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A Time Series Analysis of Australian Regular Army Enlisted and Officer Separations

March 2022

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Department of Defense Management

Naval Postgraduate School

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ABSTRACT

Accurately determining end strength is important to be able to plan future accessions in a manpower system. Predicting separations is vital to end-strength modelling. Predicting separation rates within the Australian Amy is an identified area of required research to ascertain the best models for aiding reporting and as a decision support tool. In support of the Australian Regular Army end-strength model, this thesis examines the use of time series analysis on enlisted and officer separations over an eleven-year period. This thesis develops multiple time series models using ten of the eleven years of data to forecast Australian Regular Army separation numbers for the eleventh year. The observed separation numbers of the eleventh year are used to compare the accuracy of each of the models developed. Models developed include moving average, autoregressive, exponential smoothing, Winter's method additive, and autoregressive moving average. This thesis finds that autoregressive integrated moving averages models are the most accurate time series models in predicting separation rates, outperforming the seasonal exponential smoothing and Holtz-Winter models.

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LIST OF ACRONYMS AND ABBREVIATIONS

ADF	Australian Defence Force
AFS	Average Funded Strength
AIC	Akaike Information Criteria
ARA	Australian Regular Army
ARIMA	Autoregressive Integrated Moving Average
DPG	Defence People Group
DSWPA	Defence Strategic Workforce Planning and Analysis
FY	Financial Year
MAPE	Mean Absolute Percentage Error

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EXECUTIVE SUMMARY

The Defence People Group (DPG) has the responsibility to the Australian Government of "delivering integrated people systems and building a capable workforce" (Australian Government Department of Defence, 2022). As such, they are the primary stakeholder with respect to recruitment and separation within the Australian military services. The accurate prediction of Australian Regular Army (ARA) separations is a problem that has been recently identified because of the COVID-19 pandemic. This thesis looks to explore the use of time series analysis in estimating ARA separations.

The Australian Regular Army observed an unusual reduction in separation numbers for March, April, and May in 2020, correlated with increasing COVID-19 restrictions introduced by the Australian Federal and State governments. This subsequently led to an increase in scrutiny over workforce modeling, in particular the current Monte Carlo simulation method of forecasting separation rates. Combined with the limited academic writing on organizational separation modeling, the idea of this thesis was born.

As described by Ragsdale (2019), a "time series is a set of observations on a quantitative variable collected over time" (p. 566) and "time series analysis involves trying several modeling techniques on a given data set and evaluating how well they explain the past behavior of the time series variable (pp. 567–568). In the context of this thesis, the times series variable is the monthly separation rate of ARA full-time personnel.

At the commencement of the financial year of 2020–2021, the Monte Carlo simulation model used by DPG predicted 2,885 full-time ARA separations, 624 less than the 3,509 realized. Results of this thesis find that using Autoregressive Integrated Moving Average (ARIMA) models a prediction of 3,196 separations would have been forecasted. This represents a greater than 50% increase in accuracy of using time series analysis against the status quo Monte Carlo simulation.

Improving the accuracy of predicting attrition within the Australian Regular Army helps manpower planners direct their priorities. Attrition inevitably drives recruitment, and inaccurate predictions of separations will lead to inefficiencies in the respective recruitment targets set. Using time series modeling at the commencement of FY2020–2021 could have potentially assisted DPG by increasing their recruitment targets by the difference of 311 personnel.

The data used to conduct time series analysis was personnel movement records from 1 July 2010 to 1 July 2021 obtained from the Defence People Group. This data was aggregated and examined and developed into time series data. Seasonal Exponential Smoothing, Holtz-Winter's Additive and ARIMA models were developed from a training set consisting of observations from 1 July 2010 to 30 June 2020. These models were then used to provide separation predictions on the test set spanning 1 July 2020 to 30 June 2021. ARIMA models outperformed the Seasonal Exponential Smoothing and Holtz-Winter's models by providing a prediction of separation numbers closer to those observed.

Due to the uniqueness of FY20–21, which was impacted by the COVID-19 pandemic, the same methodology was applied to construct and validate models on prior FYs. Conducting time series on the subsequent years further reinforced the predictive power of ARIMA models for the Australian Regular Army.

References

Australian Government Department of Defence. (2022). *Defence people group.* https://www.defence.gov.au/about/people-group

Ragsdale, C. (2019). *Spreadsheet modeling and decision analysis: A practical introduction to business analytics* (8th edition). Cengage India.

I. INTRODUCTION

A. BACKGROUND

The Australian Government's Department of Defence (2020a, 2020b) outlines in the Defence Strategic Update and Force Structure Plan the requirement to increase the size of the Australian Regular Army personnel to be able to meet future capability requirements. In particular, the Defence Force Structure plan (p. 103) seeks to see "an initial increase in Australian Defence Force (ADF) and Australian Public Service (APS) personnel over the next four years, and longer-term growth across the next two decades." The Australian Defence Force and the Australian Regular Army conduct manpower planning and analysis to meet the requirements set out in these documents. In meeting end strength, the Australian Regular Army is allowed +/- 1% of the government mandated number.

The Force Structure Plan 2020 was released during the COVID-19 pandemic. The COVID-19 pandemic has seen an increase in uncertainty around employment and economic conditions across the globe. The legacy Monte Carlo simulation model used by workforce planners previously was unable to provide the necessary accuracy in predicting separations and this was further exacerbated by the "shocks" to the manpower system.

The purpose of this thesis is to develop a model to assist military manpower planners in predicting Australian Regular Army separation and meeting end-strength requirements.

B. THE END STRENGTH MODEL

Manpower planning is an important organizational function. Having the right people, at the right place, at the right time is essential to being able to achieve an organization's mission. Militaries across the globe are directed by governments to provide capability in the projection of combat power. Failure to meet manpower requirements adds to the risk of not achieving capability. On the other hand, surpassing personnel requirements results in resources being used inefficiently and money being redirected from other sources to pay for other employment within organizations. Since accurately predicting end-strength directly effects the efficient allocation of resources, militaries have an inherent interest in developing and using accurate models.

The number of personnel within the force at a given time is defined as the end strength. For example, if there are 30,000 personnel employed within the ARA on 30 June 2021, we say that the end strength for Financial Year 2020–2021 (FY20–21) is 30,000. End strength for the purposes of this thesis is the number of full-time personnel in the ARA at the end of a given financial year. The end-strength formula is given by:

$$Current\ End-Strength\ +\ E\left[Accessions\right]-\ E\left[Losses\right]\ =\ E\left[End-Strength\right] \quad (1)$$

For the purposes of predicting end strength, the assumption is made that accessions are relatively reliable and that the most important component of meeting end strength in any given year is being able to accurately forecast the number of losses. This assumption is made because of the organizational size of the Australian Regular Army and that "quit rates tend to decline as firm sizes increase" (Ehrenberg & Smith, 2017, p. 409). Furthermore, combining the size of the organization with economic cyclical effects studies in time series data show that "quit rates tend to rise when the labor market is tight and fall when it is loose" (Ehrenberg & Smith, 2017, p. 411). This time series relationship can be seen in Figure 1.

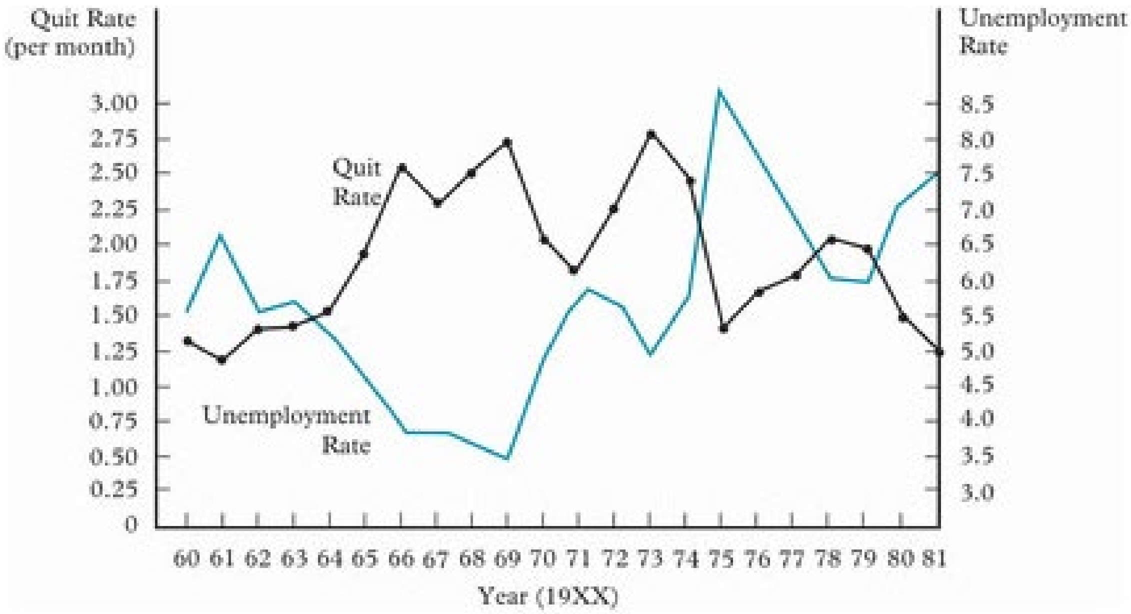


Figure 1. The Quit Rate and Labor Market Tightness. Source: Ehrenberg and Smith (2017).

In the context of end-strength planning, we assume that accessions are relatively reliable, in that recruitment efforts and targets can be determined by organizations after human resource planning has occurred. In meeting end strength, the Australian Regular Army can implement talent management and retention policies to reduce separations. Alternatively, accession targets can be increased. The latter in this case is likely to be more cost-effective.

C. THESIS OBJECTIVE

This section outlines the object of this thesis and well as its organization.

1. Objective

The objective of this thesis is to examine the use of time series analysis of historical Australian Regular Army separations to identify the most accurate and appropriate model for forecasting expected losses. It aims to analyze potential time series models that the Australian Regular Army can use in predicting future end strength and thus adding value by assisting in meeting capability and reducing resource waste. The following tasks were performed:

a. Individual accession and loss event records data was provided by DPG and monthly historical loss rates were constructed;

b. Defence Workforce Reports, ADF Permanent and Reserve Strength Summaries, and the ADF AFS were used to validate the data as well as provide the predictions from the current forecasting technique, Monte Carlo Simulation;

c. Time series models were constructed;

d. The models were evaluated using various measures of accuracy;

e. Analysis was conducted across the various models to identify the most accurate; and

f. Data splitting was conducted to test the accuracy of the predictions.

2. Organization

This current chapter, Chapter I, provides a background of ARA personnel requirements, end strength planning, and the objective of this thesis, including its organization.

Chapter II contains a review of the literature on end strength and attrition research. It looks at distinguishing between quantitative and qualitative approaches to predicting and investigating attrition.

Chapter III is the methodology. It describes how time series models were developed. Firstly, it describes the data used. Secondly, it describes the time series models developed and their respective forecast of separations.

Chapter IV provides an analysis of the results. It goes into further detail of the models and compares them in a table format. The best candidate modes are then compared using data splitting methods to demonstrate their forecasting potential.

Chapter V provides the recommendations and conclusion on the results and the implications to end-strength planning. Alternative methods and potential future areas for research are recommended in this chapter.

II. LITERATURE REVIEW

Studies into end strength and attrition can be divided into two categories. The first category is qualitative approaches, those that look to answer questions of causation. The second is quantitative approaches, those that look to answer questions of predictions.

A. QUALITATIVE APPROACHES

Qualitative approaches look to address the characteristics, qualities and causes of attrition. Qualitative approaches may look to questions such as those mentioned in Mathis and Jackson (2010, p. 64) if "expenditures in employee leadership development training can be linked to lower employee turnover." Approaches such as multivariate linear regression analysis, logistic and probit regression, and cox proportional hazards regression were investigated in the literature.

Qualitative studies on attrition within the Australian Regular Army are limited. One that was reviewed was Hoglin's (2012, p. viii) research question to "identify those characteristics which can be used to predict the first-term completion of *ab initio* sailors, soldiers, airmen and airwomen in the ADF." This paper looks at first-term attrition, in other words, attrition amongst new recruits and trainees. Through logit and probit models, the paper finds that the strongest predictors of first-term attrition among Australian Regular Army enlistees are the level of education, general aptitude score, psychologist interview score, country of birth, and their previous occupation (p. ix).

Dodds's (2018, p. 41) primary research question was "What are the length of service/survival profiles for RAN Officers and Sailors?" Apart from an analysis into a separate service and specific rank group within that service, Dodds's research differs from my proposed topic in its methodology. Dodds uses Kaplan-Meier and Cox proportional hazards (p. v), with his most relevant conclusion with respect to my proposed topic being that an "economic conditions effect" was observed in their study and that those personnel who joined during the Global Financial Crisis were less likely to separate (p. 128).

Dodds's (2018) and Hoglin's (2012) papers look at separation from an Australian Defence Force perspective and both look at causal factors that can be examined to provide probabilities that a given individual will attrite. Whilst both these studies are important to decision makers contributing to manpower polices, they do not develop models that predict separation numbers that can be used in providing end-strength forecasts.

B. QUANTITATIVE APPROACHES

Quantitative approaches look to answers questions of "how many" or "what" is being attrited. Time series analysis is the predominate quantitative approach investigated by the literature.

With respect to the use of time series analysis to forecast losses, Sparling's (2005) research ascertained that there was no universal best fit forecasting technique. Sparling developed several time series models to forecast Captain and Major losses within the U.S. Army, and determined that a seasonal exponential smoothing model and a Winter's method-additive model were the best at forecasting for the U.S. Army.

DeWald's (1996) study conducted a time series analysis of U.S. Army enlisted loss rates. This research used four methods: arithmetic mean, exponential smoothing, seasonal exponential smoothing and an autoregressive moving average model. By examining the loss rates due to a "stop loss" policy being implemented as a result of Desert Storm, he concluded that "only the ARMA model could analytically incorporate such external factors into the prediction of loss rates" (p. 42). This finding is particularly relevant to the work of this thesis, given the context of the COVID-19 pandemic and the shocks observed to separation rates that have been observed by manpower planners.

DeWald's research is probably the most pertinent relating to this thesis. In the backdrop of the COVID-19 pandemic, this thesis will look to determine if an ARMA model will provide better forecasts than the seasonal exponential smoothing and Winter's method additive models that were determined to be most accurate by Sparling.

III. DATA AND METHODOLOGY

The purpose of this chapter is to provide an overview of the data used in the forecast model and the methodology used to forecast ARA separations.

A. DATA

Data was provided by the sponsoring organization, the Directorate of Strategic Workforce Planning and Analysis (DSWPA). The data set is comprised of transactional data from ADF Human Resources systems from July 2010 to June 2021. The data had been stripped of Personally Identifiable Information (PII) by DSWPA prior to analysis. Each observation in the data represents an enlistment or separation event for an individual, along with employment and demographical variables.

B. INITIAL DATA PREPARATION AND VALIDATION

Before the data set could be analyzed using time series methods, it had to be prepared and validated. To do this, the data set was cleaned to only include separations of full-time ARA personnel. Once the data set was cleaned, monthly separation numbers starting from July 2010 to June 2021 were formulated into an Excel document. Total separation numbers were validated against the ADF Strength Summary reports produced by DSWPA. Once the cleaned data set had been validated, it was separated into an "officer" and an "enlisted" component. Each of these time series has 132 observations representing individual months, commencing in July 2010 and concluding in June 2021.

C. INITIAL DATA OBSERVATIONS

JMP (pronounced Jump) was the statistical software used to conduct time series analysis for this thesis. JMP's utility of hiding observations from analysis was used in the approach for this research. This in effect creates a training and a test set for the data.

By inputting the time series into JMP and hiding the last 12 observations, we get Figure 2 and Figure 3 for soldier and enlisted separations respectively.

