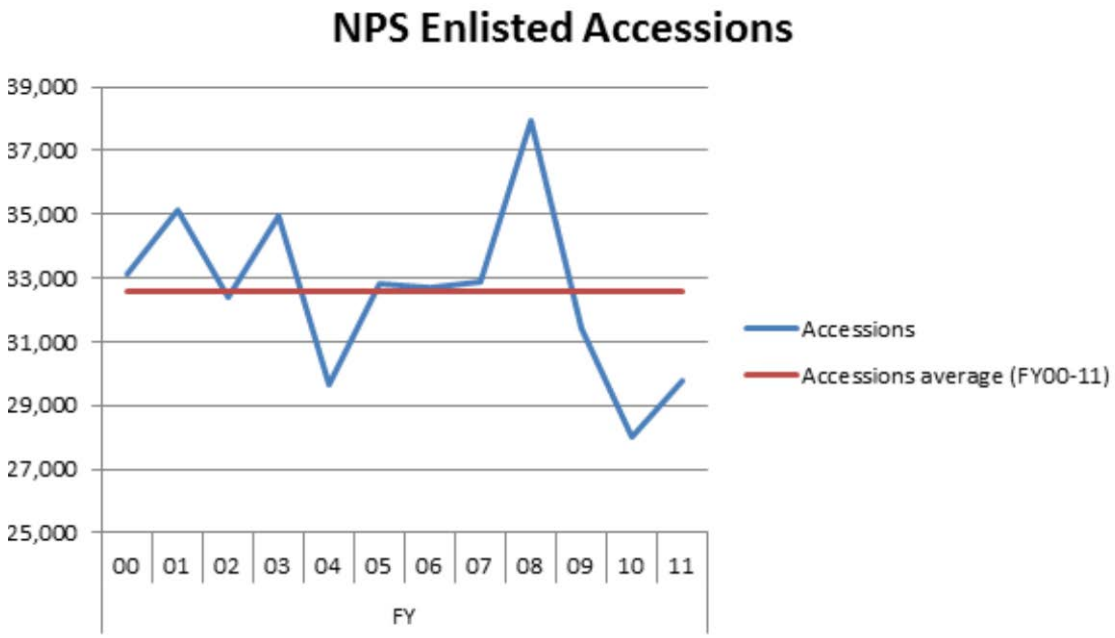


Figure 2. NPS Enlisted Accessions

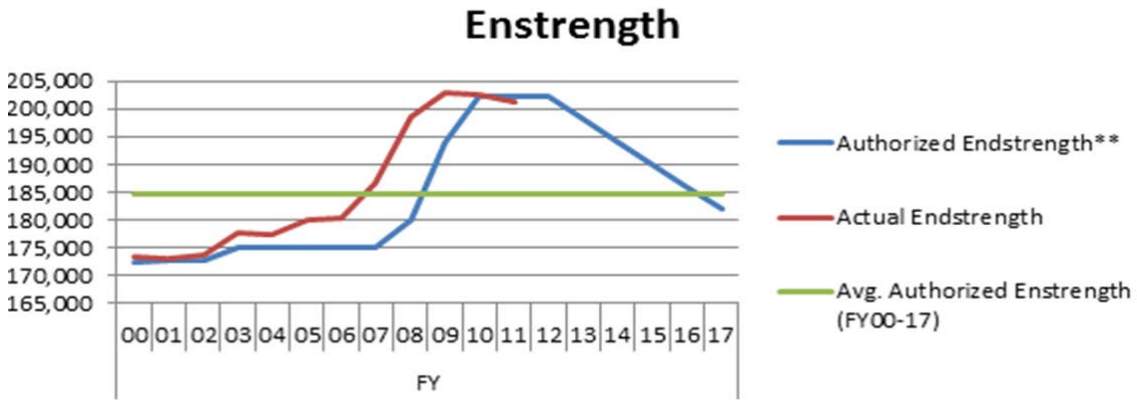


Figure 3. Endstrength

As the previous tables show, both accessions and endstrength numbers have experienced substantial variation over the past ten years of observations. Further, recent press releases from the Commandant of the Marine Corps project that endstrength requirements will continue to decline from the current endstrength of 202,200 to 182,100 by FY17 (Amos, 2012). At least taken together, it appears there exist reasons to question the validity of the steady-state assumption.

C. INPUTS TO THE ANALYSIS

1. Description of GAR Data

MOS target inventories are derived from the FY00–11 GARs. In addition to each FY's base year, each FY forecasted manpower requirements by MOS for each of the upcoming years in the future years defense plan (FYDP). We compare future requirements (i.e., the FY06 build year from the FY04 GAR) with present-year requirements (FY06 requirements from the FY06 GAR) to assess the steady-state assumption.

2. Transition Probabilities

The data from which we have to build the models are all active duty Enlisted, first-term Marines from 1996 to 2008. In order to estimate transition probabilities, we categorize each Marine by MOS and YCS. So, for each category and build year, we have total number of Marines that began the year, the number that left during that year as an

attrite, the number that continued to the next year, and the number that accessed into that state during the next year. Additionally, both models use the same probability matrix as an input to the analysis (Seagren, (working draft)).

3. Target Population by MOS

Starting with FY00 and continuing through FY11, each years' base GAR and accompanying FYDP requirements by rank and MOS were analyzed. From each of these FYs' GARs, a four and five year term of enlistment (TOE) target number was developed. The four-year TOE figure was the sum of all E–4 and below requirements. The five-year TOE requirement was the sum of the E–4 and below population and 22% of the E–5 population requirement. The Enlisted Career Force Control Program within the Marine Corps is used to both actively shape the inventory of Marines by grade and MOS to meet the requirements of the Marine Corps and to stabilize retention in order to standardize promotion tempos across all MOSs. Further, the time in service (TIS) promotion targets to Sergeant (E–5) is four years. Therefore, on the aggregate (meritorious promotions aside), we assume that those with a four-year TOE is a Corporal (E-4) or below. In addition, promotion to Staff Sergeant (E–6) is targeted at the 8.5 year TIS mark. Since an individual Sergeant would then remain in that grade for 4.5 years, approximately 22% of Sergeants would have no more than 12 months' time in grade (TIG) as a Sergeant (assuming that the population distribution of Sergeants was consistent across that 4.5-year period (MarAdmin 433/11, 2011).

4. Distributions of Accessions

Although most Marines attain their MOS within the first year of an individual's enlistment a sizable portion of Marines accessed each year do not ultimately attain their MOS until into their second year of service. Prior to attaining their MOS all Marines attend recruit training for approximately three months. Following recruit training, Marines diverge into MOS producing pipelines (MOS dependent), each with varying timelines.

The key factor for consideration that manpower planners must account for is this population that has been accessed, but not yet attained an MOS. This dynamic of

accessed future gains to an MOS is partially mitigated with the assignment of training MOSs (0100 as an example for future 0111s). This relationship is moderately correlated, at best, due to classification errors, MOS school attrition, etc. It would almost be analogous to knowing that your spouse wrote a check, but you are not 100% certain of its dollar amount.

With the knowledge that the distribution of accessions (into classified MOSs) are seen over multiple stages (YCS) and the assignment of training MOSs is unable to provide a sufficiently reliable and clear picture of MOS health, manpower planners rely upon analyzing their populations of interest after they've been classified with a primary MOS. This distribution of assignment of an MOS over the YCS was then used as a proxy to account for the average time-to-train (TTT). Therefore, this TTT then accounted for the time an individual Marine attended recruit training, Marine Combat Training (MCT), and/or MOS producing school.

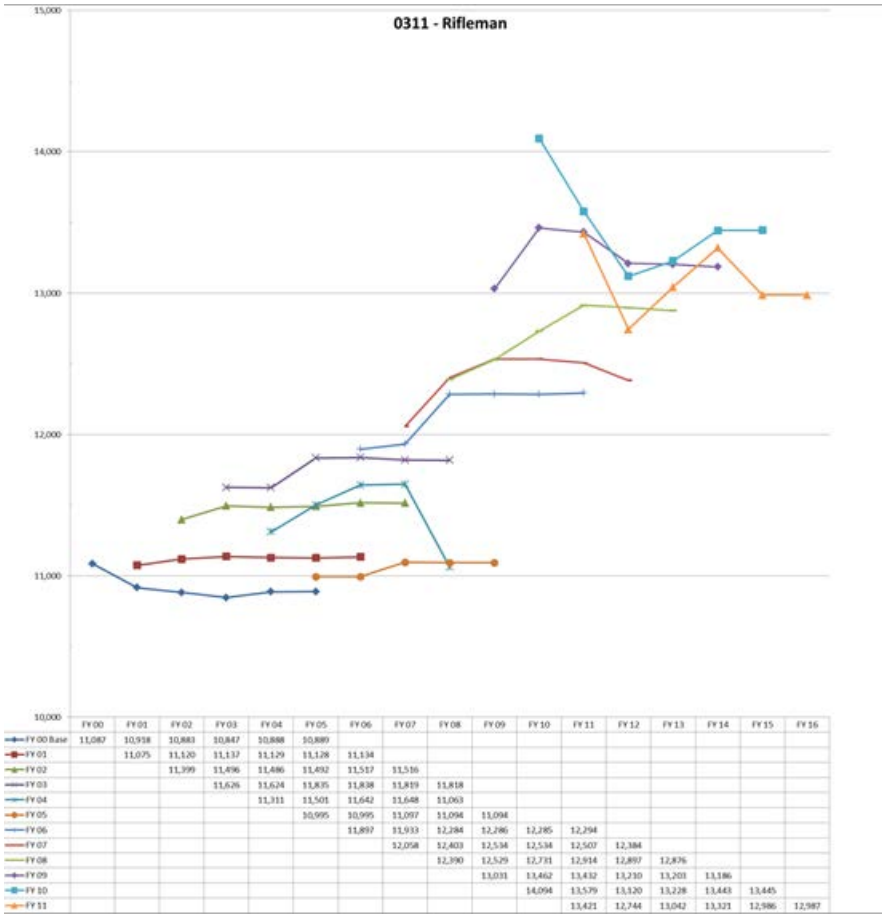
After reviewing the average TTT by MOS, the author then made the assumption (grounded in a personal knowledge of sample MOSs) whether to use the 4- or 5-year targets by MOS. Generally speaking, the TTT could be viewed as a bimodal distribution. Although ranging from a minimum TTT of .388 YCS (approximately 4.5 months) for assignment as a Correctional Specialist (5831) to a maximum of 2.49 YCS (approximately 30 months) for Middle East and Asia-Pacific Cryptological Linguists (2671 and 2673), the 4-year TTT observations were predominately in the .6–.9 YCS (approximately 7–10 months) and the 5-year TTT observations were in the 1.1–1.5 YCS (approximately 13–18 months) window.