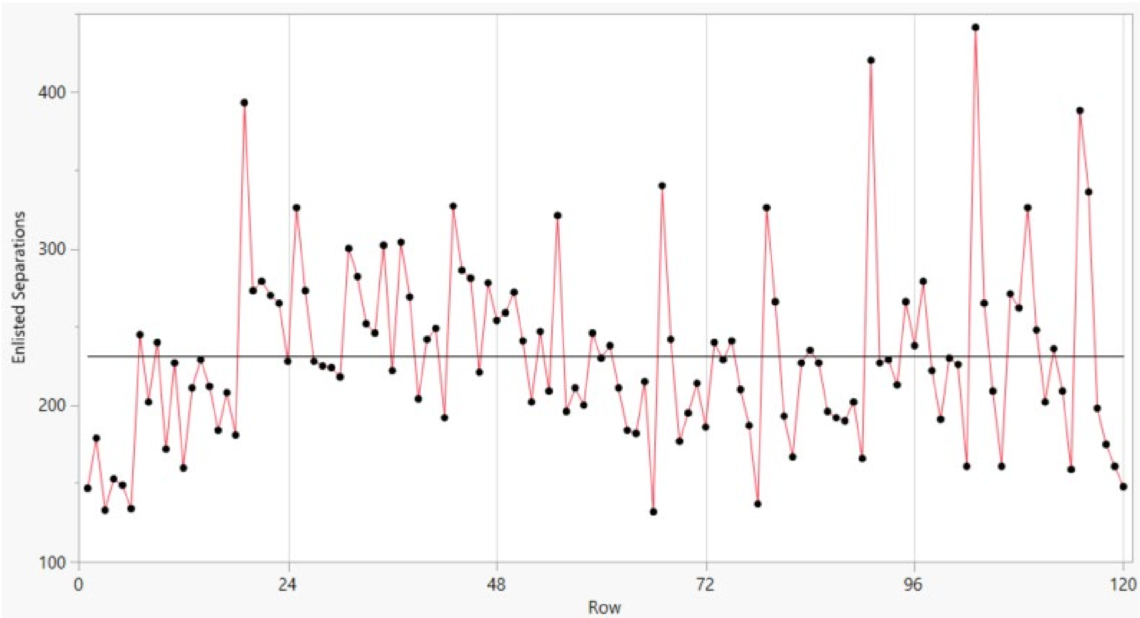


Figure 2. Time Series Enlisted Separations

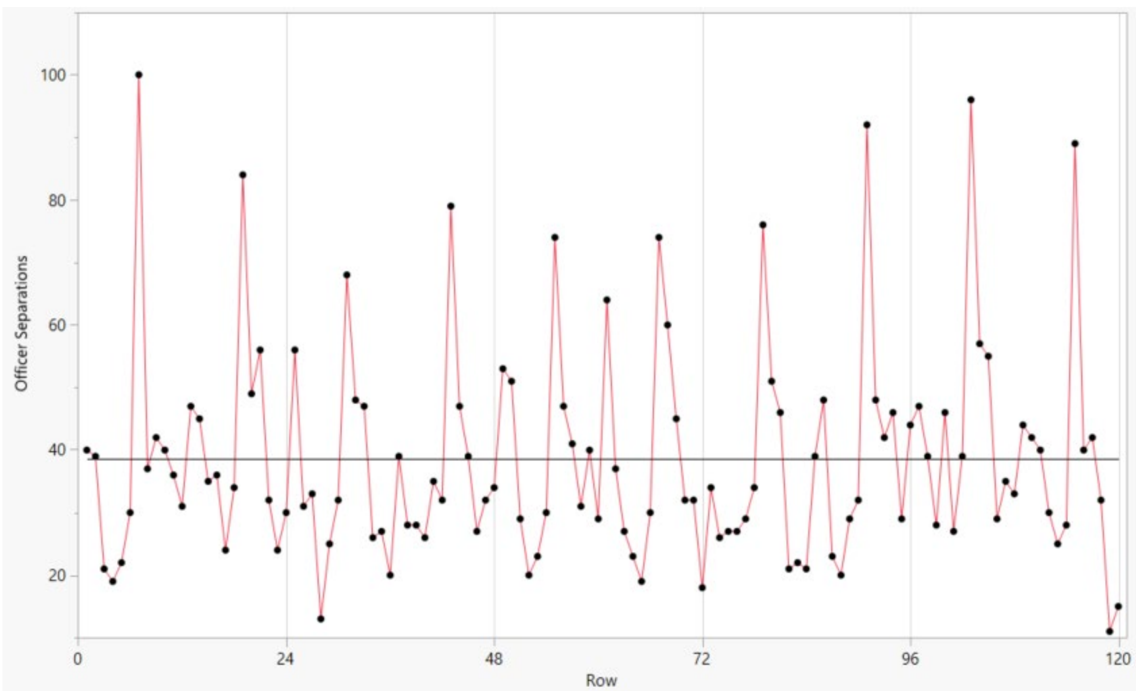
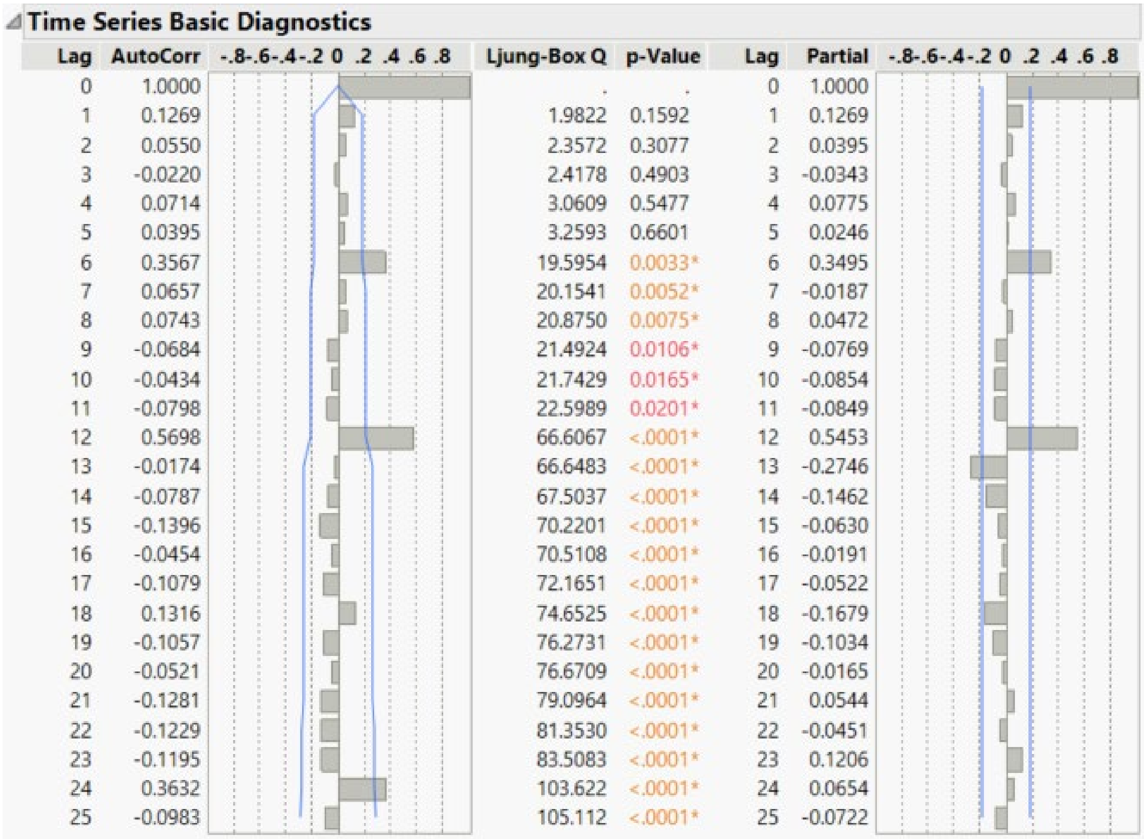


Figure 3. Time Series Officer Separations

Initially inspecting the time series plots, we observe peaks and troughs representing months with high separations and low separations respectively. The correlograms of both series are then examined to determine if the time series were stationary. The correlograms can be found in Figures 4 and 5.


Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.1269	1.9822	0.1592	1	0.1269
2	0.0550	2.3572	0.3077	2	0.0395
3	-0.0220	2.4178	0.4903	3	-0.0343
4	0.0714	3.0609	0.5477	4	0.0775
5	0.0395	3.2593	0.6601	5	0.0246
6	0.3567	19.5954	0.0033*	6	0.3495
7	0.0657	20.1541	0.0052*	7	-0.0187
8	0.0743	20.8750	0.0075*	8	0.0472
9	-0.0684	21.4924	0.0106*	9	-0.0769
10	-0.0434	21.7429	0.0165*	10	-0.0854
11	-0.0798	22.5989	0.0201*	11	-0.0849
12	0.5698	66.6067	<.0001*	12	0.5453
13	-0.0174	66.6483	<.0001*	13	-0.2746
14	-0.0787	67.5037	<.0001*	14	-0.1462
15	-0.1396	70.2201	<.0001*	15	-0.0630
16	-0.0454	70.5108	<.0001*	16	-0.0191
17	-0.1079	72.1651	<.0001*	17	-0.0522
18	0.1316	74.6525	<.0001*	18	-0.1679
19	-0.1057	76.2731	<.0001*	19	-0.1034
20	-0.0521	76.6709	<.0001*	20	-0.0165
21	-0.1281	79.0964	<.0001*	21	0.0544
22	-0.1229	81.3530	<.0001*	22	-0.0451
23	-0.1195	83.5083	<.0001*	23	0.1206
24	0.3632	103.622	<.0001*	24	0.0654
25	-0.0983	105.112	<.0001*	25	-0.0722

Figure 4. Correlogram of Enlisted Separations Time Series

Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.2086	5.3558	0.0207*	1	0.2086
2	-0.0584	5.7788	0.0556	2	-0.1066
3	-0.3192	18.5287	0.0003*	3	-0.2998
4	-0.2876	28.9700	<.0001*	4	-0.1903
5	-0.0514	29.3059	<.0001*	5	-0.0004
6	0.2953	40.5077	<.0001*	6	0.2353
7	-0.0026	40.5086	<.0001*	7	-0.2688
8	-0.1766	44.5832	<.0001*	8	-0.2642
9	-0.2629	53.6988	<.0001*	9	-0.1148
10	-0.0734	54.4148	<.0001*	10	0.0849
11	0.1690	58.2491	<.0001*	11	0.0688
12	0.6927	123.294	<.0001*	12	0.5526
13	0.1438	126.124	<.0001*	13	-0.1308
14	-0.0753	126.908	<.0001*	14	-0.0325
15	-0.3425	143.262	<.0001*	15	-0.0437
16	-0.3093	156.728	<.0001*	16	-0.0218
17	-0.0931	157.961	<.0001*	17	-0.0987
18	0.2630	167.887	<.0001*	18	-0.0229
19	-0.0261	167.986	<.0001*	19	-0.1717
20	-0.1802	172.739	<.0001*	20	-0.2055
21	-0.2799	184.325	<.0001*	21	-0.1478
22	-0.1016	185.866	<.0001*	22	-0.0619
23	0.1115	187.742	<.0001*	23	-0.1429
24	0.5816	239.328	<.0001*	24	0.0676
25	0.1417	242.422	<.0001*	25	-0.0408

Figure 5. Correlogram of Officer Separations Time Series

The correlograms are inspected visually to determine statistically significant relationships between observations in the time series. Looking at the autocorrelation function (the left-hand side of the correlograms), significant autocorrelation can be found where the bars exceed the blue bands. On the enlisted time series, we see autocorrelation at lags 6, 12, and 24—our time series is not stationary. Bi-annual separation behavior is being observed in this time series. Similarly, the correlogram for officer separations shows peaks at 3, 6, 9, 12, 15, and 24, meaning that this time series is also not stationary due to seasonality. In the case of officers, we observe a quarter annual relationship between separations.

D. MODEL SELECTION

From observing the time series plots and the correlograms, there are two methods by which we can construct a model. Firstly, we can use a model that accounts for seasonality and trends, such as a seasonal smoothing or Holtz-Winter's additive model. Alternatively, we can remove the seasonality component from the series, thereby creating an officer and an enlisted time series with the seasonality removed. Removing seasonality from the time series, we render it stationary, and thus able to be analyzed using ARIMA models.

E. RENDERING THE TIME SERIES STATIONARY

Both the enlisted and the officer time series were rendered stationary using Excel. This was done by calculating the average of the separations by month for the 10 years of data within the training set. The resulting seasonal component can be found in Table 1.

Table 1. Seasonal Component of Separation Time Series

Month	Enlisted Seasonal Component	Officer Seasonal Component	Total Seasonal Component
July	256	46	302
August	233	39	271
September	203	29	232
October	205	26	231
November	212	26	237
December	169	32	201
January	350	83	433
February	258	48	306
March	227	46	272
April	202	32	234
May	246	29	275
June	216	28	244

To interpret this table, we can see that the month with the highest average enlisted separation is January, with 350. Removing the above seasonal component from the time series, we now form two additional time series—a seasonally adjusted enlisted separations time series, and a seasonally adjusted officer separations time series. Figures 6 and 7 depict the resultant time series with the seasonality component removed. We observe on the y-axis that the range of numbers has reduced as a result of removing the seasonal component shown in Table 1; what we are left with now is the signal from our data set.

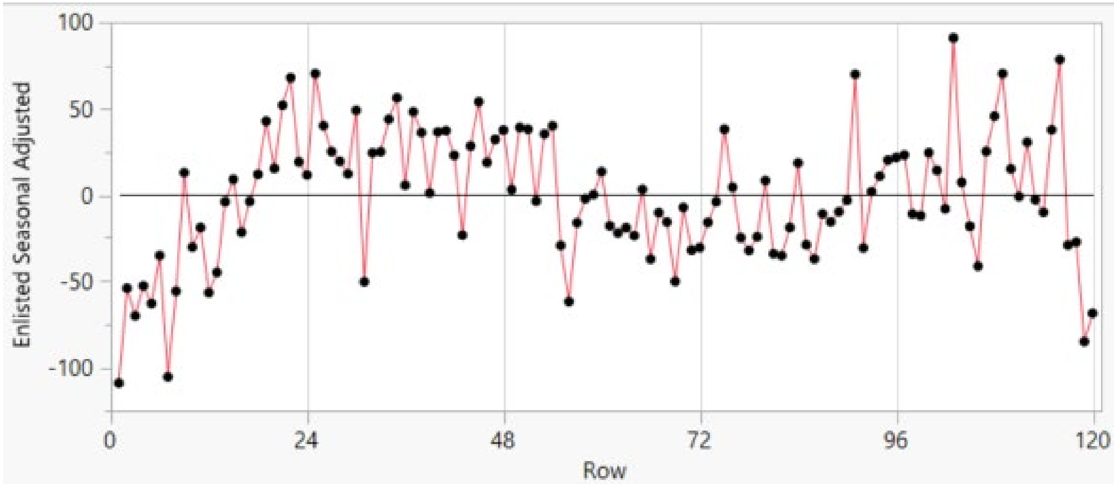


Figure 6. Seasonal Adjusted Enlisted Separations Time Series

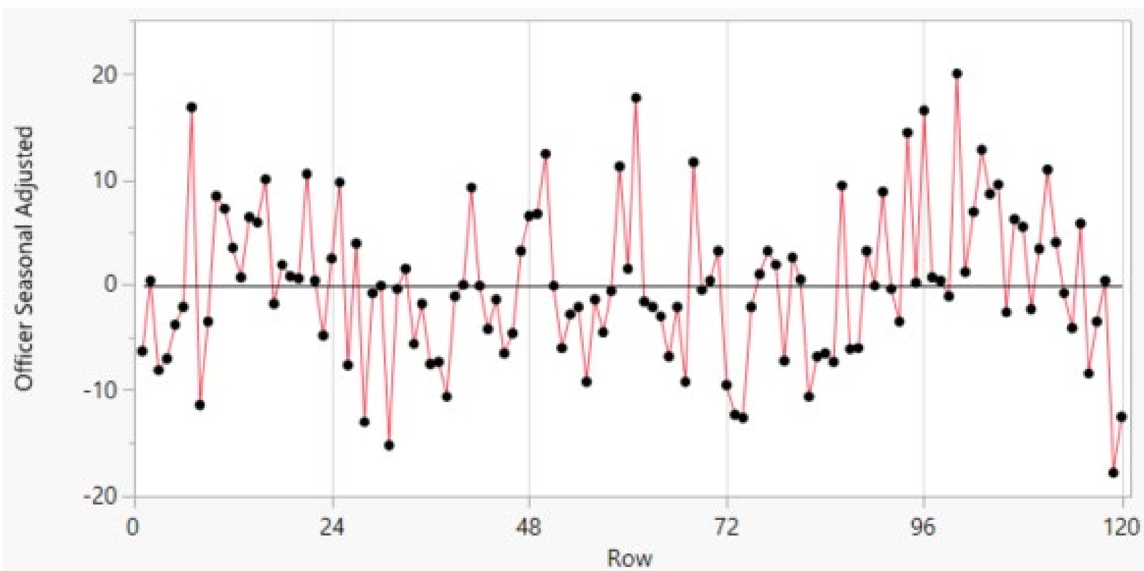
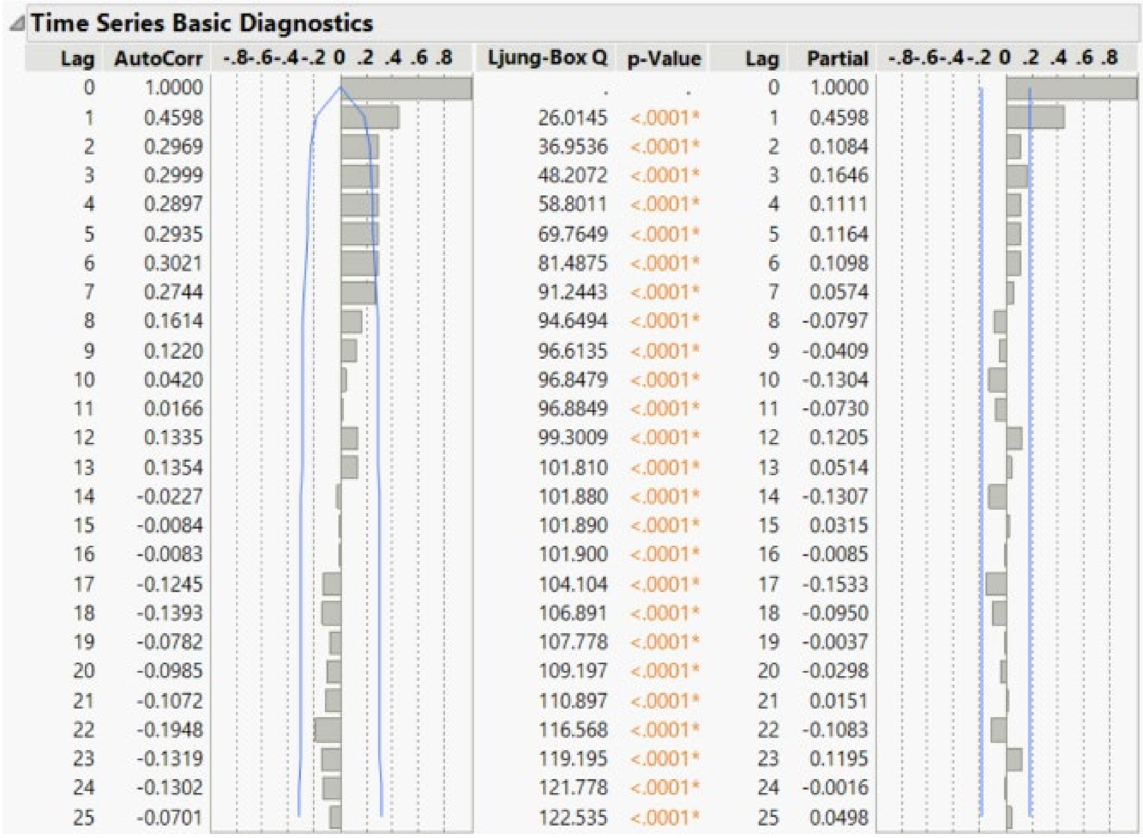