D. TESTING OF THE STEADY-STATE ASSUMPTION

In this section, we examine the validity of the steady-state assumption at the level of the MOS. We assert that a necessary condition for a system to achieve steady-state is some amount of relative stability in the desired target of the population. The GAR provides target levels of each grade and each MOS for the present year and each of the six years throughout the FYDP.

This means that the target inventory level for a given MOS for a given FY has been crafted multiple times before the execution year. We examine the relative stability of these targets for given years through time to determine the extent of volatility.

Figure 4 illustrates this phenomenon for the Rifleman MOS. Notice that for any particular year, there exist multiple target levels, only one of which was in effect during the year of execution. This volatility is especially pronounced in the latter half of the decade as endstrength and accessions increased.



	FY00	FY01	FY02	FY03	FY04	FY05	FY06	FY07	FY08	FY09	FY10	FY11	FY12	FY13	FY14	FY15	FY16
FY00 Base	11,087	10,958	10,883	10,847	10,888	10,889											
FY01		11,075	11,120	11,137	11,129	11,128	11,134										
FY02			11,399	11,496	11,486	11,492	11,517	11,516									
FY03				11,626	11,624	11,835	11,838	11,819	11,818								
FY04					11,311	11,501	11,642	11,648	11,063								
FY05						10,995	10,995	11,097	11,094	11,094							
FY06							11,897	11,933	12,284	12,286	12,285	12,294					
FY07								12,058	12,403	12,534	12,534	12,507	12,384				
FY08									12,390	12,529	12,731	12,914	12,897	12,876			
FY09										13,031	13,462	13,432	13,210	13,203	13,186		
FY10											14,094	13,579	13,320	13,228	13,443	13,445	
FY11												13,421	12,744	13,042	13,321	12,986	12,987

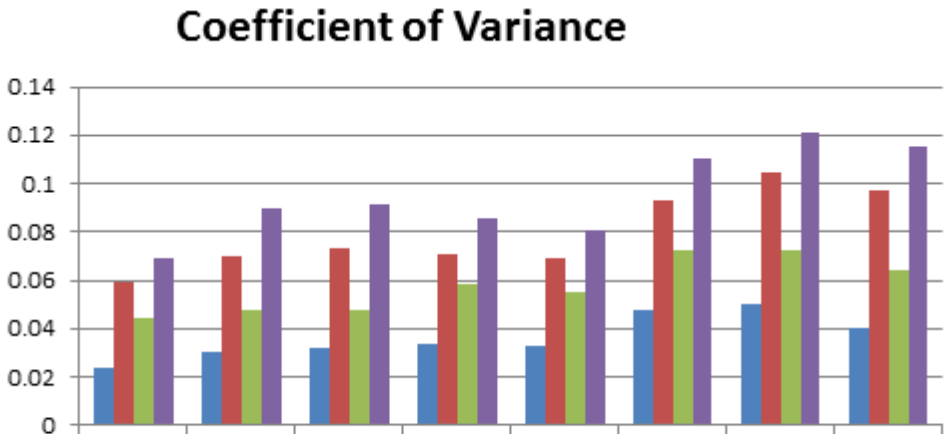
Figure 4. Rifleman MOS

1. Coefficient of Variation

One step in the analysis is to understand the relative variance in MOS target populations over the previous FYDP years' forecast as they compare to their base year

GAR (i.e., FY04–07's projected FY08 target compared to the actual FY08 target). This variation (standard deviation) then divided by the average of those forecasts and actual target (mean for the MOS) produces a coefficient of variation (CV). The value to this measure is that it puts the magnitude of variation into a common perspective rather than a sheer number (Keller, 2009).

The following figure represents the summary of the relative CV for FY04–11's GARs. As the bar graph shows, there has been a steady increase in the size of the CV over the past years. This increase in CV is an indication that more and more volatility has existed in recent manpower planning. Not surprisingly, this indication of volatility (increasing CV) has been parallel with the recent growth in the Marine Corps' endstrength. Further, this greater volatility should persist as the Marine Corps is estimated to cut endstrength by 5,000 per year over the upcoming four FYs (Amos, 2012).



	FY04	FY05	FY06	FY07	FY08	FY09	FY10	FY11
25th Percentile	0.024	0.03	0.032	0.034	0.033	0.048	0.05	0.04
Mean	0.059	0.07	0.073	0.071	0.069	0.093	0.105	0.097
Median	0.044	0.048	0.048	0.058	0.055	0.072	0.072	0.064
75th Percentile	0.069	0.09	0.091	0.086	0.081	0.11	0.121	0.115

Figure 5. Summary of distribution of Coefficient of Variance of GAR targets across MOSs for FY04–11

Figure 6. CV Distribution Comparison

The above output highlights the difference between relatively "good" (minimal volatility, cv_04 and cv_05) compared against "bad" (increased volatility, cv_10 and cv_11) year. However, during bad years the CV increased to between 9.5 and 10.5 percentage points and had a fourth of observations exceeding 12 percentage points.

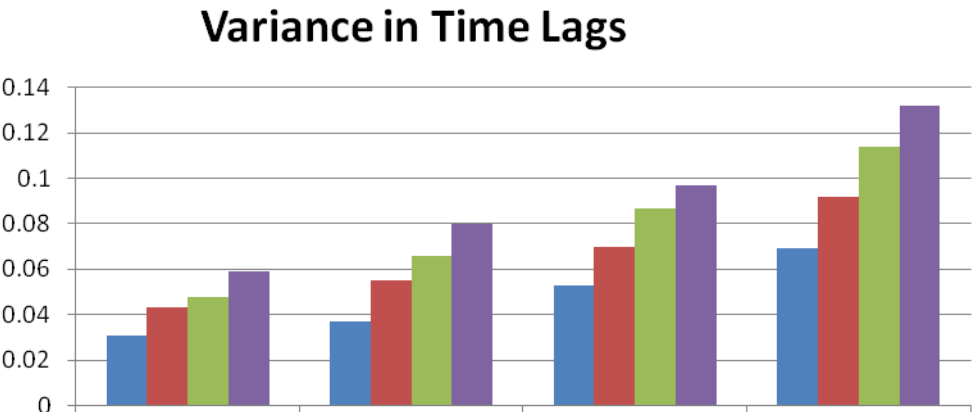
Additional details on the CVs for each FY can be found in Appendix A.

2. Variability Over Time Lags

A common technique when employing the steady-state model is to select as a target the GAR requirements for the third year of the FYDP. The thought is that accessing the steady-state requirement for a future year will result in a smoother trajectory in achieving steady-state. In this section, we compare the relative changes between future targets at various lags (1 through 4 years) and the actual requirement as executed.

In other words, the FY01 GAR contains an FY04 future requirement. Comparing those targets with the actual FY04 GAR as executed is one of the comparisons included in the 3-year lags.

As shown in the following figure, the longer the lag (and further away the forecasted time period is from execution), the less the greater the variance between the future expected requirement and the requirement as executed.



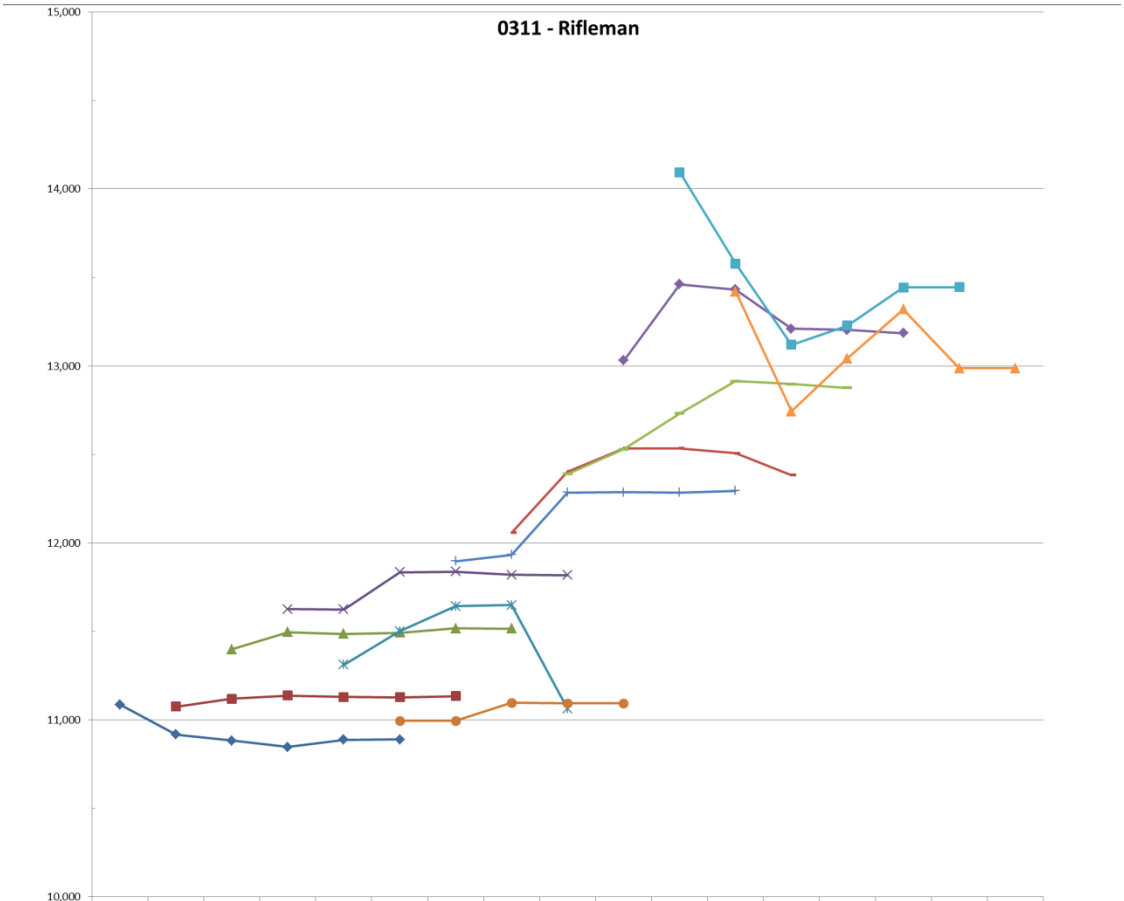
	Lag_1	Lag_2	Lag_3	Lag_4
25th Percentile	0.031	0.037	0.053	0.069
Median	0.043	0.055	0.07	0.092
Mean	0.048	0.066	0.087	0.114
75th Percentile	0.059	0.08	0.097	0.132

Figure 7. Summary of Distribution of Variance in Time Lags Across MOSs

As Figure 7 indicates, at lags 3 and 4, greater than 25% of all MOSs have a difference of 10% or more. Additional details on the Lags for each time period can be found in Appendix B.

This variability over time is shown specifically for the 0311, Rifleman, MOS in Figure 8 below. The figure shows how the target population changes from the original base year GAR target thru the build years of the FYDP. A cross-section of MOSs is included in Appendix C for review.

These MOSs were selected by the author because they were not only larger in population size, but also representative of the Marine Corps' Marine Air-Ground Task Force (MAGTF) and a combination of combat arms, combat support, combat service support, and aviation MOSs.



	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	11,087	10,918	10,883	10,847	10,888	10,889											
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FY 10											14,094	13,579	13,120	13,228	13,443	13,445	
FY 11												13,421	12,744	13,042	13,321	12,986	12,987

Figure 8. Example GAR Requirements Over the FYDP

3. Summary

Building upon the intuition that manpower planners operate in a dynamic environment, an examination of recent GARs reveals that the current steady state model is out performed by an enhanced model across a range of measurements. Further, the common practice of using a three-year lag/time horizon as the "gold standard" for planners is currently subject to mean forecast error of nearly 10 percentage points across all MOSs.

E. ATTRITION PREDICTION

In this section, we compare estimated attrition versus actual attrition for each model. Given the dynamic nature of the environment in which manpower planners must forecast, this section puts into context the relative comparison of how much better does the transient model perform over the steady-state model?

1. Notation and Mathematical Description

For each year between FYs 1996 and 2011, a comparison of the estimated attrition for the legacy and transient models is conducted. Actual data from those years were inputs to the transition matrices (**P**) and recruit distribution vectors (**r**). Additionally, we vary the window size for each model from one year to nine. For example, for the build year 2001, we have five prior years of history with which to build our model, so we consider windows of sizes from 1 year to 5. However, for build year 2010, we vary window size form one to nine. Recent research suggests that shorter windows of 1 to 3 years typically yield the best prediction of attrition behavior (Tamayo, 2011), but window size up to nine was used to ensure that any differences in the performance between the models did not depend on window size.

Given that the estimate of the transition probability from state *i* to state *j* is given by:

$$\hat{p}_{ij} = \frac{f_{ij}}{n_j}$$

where f_{ij} is the total flow of Marines from state *i* to state *j* in one time period, and n_j is the total number that began the time step in that state (Bartholomew, Forbes, & McClean, 1991). Let **w** be the wastage rates and associated vector for a given MOS, build year, and window combination and is defined as follows:

$$\mathbf{w} = \left\{1-\hat{P}_{01}, 1-\hat{P}_{12}, 1-\hat{P}_{23}, 1-\hat{P}_{34}\right\}.$$

Note for a five year TOE, this vector has five elements. The dot product of this vector and an inventory vector yields an estimate of the number of Marines who attrite for that year. It is also important to note that **w** is the same for both the legacy and transient models. The difference between the models is the inventory vector to which it is applied. For the legacy model, this inventory is the long term inventory vector **n***.

$$a_s(t) = \mathbf{n}^*(t) \cdot \mathbf{w}(t)$$

where t denotes the build year, which varies from FY2001 to FY2011. For the transient model, the inventory vector corresponding to the build year is used to for the attrition estimate.

$$a_T(t) = \mathbf{n}(t) \cdot \mathbf{w}(t)$$

The respective attrition estimates are then compared to the actual number of attrites for each year. Let *a(t)* be the number of attrites for build year t. Then trans_MAPE is given by:

$$trans_{MAPE} = \frac{a(t) - a_T(t)}{a(t)}.$$

And ss_MAPE is given by:

$$ss_{MAPE} = \frac{a(t) - a_s(t)}{a(t)}.$$

Thus, for each build year, initial training MOS, and window, a total of 8847 design points, we have a value for trans_MAPE and ss_MAPE.

2. Number of Observations (Counts)

The most straight forward method of comparing the performance of the two models is by simply counting the number of times the transient model produces a better estimate than the steady state model. We find that the transient model produced a more accurate forecast for 5,321 out of 7,379 design points (approximately 72% of the observations).

Although the transient model produced more accurate forecasts over 70% of the time and this may be sufficient to address the primary research question, the differences in forecasting accuracy must be put into further context to get at the heart of addressing the secondary, and perhaps more important and relevant, research question.

3. MOE Comparisons

In this section, we examine the significance of the fact that the transient model tends to generate better estimates relative to the steady-state model. In particular, we seek to determine the magnitude of the improvement and consider whether the better performance is worth the extra requirements for input data and computation.

Figure 9 shows that across all MOS, build year, and window combinations, the transient model has a forecast error mean of 26 percentage points from the actual observations. These forecasts are put into additional perspective by reviewing the median and quartile distribution. With a median value of 12.2 percentage points, more than half of the over 7,300 forecasts were off from the actual by greater than 10 percentage points. Further, approximately one-fourth of the forecasts were off by greater than 25 percentage points (75% quartile).

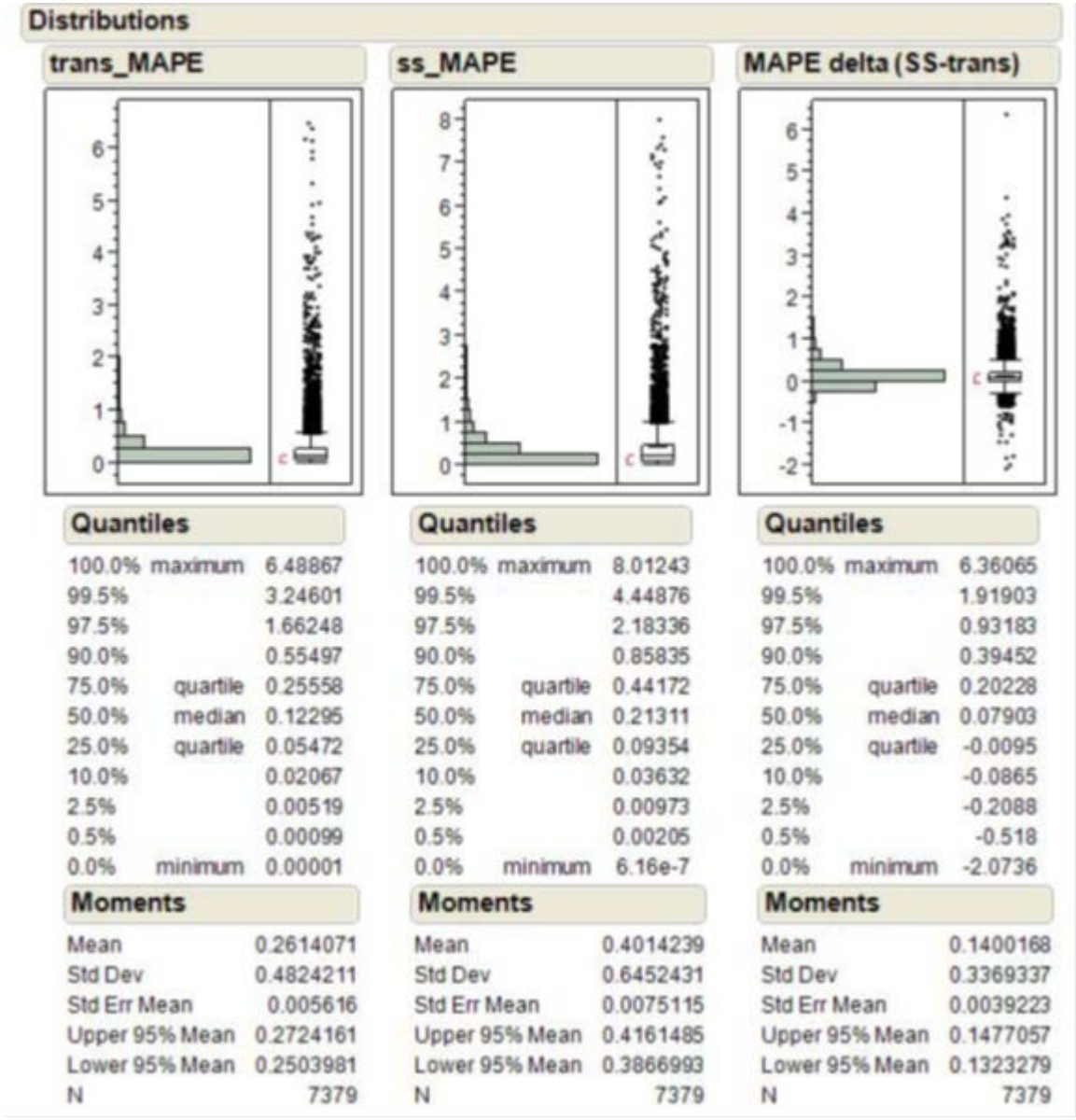

Figure 9. Models' MAPE Distribution

However, an analysis of the steady-state model reveals that produced a forecast error mean of 40 percentage points. Further, over half of the observations exceeded a 21-percentage point error (median), and approximately one-fourth was over 44 percentage points off (75% quartile) from the actual observation.