Figure 7. Seasonal Adjusted Officer Separations Time Series

Figures 8 and 9 depict the resulting correlograms from the seasonally adjusted enlisted and officer time series respectively. We note that the significant autocorrelations have been removed from the previous correlograms.



Time Series Basic Diagnostics

Lag	AutoCorr	-.8-.6-.4-.2 0 .2 .4 .6 .8	Ljung-Box Q	p-Value	Lag	Partial	-.8-.6-.4-.2 0 .2 .4 .6 .8
0	1.0000		.	.	0	1.0000	
1	0.4598		26.0145	<.0001*	1	0.4598	
2	0.2969		36.9536	<.0001*	2	0.1084	
3	0.2999		48.2072	<.0001*	3	0.1646	
4	0.2897		58.8011	<.0001*	4	0.1111	
5	0.2935		69.7649	<.0001*	5	0.1164	
6	0.3021		81.4875	<.0001*	6	0.1098	
7	0.2744		91.2443	<.0001*	7	0.0574	
8	0.1614		94.6494	<.0001*	8	-0.0797	
9	0.1220		96.6135	<.0001*	9	-0.0409	
10	0.0420		96.8479	<.0001*	10	-0.1304	
11	0.0166		96.8849	<.0001*	11	-0.0730	
12	0.1335		99.3009	<.0001*	12	0.1205	
13	0.1354		101.810	<.0001*	13	0.0514	
14	-0.0227		101.880	<.0001*	14	-0.1307	
15	-0.0084		101.890	<.0001*	15	0.0315	
16	-0.0083		101.900	<.0001*	16	-0.0085	
17	-0.1245		104.104	<.0001*	17	-0.1533	
18	-0.1393		106.891	<.0001*	18	-0.0950	
19	-0.0782		107.778	<.0001*	19	-0.0037	
20	-0.0985		109.197	<.0001*	20	-0.0298	
21	-0.1072		110.897	<.0001*	21	0.0151	
22	-0.1948		116.568	<.0001*	22	-0.1083	
23	-0.1319		119.195	<.0001*	23	0.1195	
24	-0.1302		121.778	<.0001*	24	-0.0016	
25	-0.0701		122.535	<.0001*	25	0.0498	

Figure 8. Seasonal Adjusted Enlisted Time Series Correlogram

Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.1680	3.4737	0.0624	1	0.1680
2	0.1717	7.1326	0.0283*	2	0.1477
3	0.1588	10.2884	0.0163*	3	0.1151
4	-0.0024	10.2892	0.0358*	4	-0.0686
5	0.1038	11.6615	0.0397*	5	0.0773
6	-0.0137	11.6857	0.0694	6	-0.0488
7	0.0661	12.2514	0.0926	7	0.0653
8	0.1211	14.1668	0.0775	8	0.0944
9	0.1780	18.3479	0.0313*	9	0.1624
10	0.0854	19.3181	0.0364*	10	-0.0150
11	0.0621	19.8359	0.0476*	11	-0.0077
12	-0.1178	21.7174	0.0408*	12	-0.2031
13	-0.2070	27.5787	0.0104*	13	-0.2105
14	-0.0325	27.7246	0.0155*	14	0.0321
15	-0.1118	29.4676	0.0140*	15	-0.0023
16	-0.1752	33.7874	0.0058*	16	-0.1578
17	-0.1108	35.5316	0.0053*	17	-0.1004
18	-0.0229	35.6066	0.0079*	18	0.0383
19	-0.0805	36.5471	0.0090*	19	-0.0657
20	-0.0588	37.0528	0.0115*	20	0.0090
21	-0.1378	39.8623	0.0077*	21	-0.0208
22	-0.1703	44.1938	0.0034*	22	-0.0550
23	-0.1847	49.3416	0.0011*	23	-0.1275
24	-0.2346	57.7331	0.0001*	24	-0.1230
25	-0.0816	58.7599	0.0002*	25	0.0161

Figure 9. Seasonal Adjusted Officer Time Series Correlogram

With our newly created seasonally adjusted time series, we are now able to develop ARIMA models for analysis.

F. STATUS QUO FORECAST

An additional forecast was created for both the enlisted and officer time series using the separations from the previous 12 months and using that as a prediction for the next 12 months. This is useful because it provides a baseline for comparison on the time series methods used above.

G. CONSIDERED MODELS

There are an extensive number of time series models that can be selected using JMP analysis. The eight models examined by this thesis include:

1. Enlisted Seasonally Adjusted ARMA(1,1): Appendix A
2. Enlisted Seasonally Adjusted MA1: Appendix B
3. Enlisted Seasonally Adjusted AR1: Appendix C
4. Enlisted Winter's (Additive): Appendix D
5. Enlisted Seasonal Exponential Smoothing: Appendix E
6. Officer Seasonally Adjusted ARMA(1,1): Appendix F
7. Officer Winter's Method (Additive): Appendix G
8. Officer Seasonal Exponential Smoothing: Appendix H

H. MODEL VALIDATION

To validate a model, there are a number of requirements. For all models, the residuals are required to be uncorrelated, normally distributed and have constant variance. Additionally, the ARIMA models. being the Enlisted ARMA(1,1), MA1, AR1 and the Officer ARMA(1,1). are required to have statistically significant parameter coefficients. Model summaries, model forecasts and the required residual tests can be seen in the respective appendices. Upon inspection of the residual graphs, we can see that the ARIMA models tend to pass validation more easily, as their residuals demonstrate constant variance.

I. ENLISTED MODELS EVALUATION

1. Mean Absolute Percent Error

The Mean absolute percent error (MAPE) is useful in that it provides us with an average of the difference between the models' forecasted separation and actual separation. A MAPE of 10%, for example, means that on average our model forecasts within 10% of the actual separation rate. The MAPE can be used to determine the best models to use. The MAPE for the enlisted model training sets can be found below in Table 2.

Table 2. Enlisted Time Series Models MAPE

Enlisted Model	MAPE	MAPE (Seasonality Adjusted)
Enlisted Seasonally Adjusted ARMA(1,1)	201.67	11.06
Enlisted Seasonally Adjusted MA1	116.87	11.71
Enlisted Seasonally Adjusted AR1	146.88	11.4
Enlisted Winter's Method (Additive)	12.12	
Enlisted Seasonal Exponential Smoothing	12.44	

We can observe in Table 2 that the most accurate enlisted model for the training set was the seasonally adjusted ARMA(1,1) with a MAPE of 11.06%.

2. Prediction Intervals

Models developed in JMP provide a prediction interval that can be used to assess the accuracy and precision of the model. Precision is assessed by looking at the magnitude of the range between the lower and upper prediction interval. Accuracy can be determined by examining the percentage of actual separation numbers that falls within the prediction intervals. The performance of each enlisted model can be seen in Table 3.

Table 3. Enlisted Models Prediction Intervals

Enlisted Model	Range of Prediction Interval	Number of Intervals	Within Prediction Interval	Percentage
Enlisted Seasonally Adjusted ARMA(1,1)	125	120	112	93.33%
Enlisted Seasonally Adjusted MA1	134	120	114	95.00%
Enlisted Seasonally Adjusted AR1	129	120	111	92.50%
Enlisted Winter's Method (Additive)	140	109	105	96.33%
Enlisted Seasonal Exponential Smoothing	140	107	100	93.46%

From Table 3 we can see that the Enlisted Winter's Method (Additive) has the highest number of observations contained within its prediction interval spanning a range of 140 numbers. However the ARMA(1,1) contains the tightest prediction interval range, and with 93.33% of observations falling into this range, this might be considered more useful at providing monthly figures than the other models. A trade-off between having a smaller range of numbers and accuracy needs to be taken into account when deciding which model to use.

3. Akaike Information Criteria

The Akaike information criteria (AIC) is another method that can be used in determining the best models to use for predictions. The lower the AIC, generally, the better the model. Table 4 shows the performance of the enlisted models with respect to their degrees of freedom (DF) and AIC.

Table 4. DF and AIC of Enlisted Models

Enlisted Model	DF	AIC
Enlisted Seasonally Adjusted ARMA(1,1)	117	1175.76
Enlisted Seasonally Adjusted MA1	118	1176.17
Enlisted Seasonally Adjusted AR1	118	1182.89
Enlisted Winter's Method (Additive)	104	1078.68
Enlisted Seasonal Exponential Smoothing	105	1078.91

Here we observe that the Winter's method and the Seasonal Exponential Smoothing model are considered the best models with respect to AIC.

J. OFFICER MODELS EVALUATION

1. Mean Absolute Percent Error

Table 5 displays the results of the officer models with respect to their MAPE. From the table we can see that the Seasonally Adjusted ARMA(1,1) is considered the most accurate model with a MAPE of 16.85%.

Table 5. Officer Model MAPE

Officer Model	MAPE	MAPE (Seasonality Adjusted)
Officer Seasonally Adjusted ARMA(1,1)	259.77	16.85
Officer Winter's Method (Additive)	21.73	
Officer Seasonal Exponential Smoothing	21.73	

2. Prediction Intervals

Prediction intervals for the officer models on the training set can be seen in Table 6.

Table 6. Officer Models Prediction Intervals

Officer Model	Range of Prediction Intervals	Number of Intervals	Within Prediction Interval	Percentage
Officer Seasonally Adjusted ARMA(1,1)	27	120	113	94.17%
Officer Winter's Method (Additive)	31	107	98	91.59%
Officer Seasonal Exponential Smoothing	31	107	98	91.59%

We observe in Table 6 that the Seasonally Adjusted ARMA(1,1) model has both the tightest prediction interval range and the highest percentage of observations contained within.

3. Akaike Information Criteria

The AIC for the Officer Models on the training set can be seen in Table 7.

Table 7. Officer Model DF and AIC

Officer Model	DF	AIC
Officers' Seasonally Adjusted ARMA(1,1)	117	814.08
Officers' Winter's Method (Additive)	104	772.48
Officers' Seasonal Exponential Smoothing	105	770.48

Using the AIC, we observe that the Officer Seasonal Exponential Smoothing Model performs the best.

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IV. ANALYSIS OF RESULTS

This chapter gives the results obtained from the JMP Time series forecasting system. Specifically, it looks to compare the results of the models obtained in the methodology section of this paper against the test set. Looking at the results of the time series models with respect to the actual values will give us the ability to discuss managerial expectations.

To examine the performance of the models created against the test set, we can use the mean absolute percent error (MAPE) and the prediction interval. Additionally, we can compare our yearly forecast for each of the time series and compare these to the actual separation numbers. In this respect, the null hypothesis is that the time series models developed are equal to or less accurate in estimating separation numbers than the current Monte Carlo simulation method employed by DPG. This hypothesis is tested by taking the percent error of the models with respect to realized separation numbers.

A. ENLISTED MODELS RESULTS

1. Mean Absolute Percent Error

Table 8 displays the MAPE for the Enlisted Models on the test set.

Table 8. Enlisted Models Test Set MAPE

Test Set Performance	MAPE	MAPE (Seasonality Adjusted)
Enlisted Seasonally Adjusted ARMA(1,1)	248.59%	23.52%
Enlisted Seasonally Adjusted MA1	100.14%	17.61%
Enlisted Seasonally Adjusted AR1	130.85%	17.77%
Enlisted Winter's Method (Additive)	35.06%	
Enlisted Seasonal Exponential Smoothing	27.91%	

From Table 8 we observe that the best performing models are the MA1 and the AR1 with a MAPE of 17.61% and 17.77% respectively. As expected, the MAPE for the test set is larger than the MAPE from the training set. We also observe a substantial increase in the MAPE for the Winter's Method and the Seasonal Exponential Smoothing model on the magnitude of 23 and 15 percentage points respectively, compared to the increase in the MAPE of 6% to 125 for the ARIMA models. This is evidence of the fact that the ARIMA models can more accurately forecast separation into the future.

2. Enlisted Models Prediction Intervals

Table 9 displays the prediction intervals for the models on the test set. We note for all models an increase in the range is a result in the decreasing confidence of the model to predict values further into the future. Even with the larger range of values, Winter's Method and the Seasonal Exponential Smoothing model perform poorly, with only 41.67% and 58.33% of the observed separation rates falling within the prediction interval. Combining these results with those in Appendix D and E, we see that this performance is likely a result of an overfitting of the models on the training set. The ARIMA models did substantially better with the AR1 and MA1, containing 83.33% of the observations within the model's prediction intervals.

Table 9. Enlisted Models Test Set Prediction Intervals

Enlisted Model	Range (Average)	Number of Intervals	Within Prediction Interval	Percentage
Enlisted Seasonally Adjusted ARMA(1,1)	143	12	9	75.00%
Enlisted Seasonally Adjusted MA1	144	12	10	83.33%
Enlisted Seasonally Adjusted AR1	148	12	10	83.33%
Enlisted Winter's Method (Additive)	164	12	5	41.67%
Enlisted Seasonal Exponential Smoothing	157	12	7	58.33%

B. OFFICER MODELS RESULTS

1. Officer Models Test Set MAPE

Table 10 shows the performance of the Officer models MAPE on the test set. Here we can see that the Seasonally Adjusted ARMA(1,1) is the model with the smallest MAPE at 20.29%.

Table 10. Officer Models Test Set MAPE

Officer Model	MAPE	MAPE (Seasonality Adjusted)
Officers' Seasonally Adjusted ARMA(1,1)	255.58%	20.29%
Officers' Winter's Method (Additive)	24.73%	
Officers' Seasonal Exponential Smoothing	24.70%	

2. Officer Models Test Set Prediction Intervals

Table 11 displays the performance of the prediction intervals of Officer models on the test set. We see on all three models that the prediction intervals contain 91.67% of the observations. The average range for the ARMA(1,1) of 28 gives additional precision when using this model.

Table 11. Officer Models Test Set Prediction Intervals

Officer Model	Range (Average)	Number of Intervals	Within Prediction Interval	Percentage
Officers' Seasonally Adjusted ARMA(1,1)	28	12	11	91.67%
Officers' Winter's Method (Additive)	34	12	11	91.67%
Officers' Seasonal Exponential Smoothing	34	12	11	91.67%

C. END STRENGTH SEPARATION PREDICTION COMPARISON

1. Soldier Models Prediction

Table 12 displays the yearly predictions for each of the models selected. Looking at the percent error of the financial year separations, the best prediction of separation for FY20-21 was using the yearly separation numbers for FY19–20. The MA1 was the time series model that provided the best prediction of total separations with an error of 9.91%.