Although the proceeding paragraphs are relevant and demonstrate that both models are subject to forecast error, the more useful analysis is to compare the relative

"goodness" of either particular model against the other. As previously discussed, we can do this comparison by comparing the difference between the transient outputs versus the steady-state output for each estimate, which is shown in the third column. Because the mean of this comparison is 0.14, it tells us that, on average, the transient model produces forecasts with MAPEs that are 14 percentage points less than the steady-state model. Although the median is approximately 8 percentage points, in a full one-fourth of the observations (75% quartile) of the transient model were greater than 20 percentage points more accurate at forecasting actual observations. As a measure of comparison, the transient model was 20 percentage points less accurate in only 2.5% of observations.

4. Summary

On all accounts of the various methods and measurements of model performance, the transient model is superior in performance to the current model. Further, when comparing the relative "goodness" of either particular model against the other, the analysis tells us that, on average, the transient model produces erroneous forecasts 14 percentage points fewer than the steady-state model. The dynamic environment that analysts and planners operate within must employ forecasting tools that are responsive to change yet produce the minimum potential forecast error. Further, a forecast model that supports the ability to account for changes in desired endstrength would not only prove useful in the short-term and future draw down of personnel end strength, but also be flexible enough to support any future change to desired endstrength.

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V. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

A. SUMMARY

The Marine Corps is a manpower intensive organization with over 200,000 personnel. In fact, the Marine Corps recruits approximately 30,000 new enlisted personnel into its workforce annually. The number of new accessions each Fiscal Year is determined and classified as a function of attrition behavior.

Given that desired endstrength is a function of beginning (current) endstrength + accessions – attritions, it demands that the number of personnel attritions forecasted be as accurate as possible. In this formula, the desired and current personnel endstrengths are known quantities. The accessions required in the future fiscal years are predicated upon attrition. Since the actual level of attrition is an unknown variable, it must be forecasted.

The enlisted manpower and personnel analysts and planners make career force decisions (accessions, promotion, retention, training, etc.) based upon existing and forecasted personnel resources by specific MOS. These career force decisions are driven from the requirements by grade and specific MOS as outlined in the Grade Adjusted Recapitulation (GAR). As previously noted, the variable of attrition must be forecasted as a basis for these career force decisions. Therefore, the more accurately forecasted the level of attrition is as an input to this decision system, the less variability the system as a whole. Further, a forecast model that supports the ability to account for changes in desired endstrength would not only prove useful in the short-term and future draw down of personnel endstrength, but also be flexible enough to support any future change to desired end strength.

Although Marine Corps' future endstrength requirements are not conclusively known, it is generally accepted that its endstrength will be no greater than 182,200 in the upcoming years (Amos, 2012). This roughly 10% decrease in overall personnel end-strength and subsequent reshaping of its force will have an effect across all MOSs.

Additionally, technological advances, equipment changes, and unforeseen operational requirements contribute to the management of manpower and the subsequent personnel effects inherent in the Marine Corps' manpower and personnel system.

The Marine Corps currently uses a steady-state Markov model to forecast attrition behavior (retention by MOS and YCS) and subsequently determine its accession requirements. As the Marine Corps draws down in endstrength in today's fiscally constrained environment, a precise classification plan cannot be overstated. The focus of this research was to evaluate an alternative model to reduce MOS misclassifications, and better account for dynamic changes to endstrength and targets. An analysis and comparison of each models' predictive performance clearly points to the transient model as being more accurate across a range of performance measurements

B. CONCLUSIONS AND RECOMMENDATIONS

1. Primary Research Question

Would an enhanced attrition model serve as a more accurate forecasting tool to support the development of the Marine Corps' Enlisted Classification Plan? If more accurate, what is the relative magnitude in the difference in accuracy (i.e.- how much better of a predictor is the enhanced model)?

a. Conclusions

Analysis from the observed data set output noted that the transient model produced a more accurate forecast on 5,321 out of 7,379 occasions (approximately 72% of the observations). As a relative comparison, the transient model achieved a MAPE that was, on average, 14 percentage points smaller than that of the steady-state model. In over 25% of the cases, this difference exceeded 20 percentage points.

b. Recommendation

Based upon this improved performance, it is recommended that the Marine Corps adopt the transient Markov Model analyzed in this research as the

foundation for future forecasting of the annual Enlisted Classification Plan. This action reduces MOS misclassifications and more accurately account for changes in endstrength and/or GAR requirements.

C. FURTHER RESEARCH AND ACTION

1. Transient Model User Guide

Since implementation of a new model changes the current way of doing business, a user guide should be developed to serve as a desktop guide for the planners tasked to produce and analyze the annual Enlisted Classification Plan.

2. Attrition Rates by MOS and Gender

Literature has repeatedly pointed to the variable of gender as having a differing effect on attrition behavior. Building upon the established framework of the transient model, additionally precision would likely be obtainable if the model was able to account for the different attrition rates by MOS and gender.

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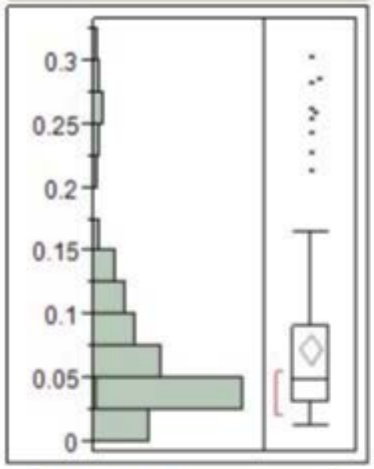
APPENDIX A.

cv_06



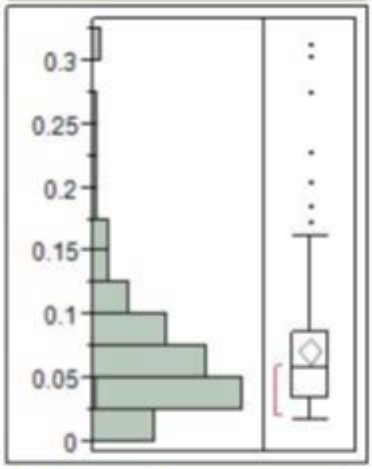
Quantiles

100.0%	maximum	0.30278
99.5%		0.30278
97.5%		0.27966
90.0%		0.14953
75.0%	quartile	0.09124
50.0%	median	0.04837
25.0%	quartile	0.03213
10.0%		0.02254
2.5%		0.01504
0.5%		0.0121
0.0%	minimum	0.0121

Moments

Mean	0.0732648
Std Dev	0.063658
Std Err Mean	0.0056937
Upper 95% Mean	0.0845343
Lower 95% Mean	0.0619953
N	125

cv_07



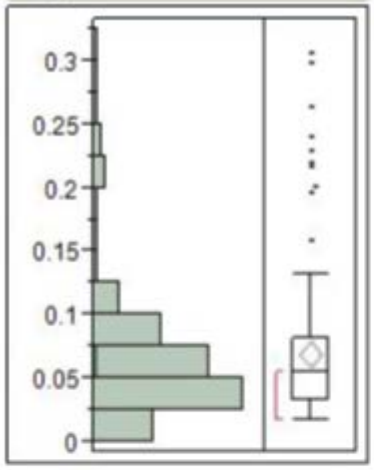
Quantiles

100.0%	maximum	0.31194
99.5%		0.31194
97.5%		0.2674
90.0%		0.13935
75.0%	quartile	0.08601
50.0%	median	0.0579
25.0%	quartile	0.03426
10.0%		0.024
2.5%		0.01929
0.5%		0.01738
0.0%	minimum	0.01738

Moments

Mean	0.071445
Std Dev	0.0546146
Std Err Mean	0.0048849
Upper 95% Mean	0.0811135
Lower 95% Mean	0.0617764
N	125

cv_08



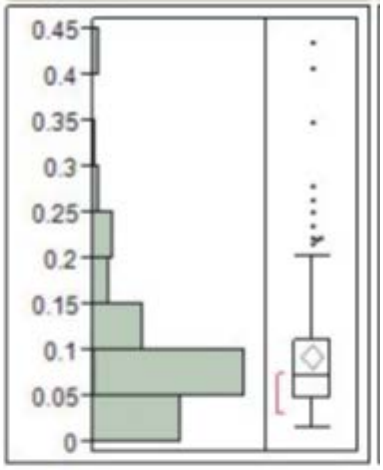
Quantiles

100.0%	maximum	0.30688
99.5%		0.30688
97.5%		0.2609
90.0%		0.12233
75.0%	quartile	0.0814
50.0%	median	0.05526
25.0%	quartile	0.03267
10.0%		0.02209
2.5%		0.01711
0.5%		0.01659
0.0%	minimum	0.01659

Moments

Mean	0.0693287
Std Dev	0.0568783
Std Err Mean	0.0051285
Upper 95% Mean	0.0794811
Lower 95% Mean	0.0591762
N	123

cv_09



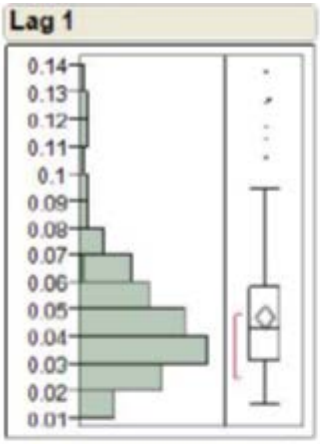
Quantiles

100.0%	maximum	0.43431
99.5%		0.43431
97.5%		0.34287
90.0%		0.20001
75.0%	quartile	0.11003
50.0%	median	0.07181
25.0%	quartile	0.04803
10.0%		0.03537
2.5%		0.01516
0.5%		0.01455
0.0%	minimum	0.01455

Moments

Mean	0.0932621
Std Dev	0.0739301
Std Err Mean	0.0066933
Upper 95% Mean	0.1065132
Lower 95% Mean	0.0800109
N	122

APPENDIX B.

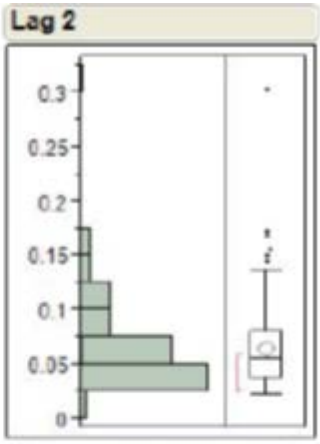


Quantiles

100.0%	maximum	0.13747
99.5%		0.13747
97.5%		0.12497
90.0%		0.07301
75.0%	quartile	0.05863
50.0%	median	0.04326
25.0%	quartile	0.03136
10.0%		0.02268
2.5%		0.01799
0.5%		0.01504
0.0%	minimum	0.01504

Moments

Mean	0.0476519
Std Dev	0.0237491
Std Err Mean	0.0021327
Upper 95% Mean	0.0518735
Lower 95% Mean	0.0434302
N	124



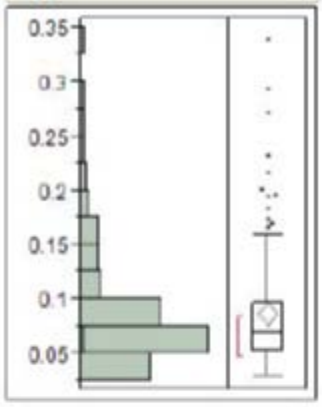
Quantiles

100.0%	maximum	0.3031
99.5%		0.3031
97.5%		0.16669
90.0%		0.11524
75.0%	quartile	0.07963
50.0%	median	0.05479
25.0%	quartile	0.03738
10.0%		0.02922
2.5%		0.02469
0.5%		0.02126
0.0%	minimum	0.02126

Moments

Mean	0.0656811
Std Dev	0.03972
Std Err Mean	0.003567
Upper 95% Mean	0.0727417
Lower 95% Mean	0.0586205
N	124

Lag 3



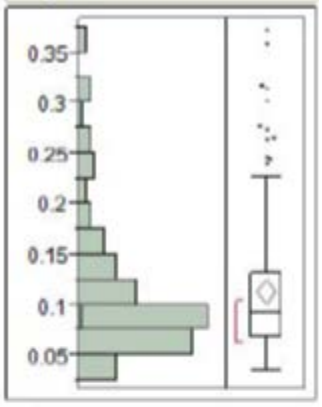
Quantiles

100.0%	maximum	0.33885
99.5%		0.33885
97.5%		0.26662
90.0%		0.16215
75.0%	quartile	0.09693
50.0%	median	0.06967
25.0%	quartile	0.0526
10.0%		0.04025
2.5%		0.03123
0.5%		0.03021
0.0%	minimum	0.03021

Moments

Mean	0.0870521
Std Dev	0.0544782
Std Err Mean	0.0048923
Upper 95% Mean	0.0967361
Lower 95% Mean	0.0773681
N	124

Lag 4



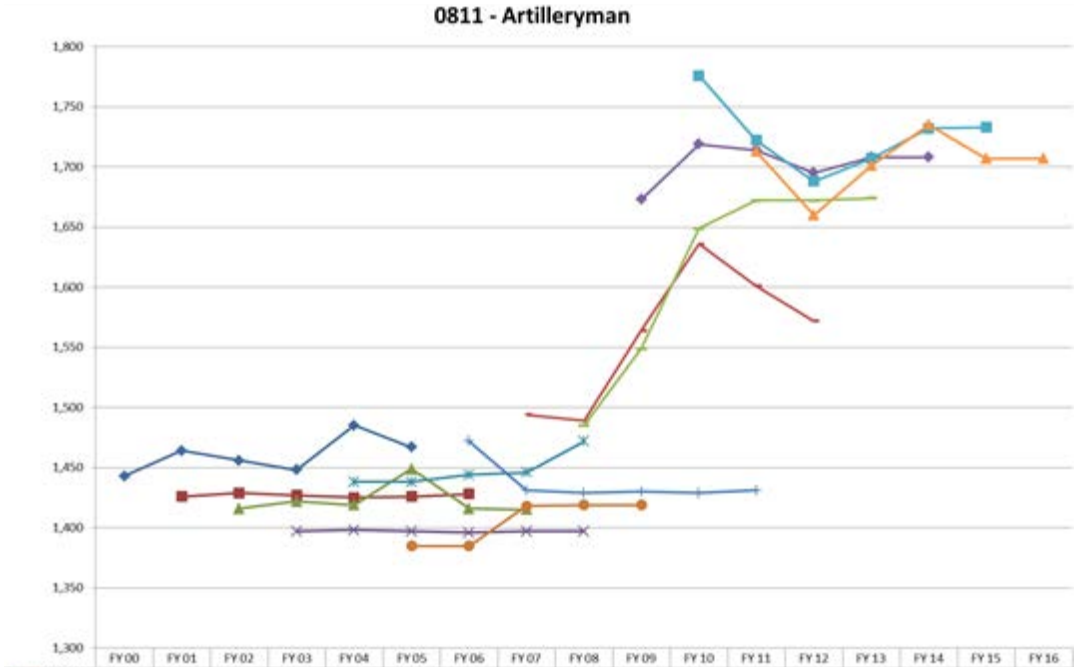
Quantiles

100.0%	maximum	0.37086
99.5%		0.37086
97.5%		0.31668
90.0%		0.23256
75.0%	quartile	0.13221
50.0%	median	0.09216
25.0%	quartile	0.06925
10.0%		0.05333
2.5%		0.04262
0.5%		0.03558
0.0%	minimum	0.03558

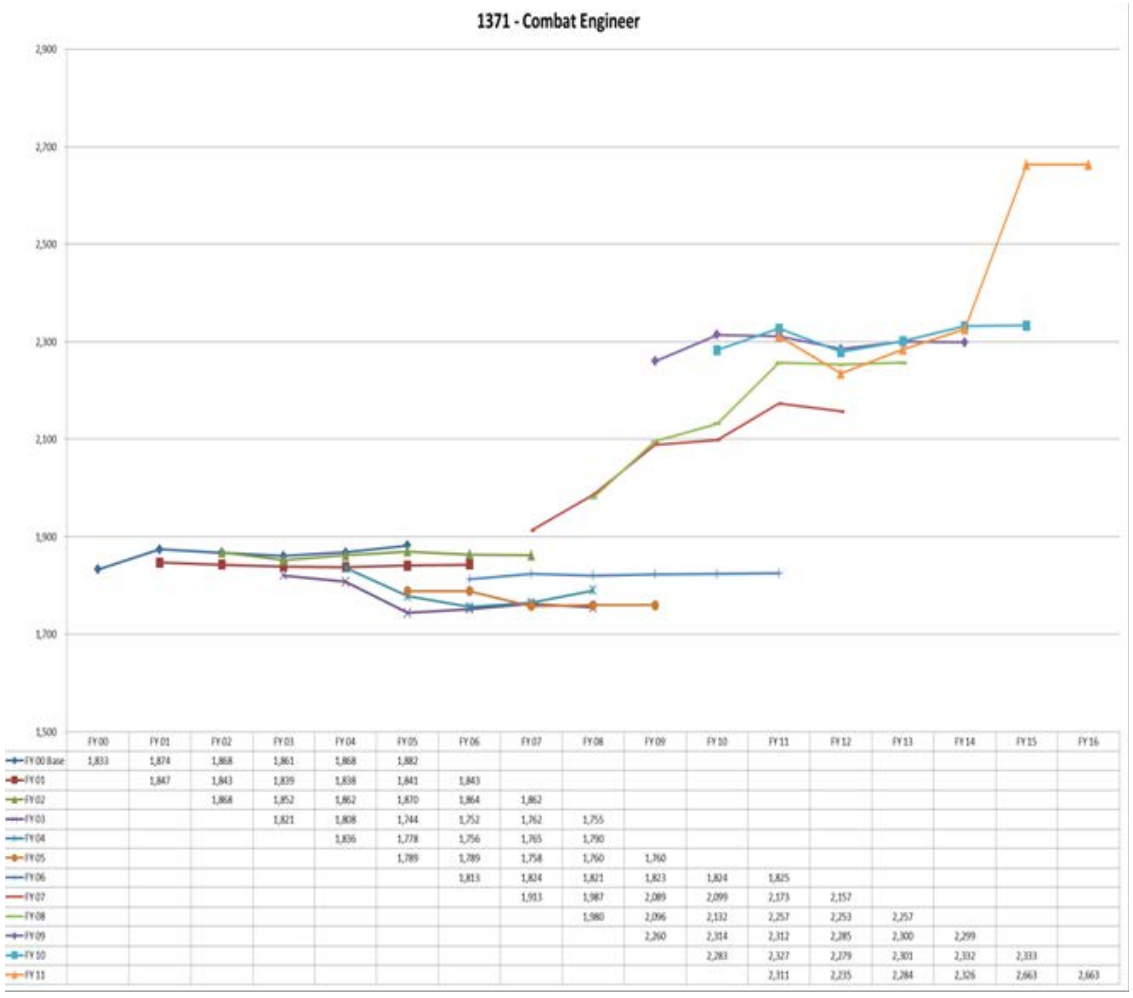
Moments

Mean	0.1142683
Std Dev	0.0701614
Std Err Mean	0.0063007
Upper 95% Mean	0.1267401
Lower 95% Mean	0.1017965
N	124