Table 12. Soldier Model Prediction

Enlisted Model	Predicted Separations	Difference Actual Separations	Percent Error	Percent Error of total Population
Legacy Model	2464	-595	19.45%	2.51%
Enlisted Seasonally Adjusted ARMA(1,1)	2419	-640	20.92%	2.70%
Enlisted Seasonally Adjusted MA1	2756	-303	9.91%	1.28%
Enlisted Seasonally Adjusted AR1	2689	-370	12.10%	1.56%
Enlisted Winter's Method (Additive)	2160	-899	29.39%	3.79%
Enlisted Seasonal Exponential Smoothing	2413	-646	21.12%	2.73%
Using Previous Years Separation Numbers	2786	-273	8.92%	1.15%
Actual Separations	3059			
Total Enlisted Population	23691			

2. Officer Models Prediction

Table 13 displays the yearly predictions for each of the models selected. For the officer models the ARMA(1,1) provided the most accurate number of predicted separations for FY20–21 with an error of 2.22%. The time series model in this instance out-performed the prediction of using FY19-20 separations, which had an error of 2.67%.

Table 13. Officer Model Predictions

Officer Model	Predicted Separations	Difference Actual Separations	Percent Error	Percent Error of total Population
Legacy Model	421	-29	6.44%	0.45%
Officers' Seasonally Adjusted ARMA(1,1)	440	-10	2.22%	0.15%
Officers' Winter's Method (Additive)	388	-62	13.78%	0.96%
Officers' Seasonal Exponential Smoothing	388	-62	13.78%	0.96%
Using Previous Years Separation Numbers	438	-12	2.67%	0.19%
Actual Separations	450			
Total Officer Population	6480			

V. SUMMARY AND RECOMMENDATIONS

A. SUMMARY

This thesis addressed a requirement by DPG to develop models to assist in estimating separation within the ARA. As a result of the recent performance of the current Monte Carlo simulation method employed by workforce modelers, further research was requested into looking at time series analysis as an alternative to improve the accuracy of separation forecasts. This thesis has found that time series can provide more accurate estimations and consequently improve the inputs into human resource planning.

This thesis developed multiple manpower models to forecast separations from the Australian Regular Army. The transactional human resources data provided by DSWPA was transformed into time series models, with the results compared to historically reported strength states to ascertain the accuracy of the results.

The seasonally adjusted MA1 model for enlisted personnel and the seasonally adjusted ARMA(1,1) model provided the most accurate prediction of separation rates. Additionally, both these models provided the most managerially useful result, by having the smallest prediction intervals that performed best on the test set.

The ARIMA models performed better with respect to the residuals being uncorrelated, normally distributed and with constant variance.

B. RECOMMENDATIONS

I recommend that that the Australian Regular Army uses ARIMA models to forecast separation rates. When used to predict the next 12 months of separation rates, the ARIMA models outperformed the Seasonal Exponential Smoothing and Holtz-Winter's models both in the FY20–21 and in previous FYs.

The improved accuracy of estimations will assist DPG in setting recruitment targets to compensate for attrition. It is not within the scope of this thesis to calculate the cost savings to the ARA. However, by using time series models, the improvement in organizational turnover planning will assist the ARA in achieving its capability requirements.

The use of this method is also preferred over the current method of using the Crystal Ball Excel add-in. The Crystal Ball add-in is an additional expense for the ARA whilst ARIMA modeling can be done in open-source software such as The R Project for Statistical Computing. This effectively provides the ARA with small cost savings in software expenses.

C. RECOMMENDATIONS FOR FURTHER STUDY

1. Cost-Benefit Analysis of Separations

Noting the limited accuracy of predictions, I recommend that a cost-benefit analysis (CBA) is conducted to determine the costs of overpredicting separations against underpredicting separations. Given the assumption that separation numbers drive future enlistment targets, it would be beneficial if the cost was determined for surpassing funded strength as opposed falling short of funded strength. Such a study would allow consideration of the applicable model, whether it be one that provides a prediction of a larger or lesser magnitude.

2. Machine Learning

It would be beneficial to use an expanded data set to include additional variables such as demographics, service history, trade description, marital status, number of dependents, etc. I recommended that a machine learning approached is tested against current methods and the time series analyses conducted by this research.

3. Time Series by Rank and Specialization

Not all separations are equal to an organization. I recommend that time series methods be applied to specific ranks and specializations to be able to determine the utility of this method in predicting separations of critical trades and occupations.

4. Correlation of Enlistments with Separations

Transforming the enlistment data set into time series offers the potential to identify a correlation between enlistments and separations. Research into this would be beneficial to decision makers, by allowing them to see the lag between enlistments and separations.

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APPENDIX A. ENLISTED SEASONALLY ADJUSTED ARMA(1,1)

Model: ARMA(1, 1)

Model Summary

DF	117	Stable	Yes
Sum of Squared Innovations	119505.181	Invertible	Yes
Sum of Squared Residuals	123428.154		
Variance Estimate	1021.41181		
Standard Deviation	31.9595339		
Akaike's 'A' Information Criterion	1175.76182		
Schwarz's Bayesian Criterion	1184.12429		
RSquare	0.27037904		
RSquare Adj	0.25790688		
MAPE	201.669157		
MAE	25.072918		
-2LogLikelihood	1169.76182		

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate	Mu
AR1	1	0.93837	0.05158	18.19	<.0001*	-0.6587821	-10.689789
MA1	1	0.65356	0.09916	6.59	<.0001*		
Intercept	0	-10.68979	16.49180	-0.65	0.5181		

Figure 10. Enlisted Seasonally Adjusted ARMA(1,1) Model Summary and Parameter Estimates

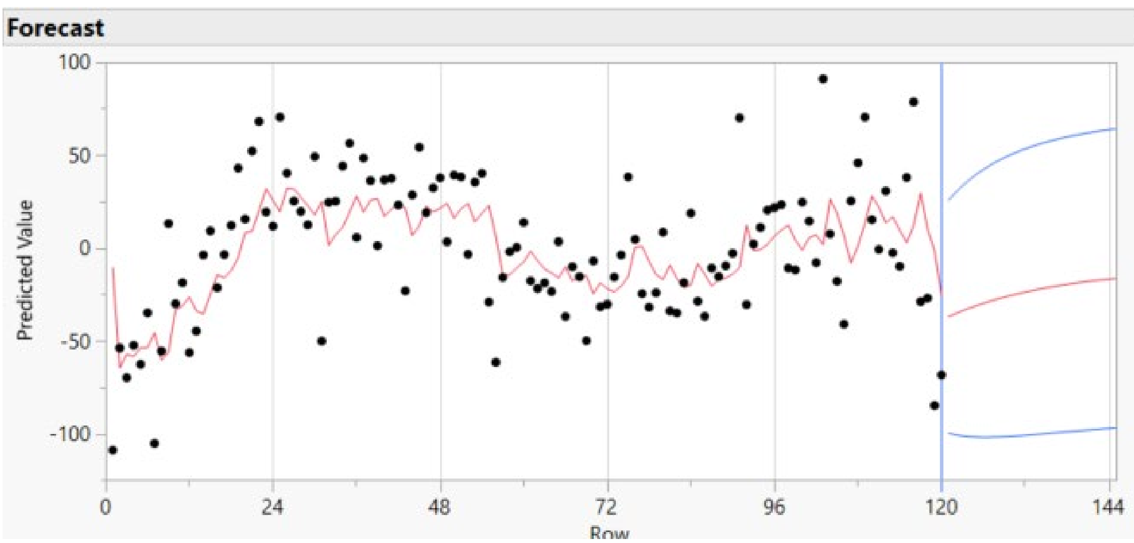
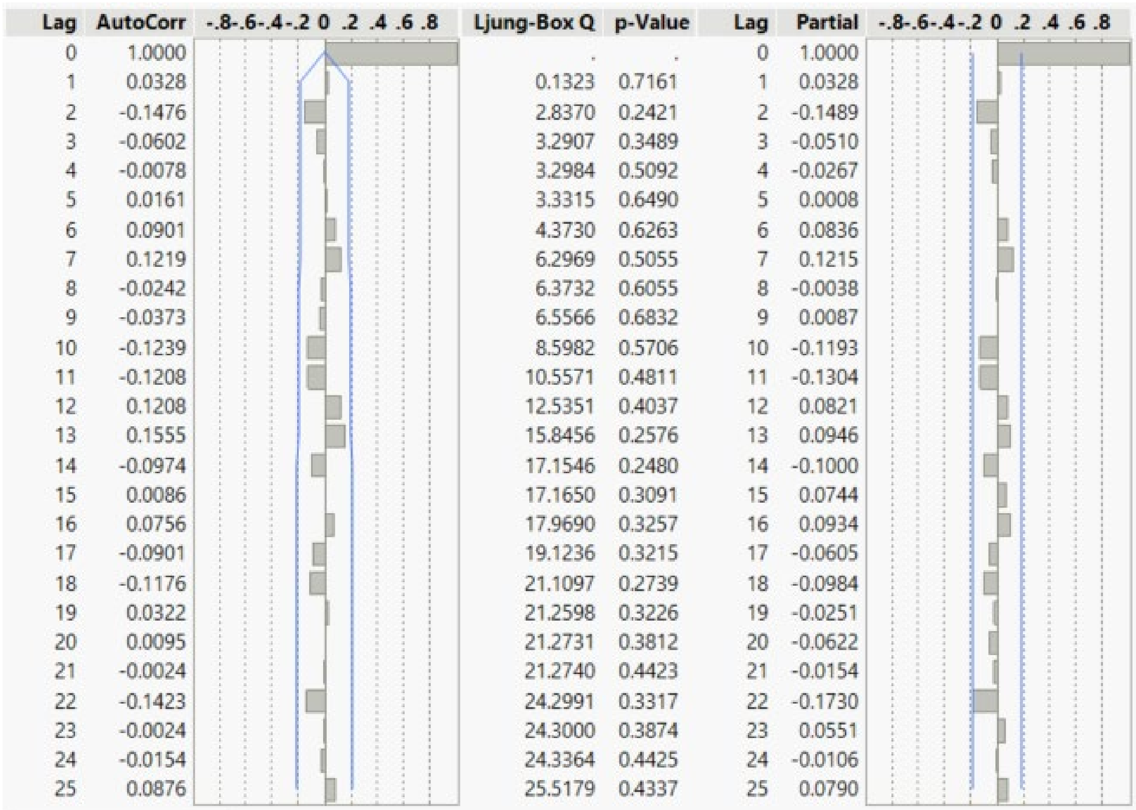


Figure 11. Enlisted Seasonally Adjusted ARMA(1,1) Forecast



Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.0328	0.1323	0.7161	1	0.0328
2	-0.1476	2.8370	0.2421	2	-0.1489
3	-0.0602	3.2907	0.3489	3	-0.0510
4	-0.0078	3.2984	0.5092	4	-0.0267
5	0.0161	3.3315	0.6490	5	0.0008
6	0.0901	4.3730	0.6263	6	0.0836
7	0.1219	6.2969	0.5055	7	0.1215
8	-0.0242	6.3732	0.6055	8	-0.0038
9	-0.0373	6.5566	0.6832	9	0.0087
10	-0.1239	8.5982	0.5706	10	-0.1193
11	-0.1208	10.5571	0.4811	11	-0.1304
12	0.1208	12.5351	0.4037	12	0.0821
13	0.1555	15.8456	0.2576	13	0.0946
14	-0.0974	17.1546	0.2480	14	-0.1000
15	0.0086	17.1650	0.3091	15	0.0744
16	0.0756	17.9690	0.3257	16	0.0934
17	-0.0901	19.1236	0.3215	17	-0.0605
18	-0.1176	21.1097	0.2739	18	-0.0984
19	0.0322	21.2598	0.3226	19	-0.0251
20	0.0095	21.2731	0.3812	20	-0.0622
21	-0.0024	21.2740	0.4423	21	-0.0154
22	-0.1423	24.2991	0.3317	22	-0.1730
23	-0.0024	24.3000	0.3874	23	0.0551
24	-0.0154	24.3364	0.4425	24	-0.0106
25	0.0876	25.5179	0.4337	25	0.0790

Figure 12. Enlisted Seasonally Adjusted ARMA(1,1) Correlogram—Test for Uncorrelated Residuals

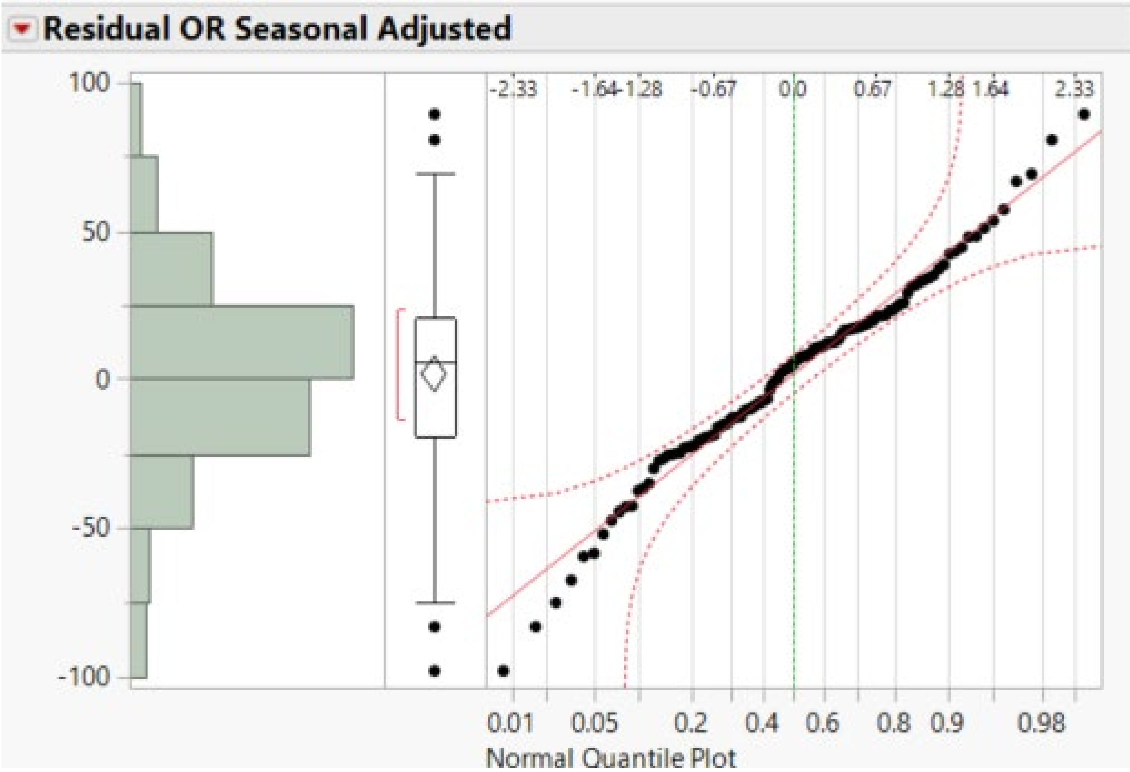


Figure 13. Enlisted Seasonally Adjusted ARMA(1,1)—Test for Normally Distributed Residuals

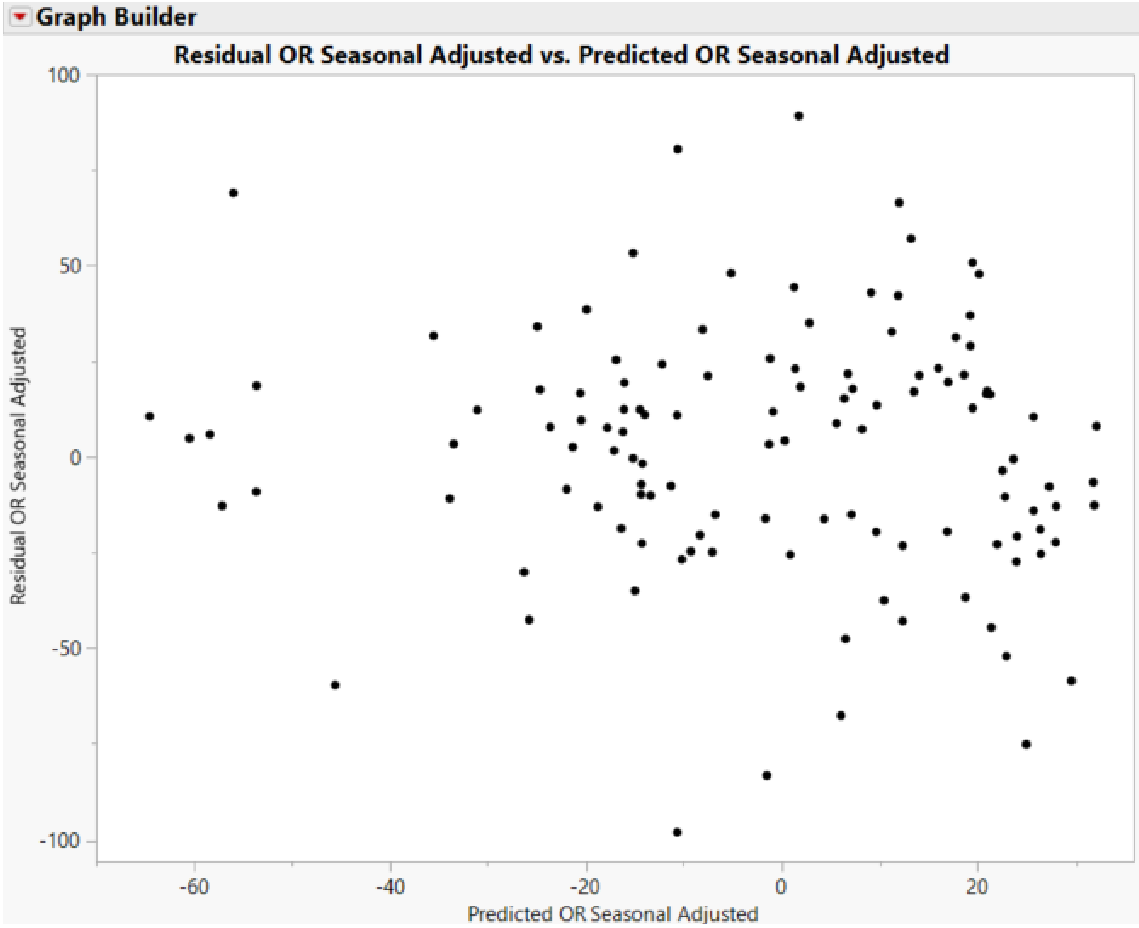


Figure 14. Enlisted Seasonally Adjusted ARMA (1,1)—Test for Constant Variance of Residuals

APPENDIX B. ENLISTED SEASONALLY ADJUSTED MA1

Model: MA(1)

Model Summary

DF	118	Stable	Yes
Sum of Squared Innovations	138788.336	Invertible	Yes
Sum of Squared Residuals	140482.569		
Variance Estimate	1176.17234		
Standard Deviation	34.295369		
Akaike's 'A' Information Criterion	1191.11296		
Schwarz's Bayesian Criterion	1196.68795		
RSquare	0.16956526		
RSquare Adj	0.16252768		
MAPE	116.871232		
MAE	26.1534792		
-2LogLikelihood	1187.11296		

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate	Mu
MA1	1	-0.4080152	0.076619	-5.33	<.0001*	-0.4434644	-0.4434644
Intercept	0	-0.4434644	4.418246	-0.10	0.9202		

Figure 16. Enlisted Seasonally Adjusted MA1 Model Summary and Parameter Estimates

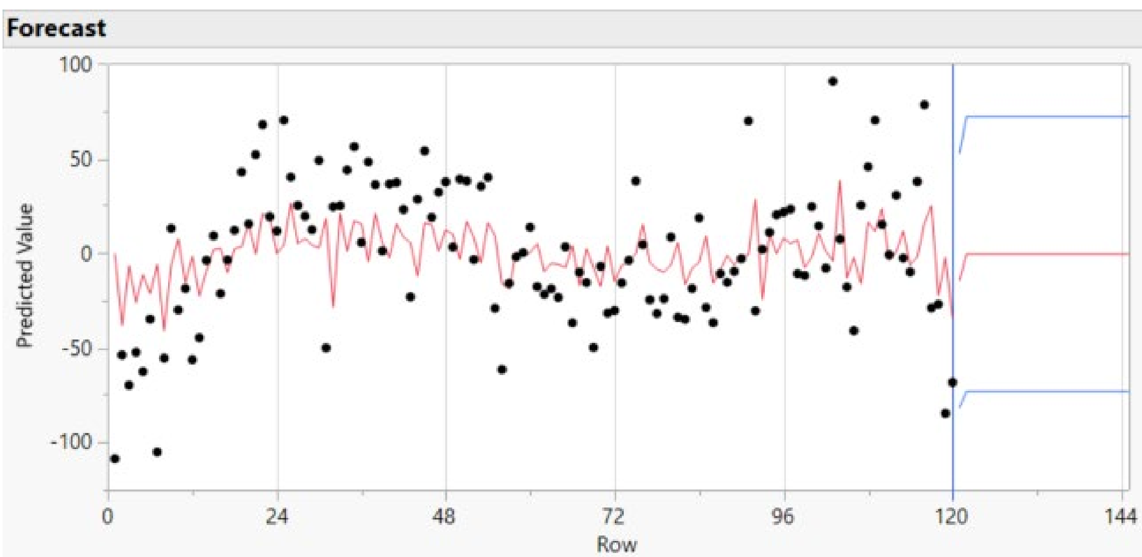
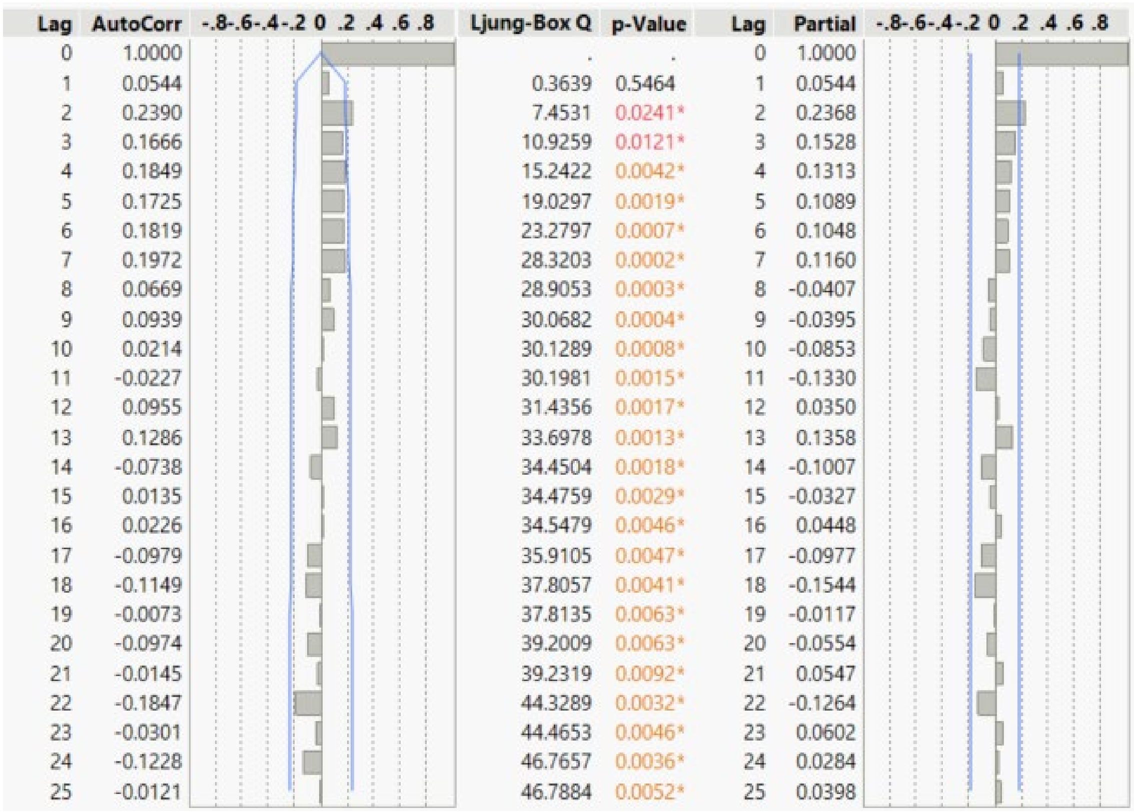


Figure 17. Enlisted Seasonally Adjusted MA1 Forecast



Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.0544	0.3639	0.5464	1	0.0544
2	0.2390	7.4531	0.0241*	2	0.2368
3	0.1666	10.9259	0.0121*	3	0.1528
4	0.1849	15.2422	0.0042*	4	0.1313
5	0.1725	19.0297	0.0019*	5	0.1089
6	0.1819	23.2797	0.0007*	6	0.1048
7	0.1972	28.3203	0.0002*	7	0.1160
8	0.0669	28.9053	0.0003*	8	-0.0407
9	0.0939	30.0682	0.0004*	9	-0.0395
10	0.0214	30.1289	0.0008*	10	-0.0853
11	-0.0227	30.1981	0.0015*	11	-0.1330
12	0.0955	31.4356	0.0017*	12	0.0350
13	0.1286	33.6978	0.0013*	13	0.1358
14	-0.0738	34.4504	0.0018*	14	-0.1007
15	0.0135	34.4759	0.0029*	15	-0.0327
16	0.0226	34.5479	0.0046*	16	0.0448
17	-0.0979	35.9105	0.0047*	17	-0.0977
18	-0.1149	37.8057	0.0041*	18	-0.1544
19	-0.0073	37.8135	0.0063*	19	-0.0117
20	-0.0974	39.2009	0.0063*	20	-0.0554
21	-0.0145	39.2319	0.0092*	21	0.0547
22	-0.1847	44.3289	0.0032*	22	-0.1264
23	-0.0301	44.4653	0.0046*	23	0.0602
24	-0.1228	46.7657	0.0036*	24	0.0284
25	-0.0121	46.7884	0.0052*	25	0.0398

Figure 18. Enlisted Seasonally Adjusted MA1 Correlogram—Test for Uncorrelated Residuals

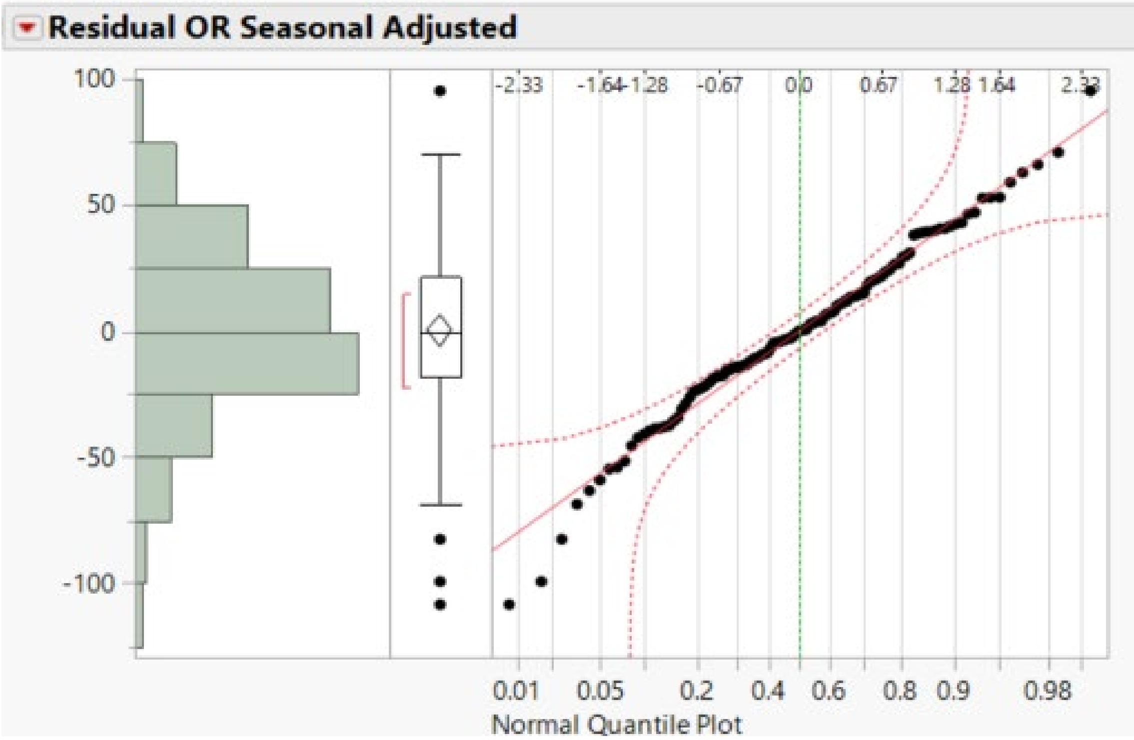


Figure 19. Enlisted Seasonally Adjusted MA1—Test for Normally Distributed Residuals

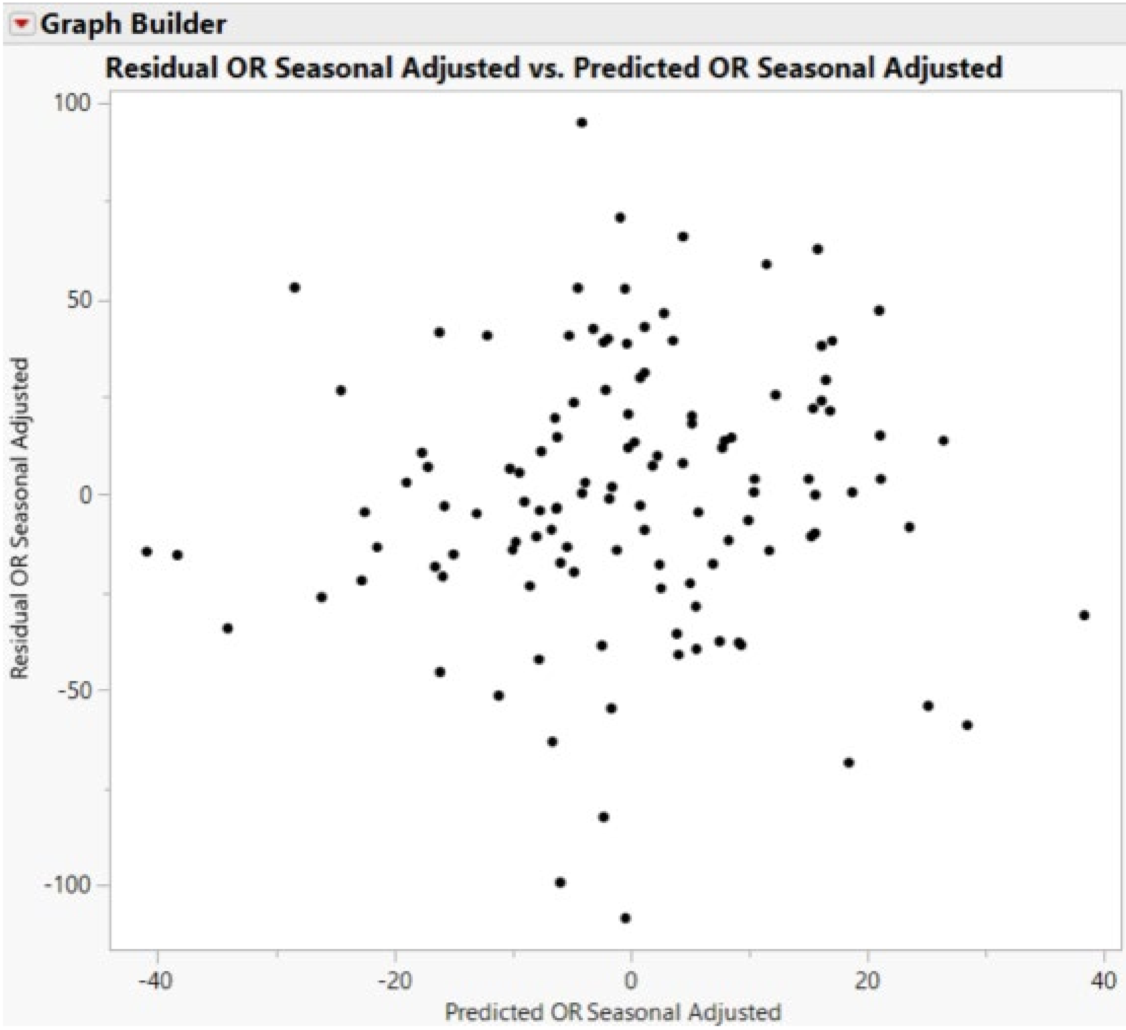


Figure 20. Enlisted Seasonally Adjusted MA1—Test for Constant Variance of Residuals

APPENDIX C. ENLISTED SEASONALLY ADJUSTED AR1

Model: AR(1)

Model Summary

DF	118	Stable	Yes
Sum of Squared Innovations	129471.621	Invertible	Yes
Sum of Squared Residuals	132409.266		
Variance Estimate	1097.21713		
Standard Deviation	33.124268		
Akaike's 'A' Information Criterion	1182.88738		
Schwarz's Bayesian Criterion	1188.46237		
RSquare	0.21728898		
RSquare Adj	0.21065584		
MAPE	146.884739		
MAE	25.8425464		
-2LogLikelihood	1178.88738		

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate	Mu
AR1	1	0.505516	0.083458	6.06	<.0001*	-0.7331437	-1.4826427
Intercept	0	-1.482643	5.973222	-0.25	0.8044		

Figure 21. Enlisted Seasonally Adjusted AR1 Model Summary and Parameter Estimates