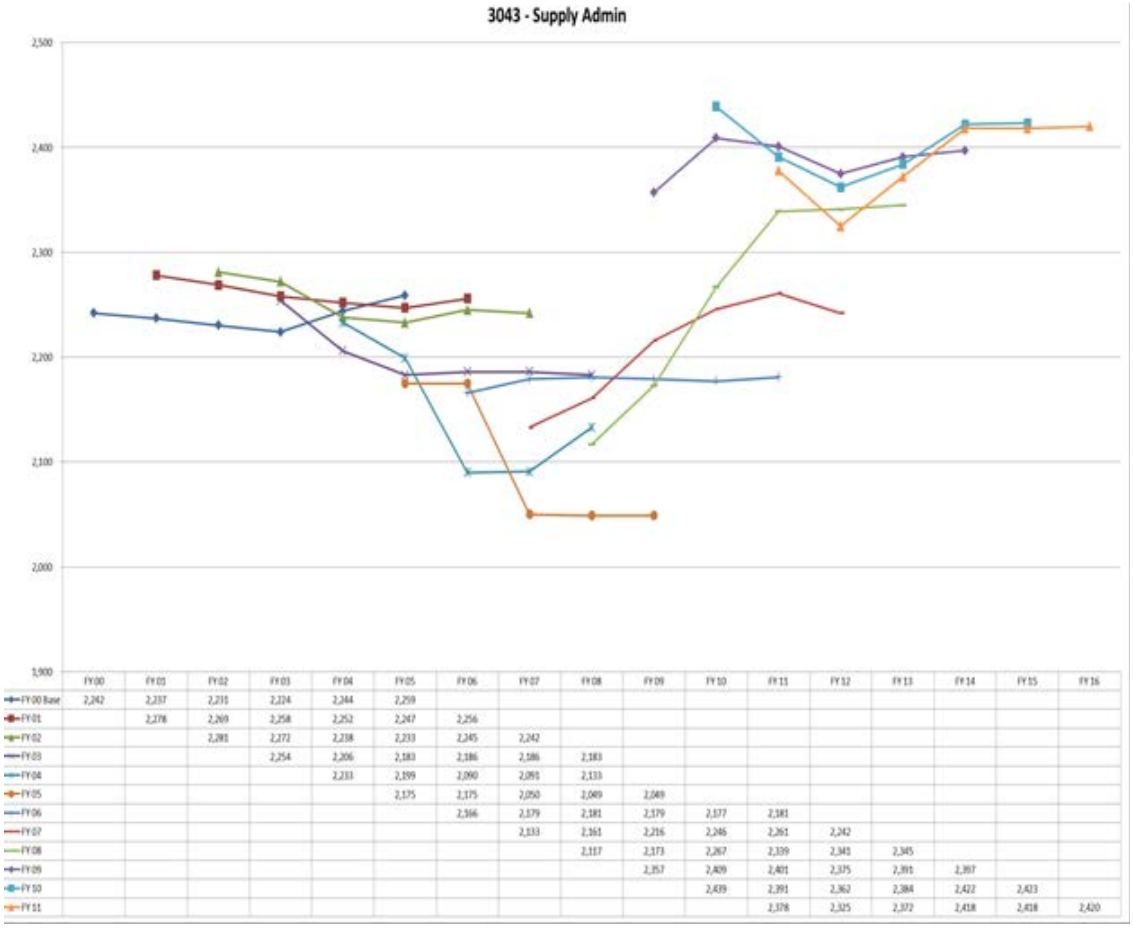
APPENDIX C.



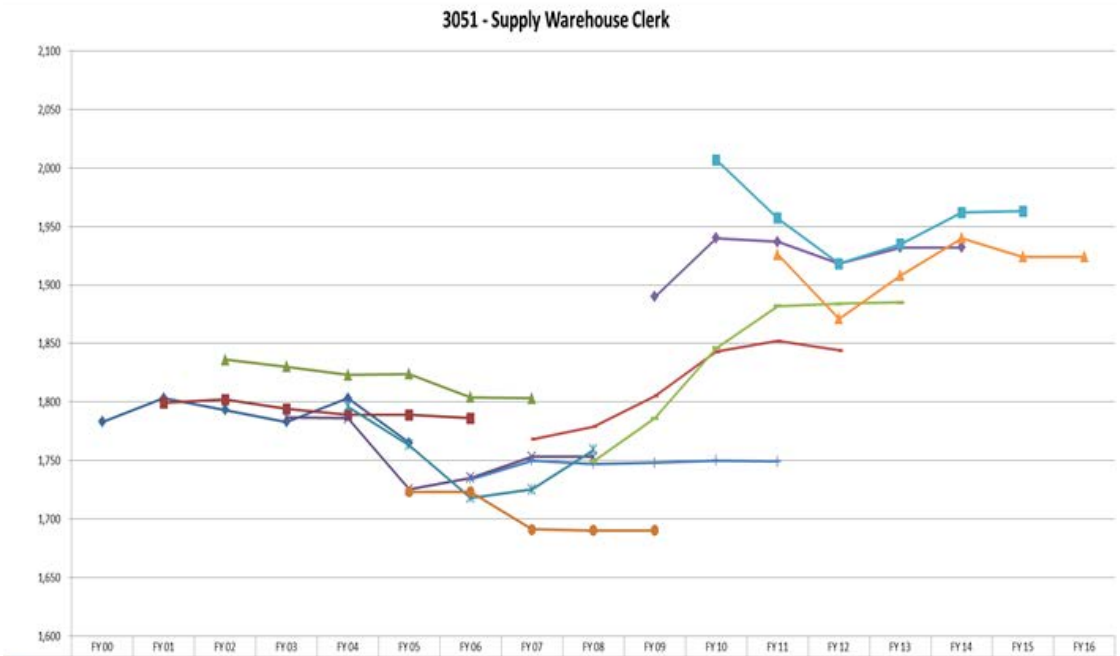
	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	1,443	1,464	1,456	1,448	1,485	1,467											
FY 01		1,426	1,429	1,427	1,425	1,426	1,428										
FY 02			1,416	1,422	1,419	1,449	1,416	1,415									
FY 03				1,397	1,398	1,397	1,396	1,397	1,397								
FY 04					1,438	1,438	1,444	1,446	1,472								
FY 05						1,385	1,385	1,418	1,419	1,419							
FY 06							1,472	1,431	1,429	1,430	1,429	1,431					
FY 07								1,494	1,489	1,564	1,636	1,601	1,572				
FY 08									1,485	1,549	1,649	1,672	1,672	1,674			
FY 09										1,673	1,719	1,714	1,695	1,708	1,708		
FY 10											1,776	1,722	1,688	1,707	1,732	1,733	
FY 11												1,713	1,660	1,701	1,735	1,707	1,707



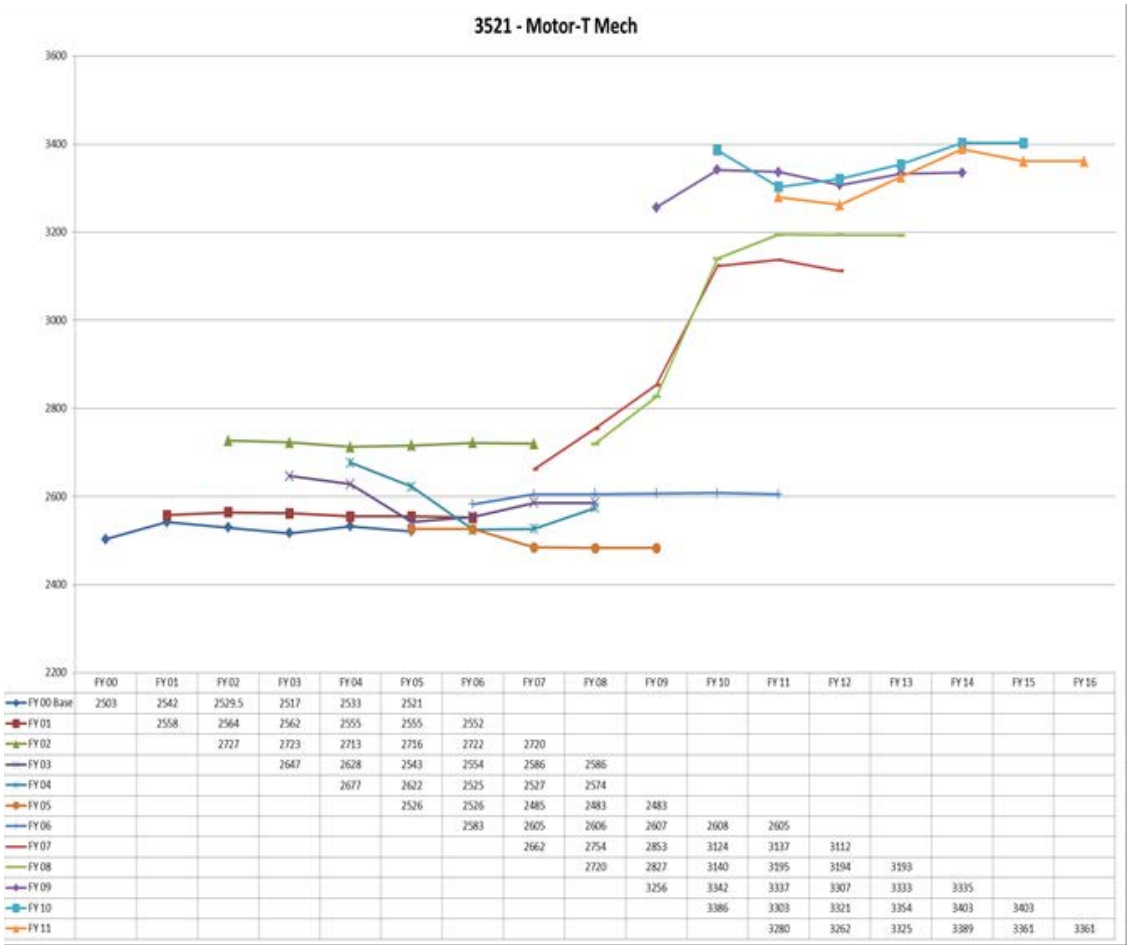
	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	1,833	1,874	1,868	1,861	1,868	1,882											
FY 01		1,847	1,843	1,839	1,838	1,841	1,843										
FY 02			1,868	1,852	1,862	1,870	1,864	1,862									
FY 03				1,821	1,808	1,744	1,752	1,762	1,755								
FY 04					1,836	1,778	1,756	1,765	1,790								
FY 05						1,789	1,789	1,758	1,760	1,760							
FY 06							1,813	1,824	1,821	1,823	1,824	1,825					
FY 07								1,913	1,987	2,089	2,099	2,173	2,157				
FY 08									1,980	2,096	2,132	2,257	2,253	2,257			
FY 09										2,260	2,314	2,312	2,285	2,300	2,299		
FY 10											2,283	2,327	2,279	2,301	2,332	2,333	
FY 11												2,311	2,235	2,284	2,326	2,663	2,663