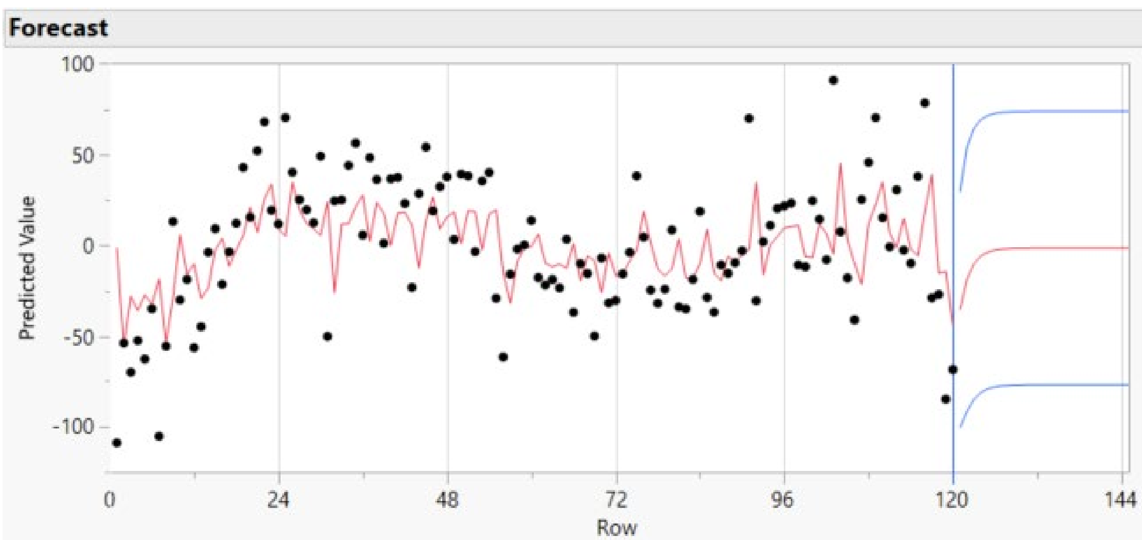


Figure 22. Enlisted Seasonally Adjusted AR 1 Forecast

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	-0.0931	1.0674	0.3015	1	-0.0931
2	0.0043	1.0697	0.5858	2	-0.0044
3	0.1058	2.4702	0.4807	3	0.1067
4	0.0999	3.7292	0.4439	4	0.1221
5	0.0736	4.4193	0.4908	5	0.0980
6	0.1067	5.8822	0.4365	6	0.1174
7	0.1438	8.5616	0.2857	7	0.1540
8	0.0086	8.5712	0.3797	8	0.0193
9	0.0567	8.9958	0.4377	9	0.0240
10	-0.0193	9.0454	0.5278	10	-0.0759
11	-0.0809	9.9252	0.5371	11	-0.1625
12	0.1044	11.4016	0.4948	12	0.0154
13	0.1379	14.0030	0.3736	13	0.1243
14	-0.1298	16.3285	0.2937	14	-0.1001
15	0.0154	16.3615	0.3584	15	-0.0027
16	0.0789	17.2376	0.3704	16	0.0714
17	-0.0935	18.4795	0.3592	17	-0.0623
18	-0.1166	20.4304	0.3091	18	-0.1386
19	0.0326	20.5843	0.3602	19	-0.0443
20	-0.0379	20.7948	0.4093	20	-0.0634
21	0.0101	20.8098	0.4706	21	0.0415
22	-0.1563	24.4583	0.3237	22	-0.1473
23	0.0046	24.4615	0.3786	23	0.0393
24	-0.0808	25.4578	0.3812	24	-0.0076
25	0.0313	25.6091	0.4287	25	0.0533

Figure 23. Enlisted Seasonally Adjusted AR1—Test for Uncorrelated Residuals

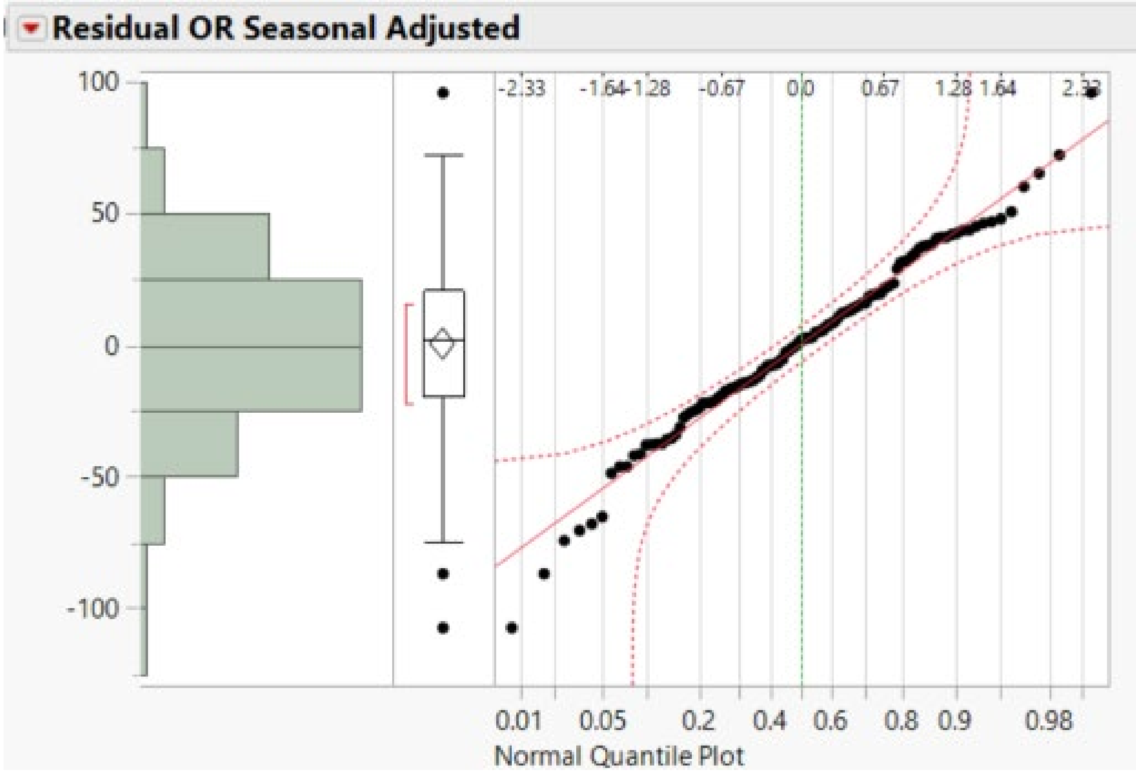


Figure 24. Enlisted Seasonally Adjusted AR1—Test for Normally Distributed Residuals

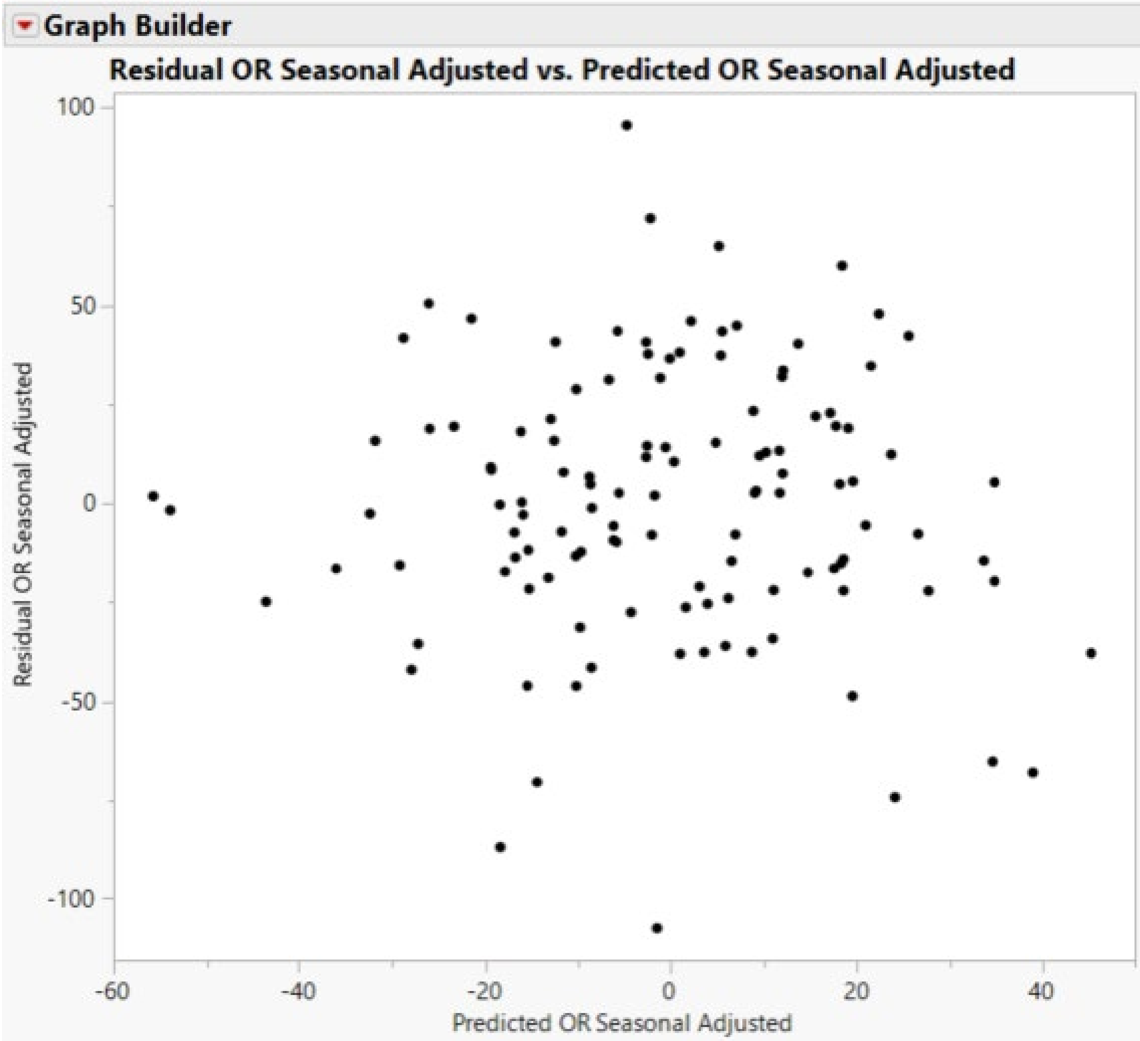


Figure 25. Enlisted Seasonally Adjusted AR1—Test for Constant Variance of Residuals

APPENDIX D. ENLISTED WINTER'S METHOD (ADDITIVE)

Model: Winters Method (Additive)

Model Summary

DF	104	Stable	Yes
Sum of Squared Innovations	134215.4	Invertible	Yes
Sum of Squared Residuals	140234.117		
Variance Estimate	1290.53269		
Standard Deviation	35.9239849		
Akaike's 'A' Information Criterion	1078.67826		
Schwarz's Bayesian Criterion	1086.69675		
RSquare	0.58491486		
RSquare Adj	0.57693246		
MAPE	12.1239409		
MAE	27.7045359		
-2LogLikelihood	1072.67826		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.16564038	0.0617956	2.68	0.0086*
Trend Smoothing Weight	0.12576426	0.0773828	1.63	0.1071
Seasonal Smoothing Weight	0.45284063	0.1117639	4.05	<.0001*

Figure 26. Enlisted Winter's Method (Additive) Model Summary and Parameter Estimates

Forecast

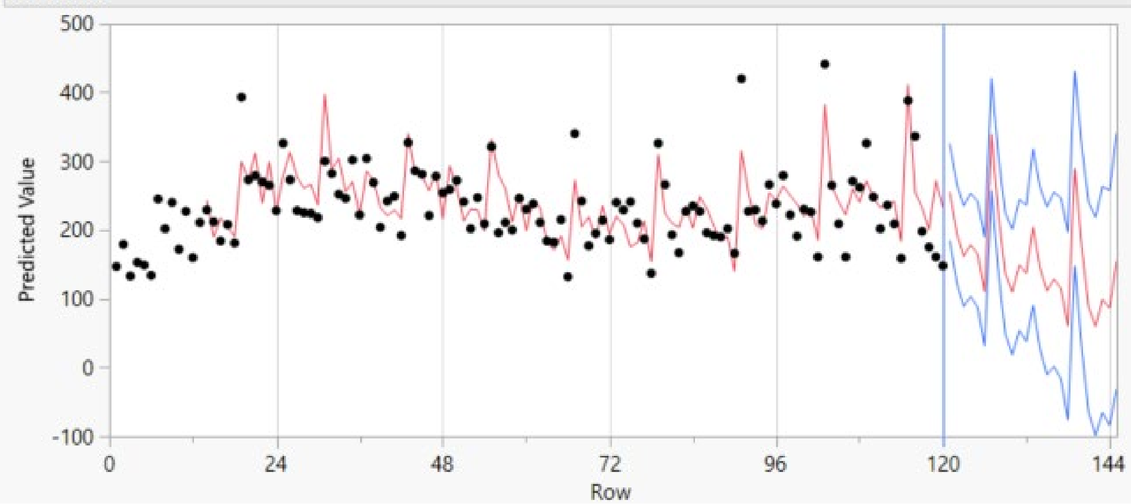


Figure 27. Enlisted Winter's Method (Additive) Forecast

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.1316	1.9053	0.1675	1	0.1316
2	-0.0265	1.9832	0.3710	2	-0.0446
3	-0.0154	2.0098	0.5704	3	-0.0060
4	-0.0659	2.5012	0.6444	4	-0.0654
5	0.0297	2.6017	0.7611	5	0.0478
6	0.0453	2.8382	0.8289	6	0.0307
7	0.0948	3.8867	0.7927	7	0.0886
8	-0.0611	4.3259	0.8266	8	-0.0903
9	-0.1038	5.6071	0.7785	9	-0.0741
10	-0.0678	6.1600	0.8016	10	-0.0476
11	-0.1747	9.8660	0.5425	11	-0.1626
12	-0.0273	9.9574	0.6197	12	-0.0055
13	0.1833	14.1267	0.3650	13	0.1755
14	-0.0229	14.1925	0.4355	14	-0.0792
15	0.0552	14.5791	0.4821	15	0.0910
16	0.0872	15.5541	0.4845	16	0.1014
17	-0.0397	15.7587	0.5410	17	-0.0421
18	-0.0311	15.8854	0.6005	18	-0.0220
19	-0.0034	15.8869	0.6648	19	-0.0243
20	0.0152	15.9177	0.7217	20	-0.0553
21	0.0086	15.9277	0.7737	21	0.0150
22	-0.0909	17.0611	0.7600	22	-0.1299
23	0.0470	17.3675	0.7908	23	0.0821
24	-0.0369	17.5585	0.8239	24	0.0353
25	0.1125	19.3579	0.7796	25	0.1519

Figure 28. Enlisted Winter's Method (Additive)—Test for Uncorrelated Residuals

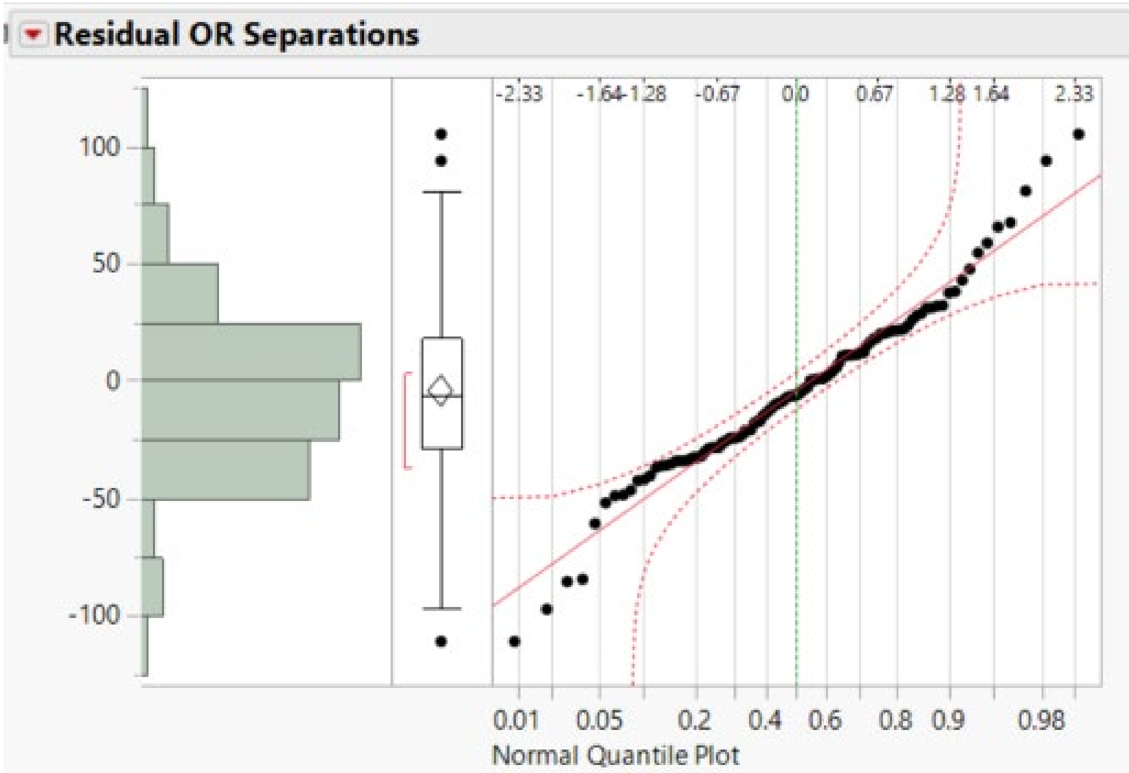


Figure 29. Enlisted Winter's Method (Additive)—Test for Normally Distributed Residuals