	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	2,242	2,237	2,235	2,224	2,244	2,259											
FY 01		2,278	2,269	2,258	2,252	2,247	2,256										
FY 02			2,281	2,272	2,238	2,233	2,245	2,242									
FY 03				2,254	2,206	2,183	2,186	2,186	2,183								
FY 04					2,233	2,199	2,090	2,091	2,133								
FY 05						2,175	2,175	2,050	2,049	2,049							
FY 06							2,166	2,179	2,181	2,179	2,177	2,181					
FY 07								2,133	2,161	2,216	2,246	2,261	2,242				
FY 08									2,117	2,173	2,267	2,339	2,341	2,345			
FY 09										2,357	2,409	2,401	2,375	2,391	2,397		
FY 10											2,439	2,391	2,362	2,384	2,422	2,423	
FY 11												2,378	2,325	2,372	2,418	2,418	2,420

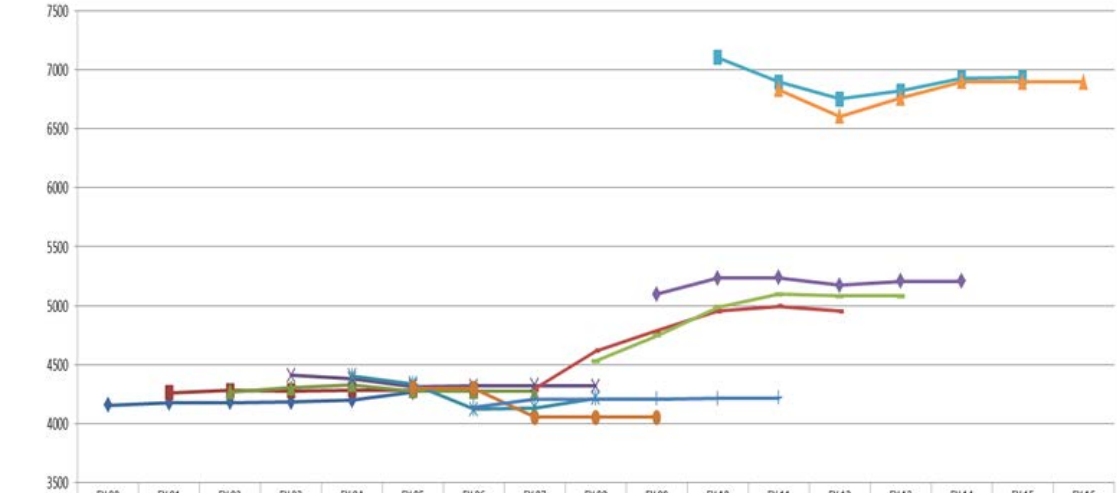


	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	1,783	1,803	1,793	1,783	1,803	1,765											
FY 01		1,799	1,802	1,794	1,789	1,789	1,786										
FY 02			1,836	1,830	1,823	1,824	1,804	1,803									
FY 03				1,787	1,786	1,725	1,735	1,753	1,753								
FY 04					1,796	1,763	1,718	1,725	1,759								
FY 05						1,723	1,723	1,691	1,690	1,690							
FY 06							1,734	1,750	1,747	1,748	1,750	1,749					
FY 07								1,768	1,779	1,805	1,843	1,852	1,844				
FY 08									1,749	1,786	1,846	1,882	1,884	1,885			
FY 09										1,890	1,940	1,937	1,918	1,932	1,932		
FY 10											2,007	1,957	1,918	1,935	1,962	1,963	
FY 11												1,926	1,871	1,908	1,940	1,924	1,924

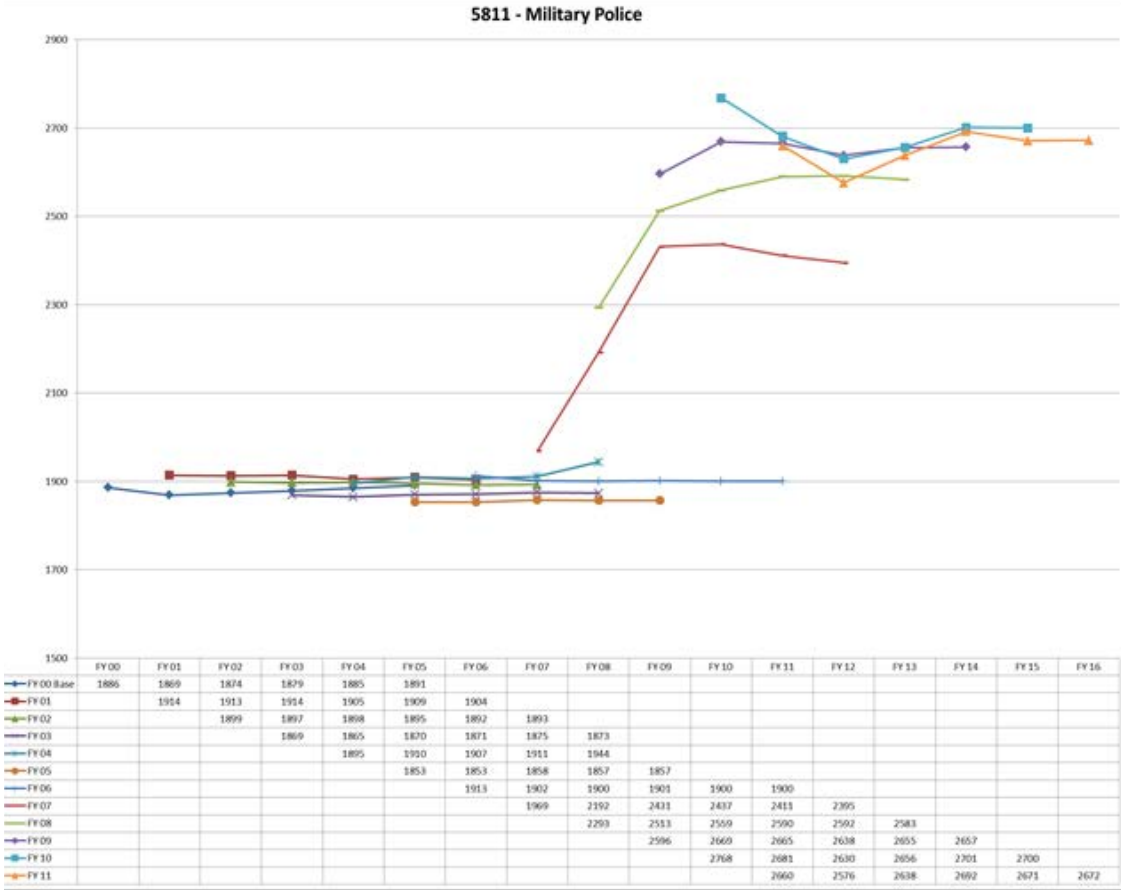


	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	2503	2542	2529.5	2517	2533	2521											
FY 01		2558	2564	2562	2555	2555	2552										
FY 02			2727	2723	2713	2716	2722	2720									
FY 03				2647	2628	2543	2554	2586	2586								
FY 04					2677	2622	2525	2527	2574								
FY 05						2526	2526	2485	2483	2483							
FY 06							2583	2605	2606	2607	2608	2605					
FY 07								2662	2754	2853	3124	3137	3112				
FY 08									2720	2827	3140	3195	3194	3193			
FY 09										3256	3342	3337	3307	3333	3335		
FY 10											3386	3303	3321	3354	3403	3403	
FY 11												3280	3262	3325	3389	3361	3361

3531 - Motor-T Driver

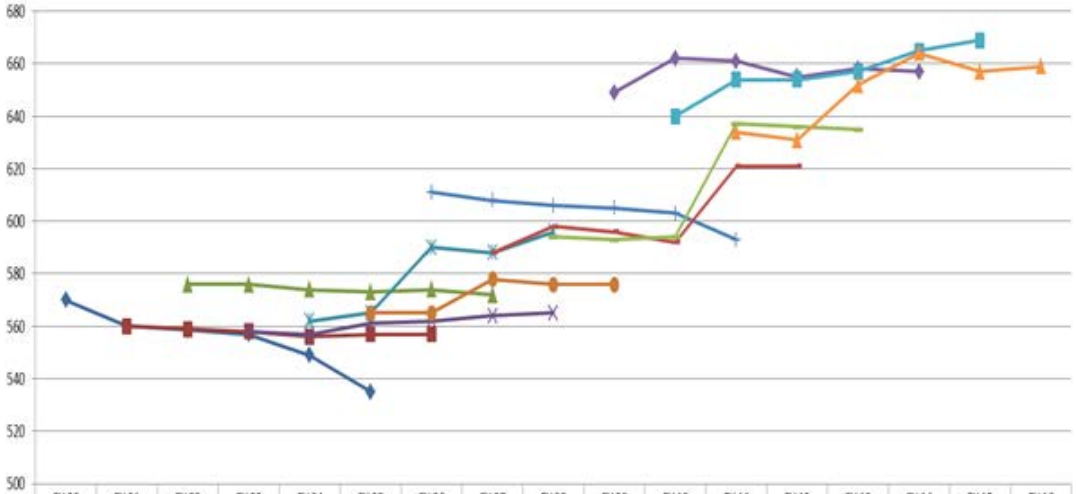


	FY00	FY01	FY02	FY03	FY04	FY05	FY06	FY07	FY08	FY09	FY10	FY11	FY12	FY13	FY14	FY15	FY16
FY00 Base	4155	4173	4177	4181	4198	4266											
FY01		4260	4279	4274	4283	4281	4288										
FY02			4270	4302	4327	4276	4271	4272									
FY03				4408	4378	4314	4316	4321	4319								
FY04					4403	4335	4119	4133	4215								
FY05						4300	4300	4051	4052	4052							
FY06							4138	4205	4206	4208	4211	4215					
FY07								4293	4617	4785	4954	4996	4952				
FY08									4530	4745	4987	5097	5080	5081			
FY09										5095	5234	5235	5171	5206	5208		
FY10											7107	6898	6755	6823	6932	6934	
FY11												6832	6605	6763	6903	6896	6897