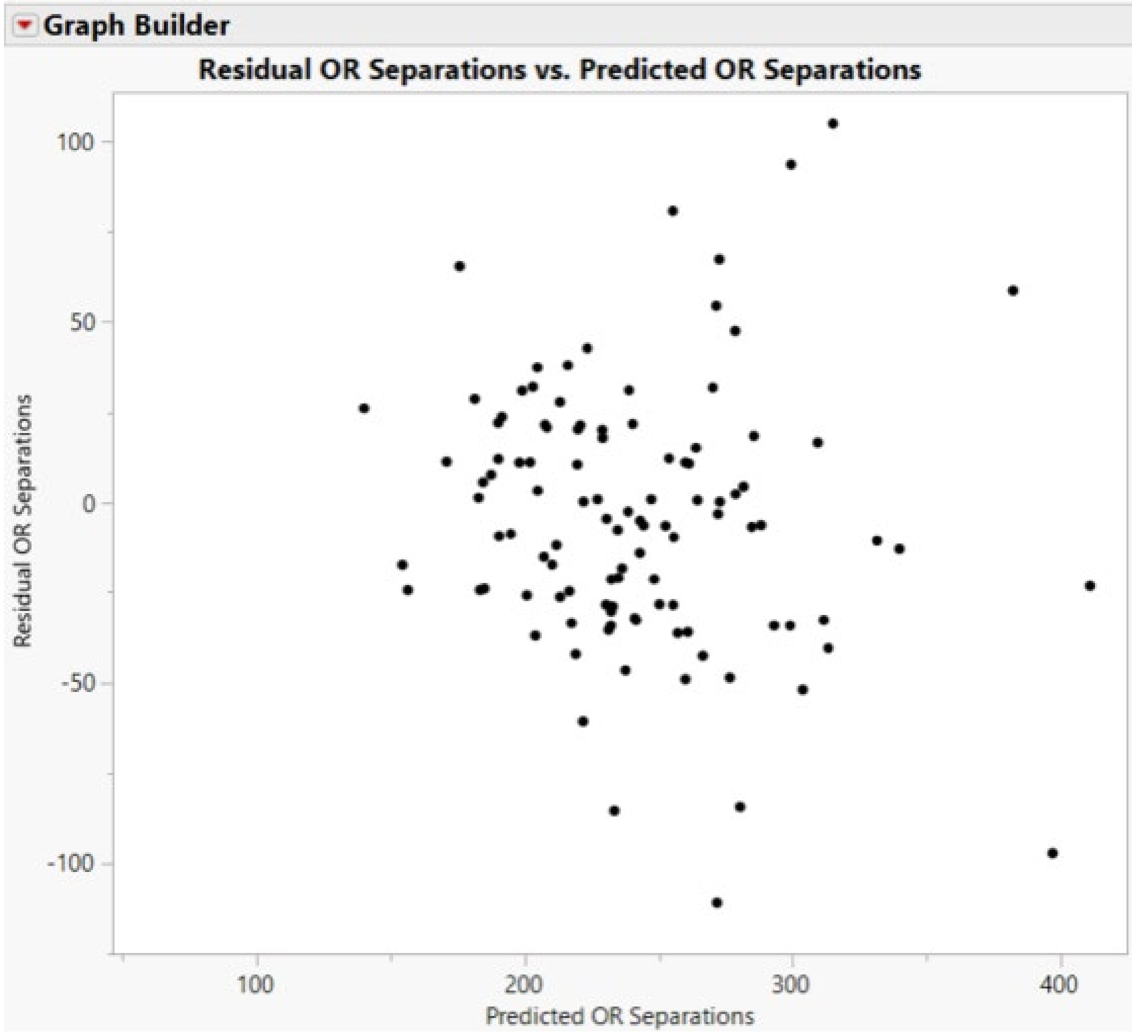


Figure 30. Enlisted Winter's Method (Additive)—Test for Constant Variance of Residuals

APPENDIX E. ENLISTED SEASONAL EXPONENTIAL SMOOTHING

Model: Seasonal Exponential Smoothing(12, Zero to One)

Model Summary

DF	105	Stable	Yes
Sum of Squared Innovations	134608.802	Invertible	No
Sum of Squared Residuals	143252.336		
Variance Estimate	1281.98859		
Standard Deviation	35.8048683		
Akaike's 'A' Information Criterion	1078.90515		
Schwarz's Bayesian Criterion	1084.25081		
RSquare	0.5759811		
RSquare Adj	0.57194283		
MAPE	12.4449064		
MAE	28.1919621		
-2LogLikelihood	1074.90515		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.21943450	0.0561704	3.91	0.0002*
Seasonal Smoothing Weight	0.51633227	0.1162797	4.44	<.0001*

Figure 31. Enlisted Seasonal Exponential Smoothing Model Summary and Parameter Estimates

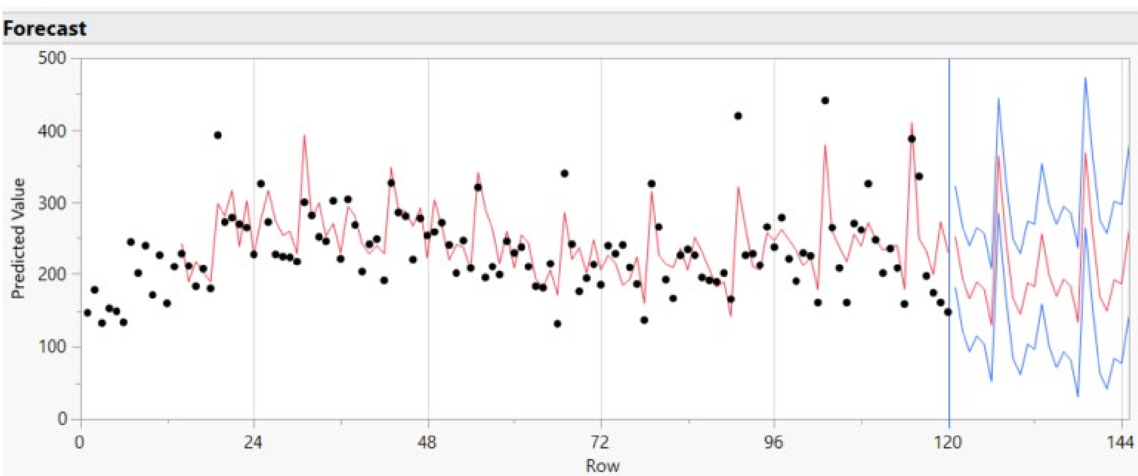


Figure 32. Enlisted Seasonal Exponential Smoothing Model Forecast

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.0635	0.4437	0.5053	1	0.0635
2	-0.0689	0.9709	0.6154	2	-0.0732
3	-0.0324	1.0887	0.7798	3	-0.0233
4	-0.0853	1.9133	0.7517	4	-0.0875
5	0.0240	1.9790	0.8520	5	0.0318
6	0.0488	2.2544	0.8949	6	0.0326
7	0.1123	[illegible].7249	0.8109	7	0.1089
8	-0.0422	[illegible]342	0.8630	8	-0.0583
9	-0.0823	4.7407	0.8563	9	-0.0551
10	-0.0227	4.8026	0.9040	10	-0.0119
11	-0.1579	7.8305	0.7284	11	-0.1558
12	-0.0299	7.9404	0.7898	12	-0.0320
13	0.2144	13.6460	0.3992	13	0.1904
14	-0.0235	13.7149	0.4712	14	-0.0695
15	0.0583	14.1461	0.5145	15	0.0899
16	0.0924	15.2414	0.5070	16	0.1139
17	-0.0517	15.5881	0.5532	17	-0.0302
18	-0.0444	15.8461	0.6033	18	-0.0194
19	-0.0148	15.8753	0.6656	19	-0.0199
20	0.0107	15.8907	0.7234	20	-0.0599
21	0.0005	15.8907	0.7758	21	0.0068
22	-0.1030	17.3464	0.7440	22	-0.1419
23	0.0501	17.6945	0.7738	23	0.0503
24	-0.0665	18.3150	0.7875	24	0.0031
25	0.1035	19.8381	0.7553	25	0.1483

Figure 33. Enlisted Seasonal Exponential Smoothing Model—Test for Uncorrelated Residuals

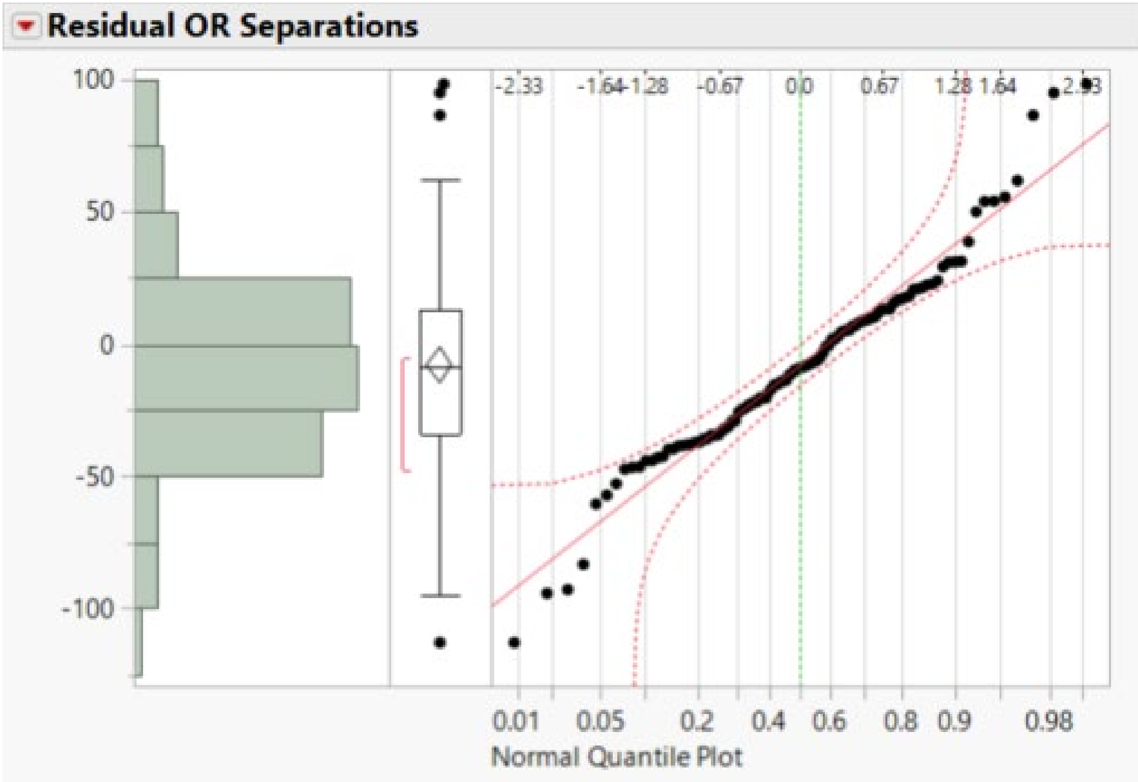


Figure 34. Enlisted Seasonal Exponential Smoothing Model—Test for Normally Distributed Residuals

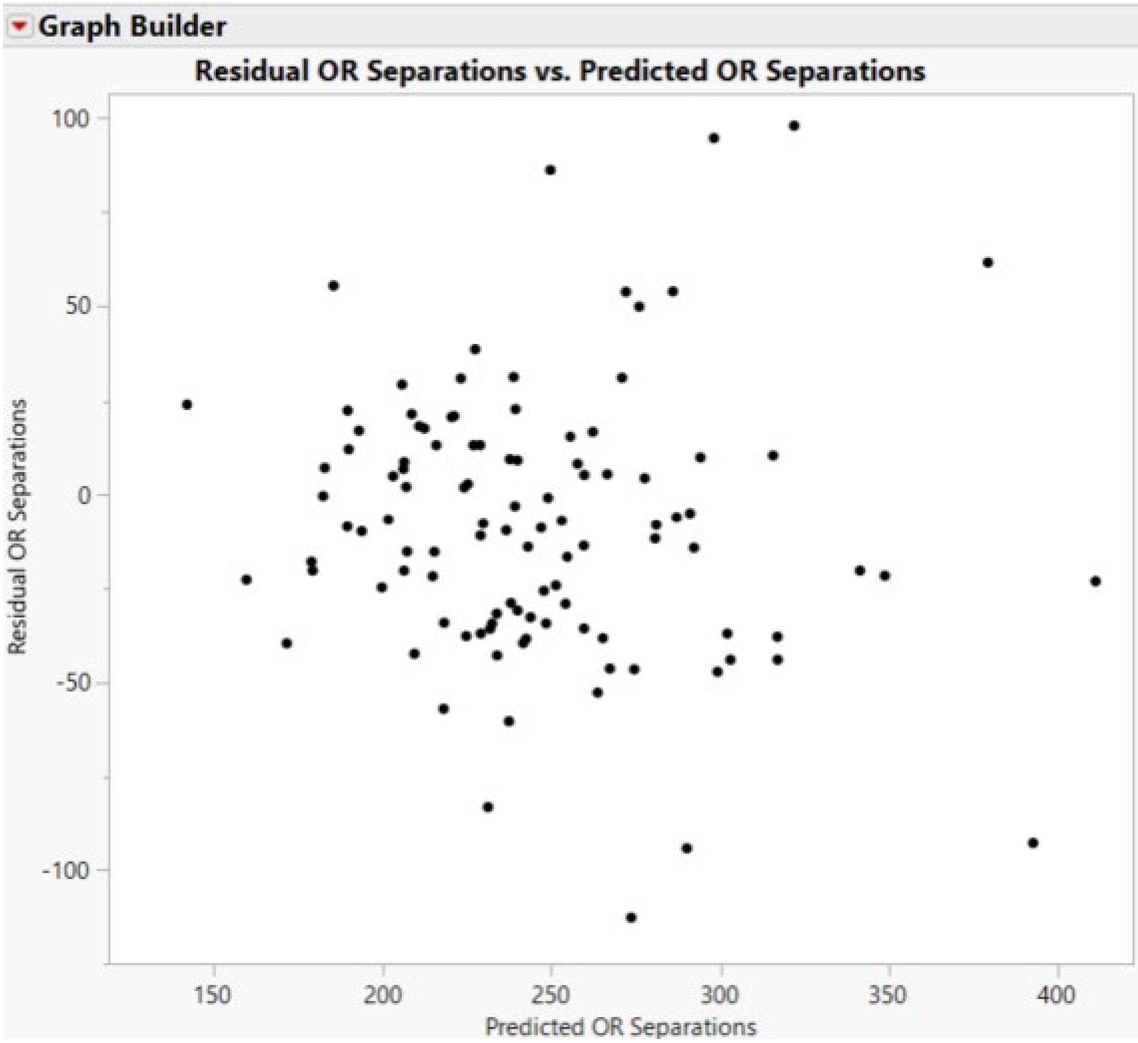


Figure 35. Enlisted Seasonal Exponential Smoothing Model—Test for Constant Variance of Residuals

APPENDIX F. OFFICERS' SEASONALLY ADJUSTED ARMA(1,1)

Model: ARMA(1, 1)

Model Summary

DF	117	Stable	Yes
Sum of Squared Innovations	5899.26133	Invertible	Yes
Sum of Squared Residuals	5902.78076		
Variance Estimate	50.421037		
Standard Deviation	7.10077721		
Akaike's 'A' Information Criterion	814.076344		
Schwarz's Bayesian Criterion	822.43882		
RSquare	0.0605006		
RSquare Adj	0.04444078		
MAPE	.		
MAE	5.49946579		
-2LogLikelihood	808.076344		

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate	Mu
AR1	1	0.8164862	0.139417	5.86	<.0001*	-0.0462347	-0.251941
MA1	1	0.6617732	0.174340	3.80	0.0002*		
Intercept	0	-0.2519410	1.157949	-0.22	0.8281		

Figure 36. Officers' Seasonally Adjusted ARMA(1,1) Model Summary and Parameter Estimates