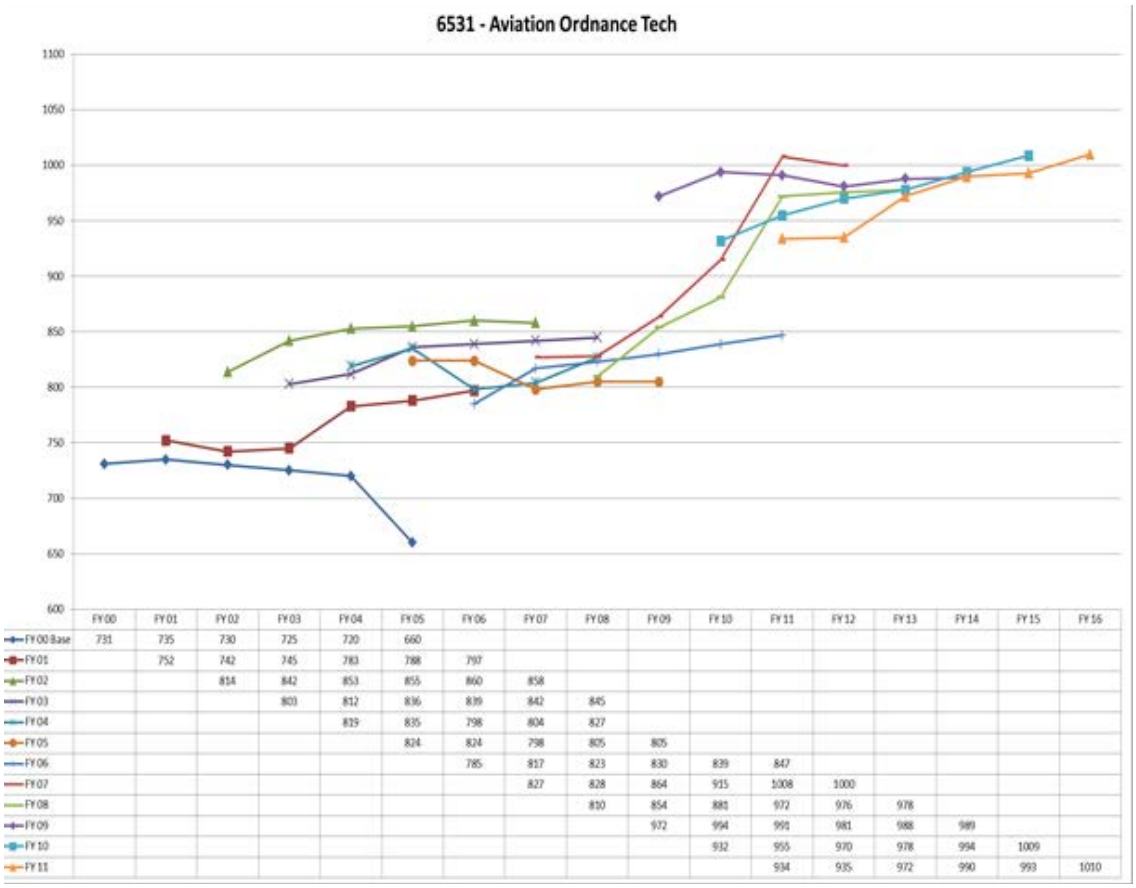


	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	1886	1869	1874	1879	1885	1891											
FY 01		1914	1913	1914	1905	1909	1904										
FY 02			1899	1897	1898	1895	1892	1893									
FY 03				1869	1865	1870	1871	1875	1873								
FY 04					1895	1910	1907	1911	1944								
FY 05						1853	1853	1858	1857	1857							
FY 06							1913	1902	1900	1901	1900	1900					
FY 07								1969	2192	2431	2437	2411	2395				
FY 08									2293	2513	2559	2590	2592	2583			
FY 09										2596	2669	2665	2638	2655	2657		
FY 10											2768	2681	2630	2656	2701	2700	
FY 11												2660	2576	2638	2692	2671	2672

6046 - Aircraft Maint, Admin

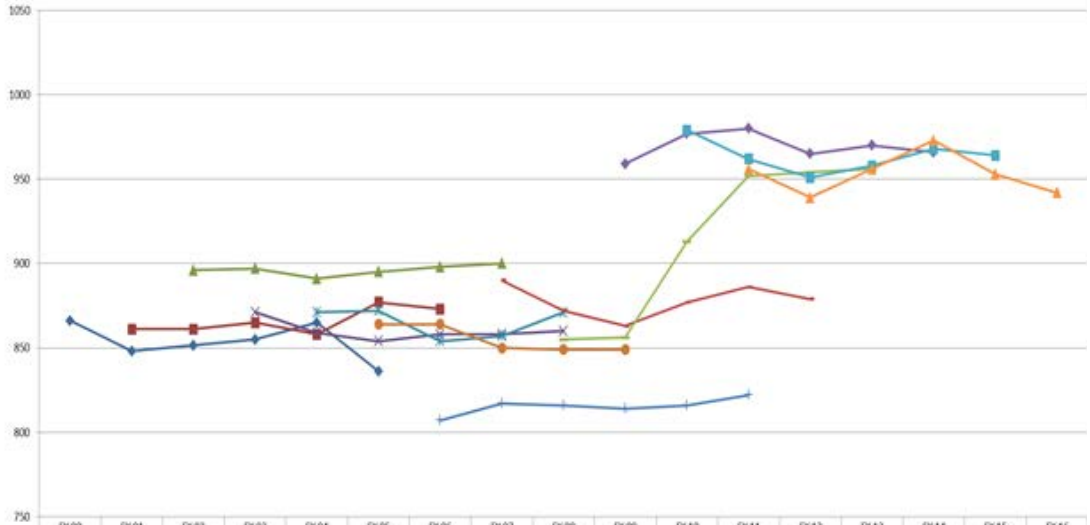


	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	570	560	558.5	557	549	535											
FY 01		560	559	558	556	557	557										
FY 02			576	576	574	573	574	572									
FY 03				558	557	561	562	564	565								
FY 04					562	565	590	588	596								
FY 05						565	565	578	576	576							
FY 06							611	608	606	605	603	593					
FY 07								588	598	596	592	621	621				
FY 08									594	593	594	637	636	635			
FY 09										649	662	661	655	658	657		
FY 10											640	654	654	657	665	669	
FY 11												634	631	652	664	657	659



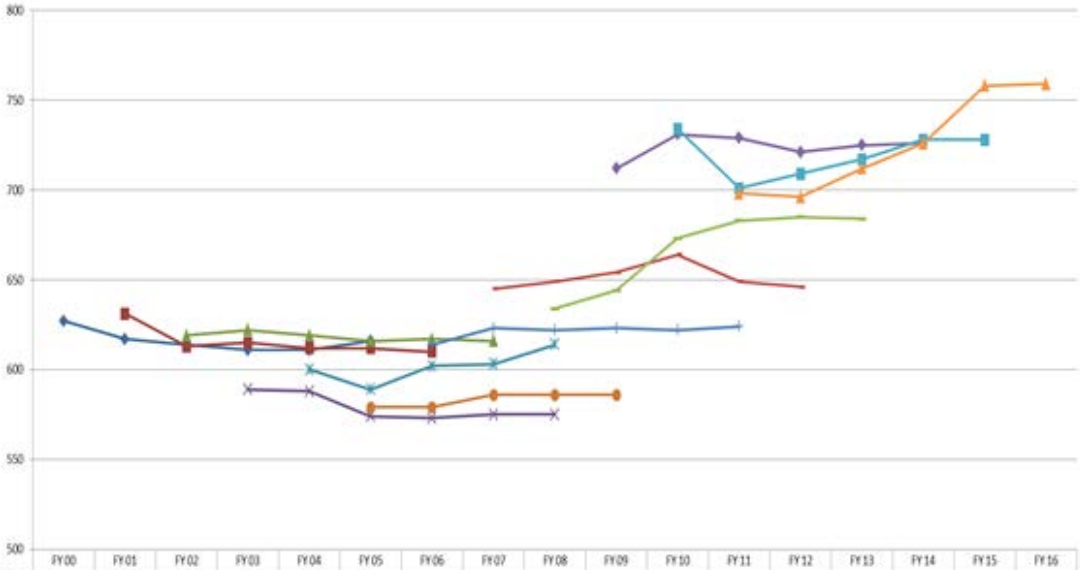
	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	731	735	730	725	720	660											
FY 01		752	742	745	783	788	797										
FY 02			814	842	853	855	860	858									
FY 03				803	812	836	839	842	845								
FY 04					829	835	798	804	827								
FY 05						824	824	798	805	805							
FY 06							785	817	823	830	839	847					
FY 07								827	828	864	915	1008	1000				
FY 08									810	854	881	972	976	978			
FY 09										972	994	991	981	988	989		
FY 10											932	955	970	978	994	1009	
FY 11												934	935	972	990	993	1010

6672 - Aviation Supply Specialist



	FY 00	FY 01	FY 02	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12	FY 13	FY 14	FY 15	FY 16
FY 00 Base	866	848	851.5	855	865	836											
FY 01		861	861	865	858	877	873										
FY 02			896	897	891	895	898	900									
FY 03				871	859	854	858	858	860								
FY 04					871	872	854	857	871								
FY 05						864	864	850	849	849							
FY 06							807	817	816	814	816	822					
FY 07								890	872	863	877	886	879				
FY 08									855	856	913	952	954	956			
FY 09										959	977	980	965	970	966		
Fy 10											979	962	951	958	968	964	
FY 11												956	939	956	973	953	942

7051 - Aircraft Rescue & Firefighter



	FY00	FY01	FY02	FY03	FY04	FY05	FY06	FY07	FY08	FY09	FY10	FY11	FY12	FY13	FY14	FY15	FY16
FY00 Base	627	617	614	611	611	616											
FY01		631	613	615	612	612	610										
FY02			619	622	619	616	617	616									
FY03				589	588	574	573	575	575								
FY04					600	589	602	603	614								
FY05						579	579	586	586	586							
FY06							614	623	622	623	622	624					
FY07								645	649	654	664	649	646				
FY08									634	644	673	683	685	684			
FY09										712	731	729	721	725	726		
FY10											734	701	709	717	728	728	
FY11												698	696	712	726	758	759

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   Monterey, California

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