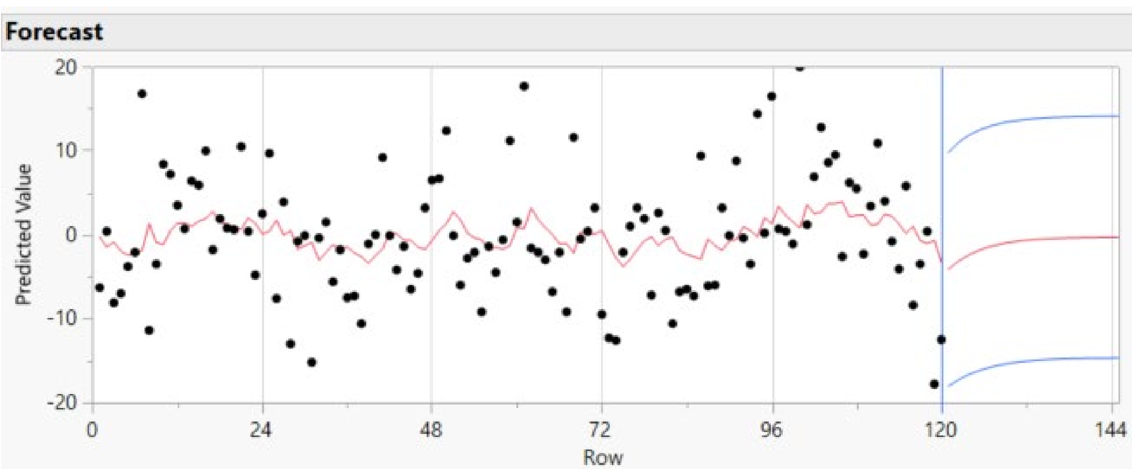


Figure 37. Officers' Seasonally Adjusted ARMA(1,1) Forecast

Lag	AutoCorr	-.8-.6-.4-.2 0 .2 .4 .6 .8	Ljung-Box Q	p-Value	Lag	Partial	-.8-.6-.4-.2 0 .2 .4 .6 .8
0	1.0000		.	.	0	1.0000	
1	-0.0250		0.0766	0.7819	1	-0.0250	
2	0.0372		0.2485	0.8831	2	0.0366	
3	0.0561		0.6423	0.8867	3	0.0580	
4	-0.1156		2.3294	0.6754	4	-0.1147	
5	0.0479		2.6212	0.7581	5	0.0390	
6	-0.0954		3.7896	0.7051	6	-0.0896	
7	0.0151		3.8190	0.8004	7	0.0224	
8	0.0892		4.8585	0.7726	8	0.0804	
9	0.1694		8.6449	0.4707	9	0.1971	
10	0.0670		9.2419	0.5093	10	0.0471	
11	0.0710		9.9193	0.5377	11	0.0688	
12	-0.1159		11.7412	0.4667	12	-0.1414	
13	-0.2048		17.4802	0.1783	13	-0.2094	
14	0.0286		17.5935	0.2259	14	0.0192	
15	-0.0563		18.0360	0.2608	15	0.0233	
16	-0.1344		20.5777	0.1953	16	-0.1525	
17	-0.0556		21.0168	0.2255	17	-0.1296	
18	0.0483		21.3520	0.2620	18	0.0122	
19	-0.0217		21.4203	0.3141	19	-0.0793	
20	0.0187		21.4717	0.3699	20	0.0074	
21	-0.0827		22.4822	0.3722	21	-0.0135	
22	-0.1071		24.1944	0.3371	22	-0.0473	
23	-0.1184		26.3089	0.2865	23	-0.1384	
24	-0.1879		31.6935	0.1348	24	-0.1605	
25	-0.0230		31.7753	0.1646	25	-0.0489	

Figure 38. Officer’s Seasonally Adjusted ARMA(1,1)—Test for Uncorrelated Residuals

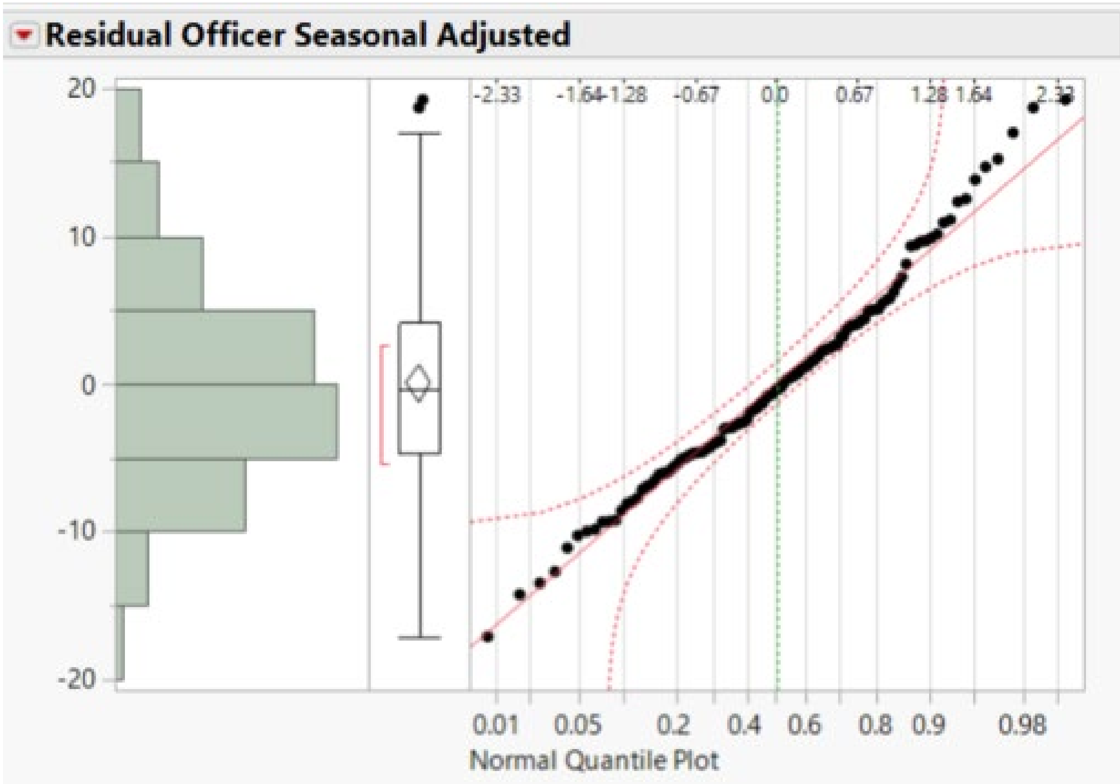


Figure 39. Officers' Seasonally Adjusted ARMA(1,1)—Test for Normally Distributed Residuals

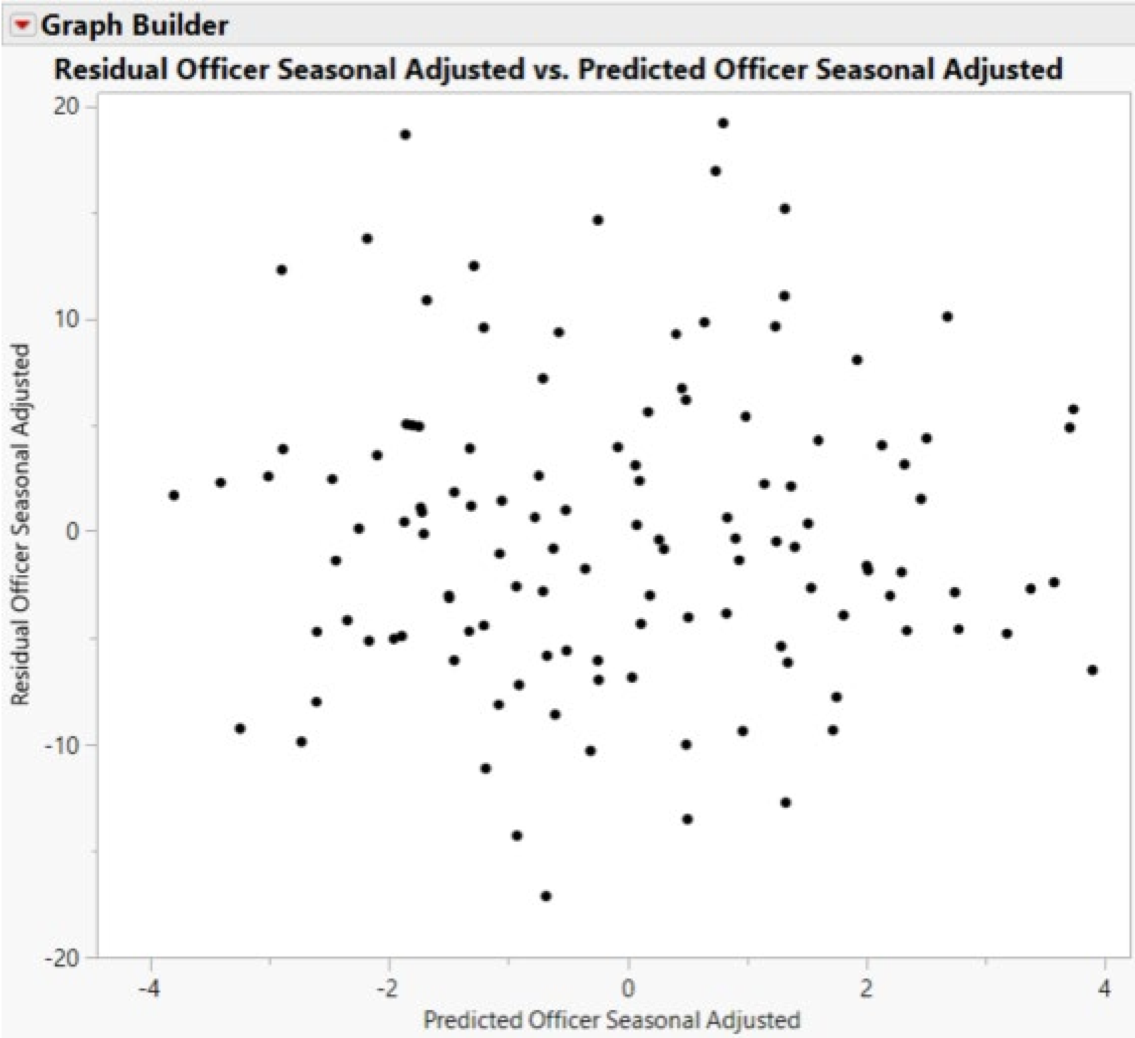


Figure 40. Officers' Seasonally Adjusted ARMA(1,1)—Test for Constant Variance of Residuals

APPENDIX G. OFFICERS' WINTER'S METHOD (ADDITIVE)

Model: Winters Method (Additive)

Model Summary

DF	104	Stable	Yes
Sum of Squared Innovations	6608.10637	Invertible	Yes
Sum of Squared Residuals	8267.56818		
Variance Estimate	63.5394844		
Standard Deviation	7.97116581		
Akaike's 'A' Information Criterion	772.484085		
Schwarz's Bayesian Criterion	780.502572		
RSquare	0.72866947		
RSquare Adj	0.72345157		
MAPE	21.7278477		
MAE	7.00295224		
-2LogLikelihood	766.484085		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.20336958	0.0693267	2.93	0.0041*
Trend Smoothing Weight	0.00181345	0.0266359	0.07	0.9459
Seasonal Smoothing Weight	0.09074212	0.1661155	0.55	0.5861

Figure 41. Officer's Winter's Method (Additive) Model Summary and Parameter Estimates

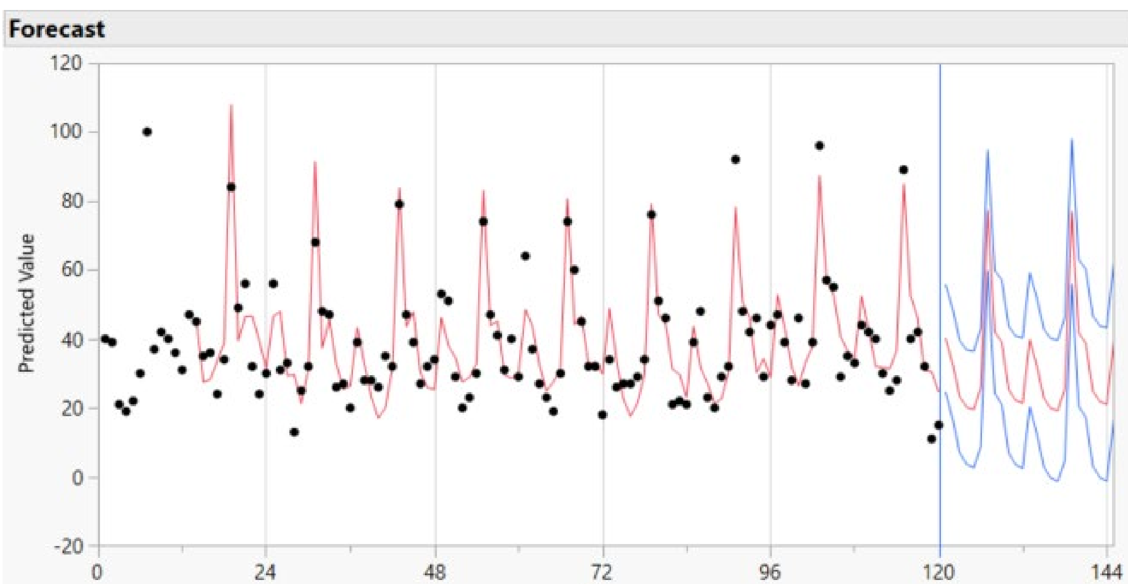
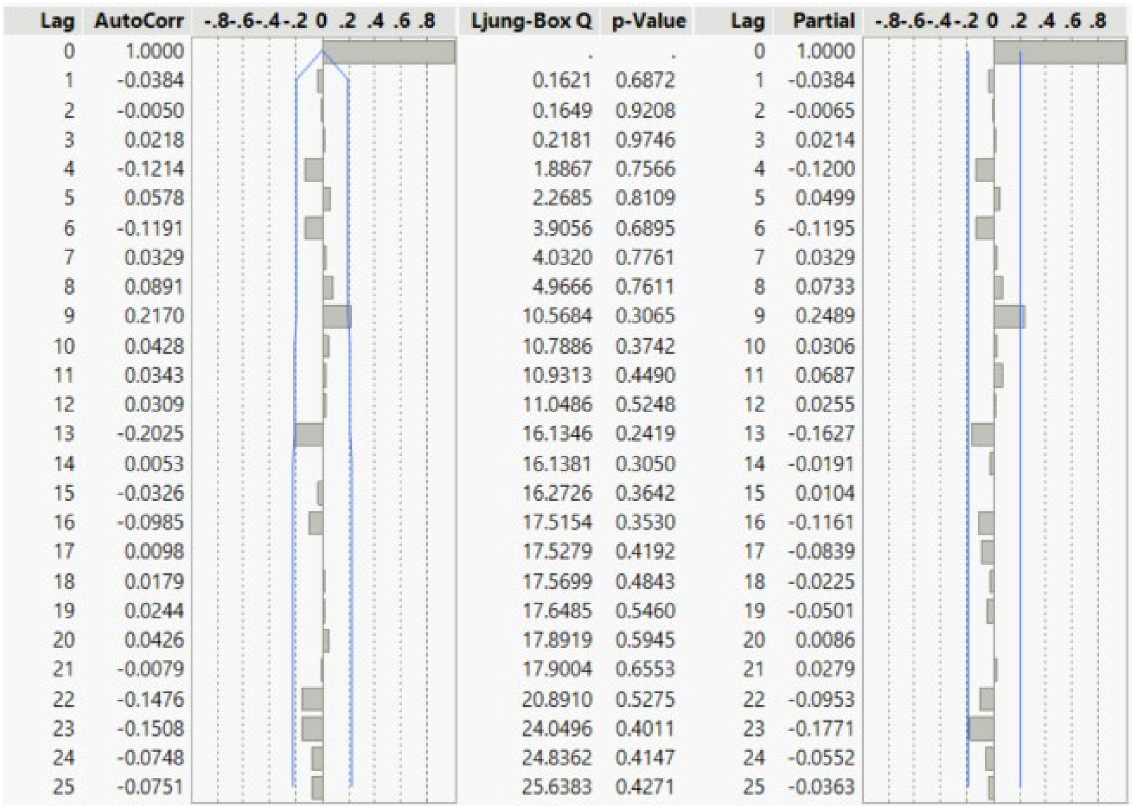


Figure 42. Officers' Winter's Method (Additive) Model Summary and Parameter Estimates



Lag	AutoCorr	-.8-.6-.4-.2 0 .2 .4 .6 .8	Ljung-Box Q	p-Value	Lag	Partial	-.8-.6-.4-.2 0 .2 .4 .6 .8
0	1.0000		.	.	0	1.0000	
1	-0.0384		0.1621	0.6872	1	-0.0384	
2	-0.0050		0.1649	0.9208	2	-0.0065	
3	0.0218		0.2181	0.9746	3	0.0214	
4	-0.1214		1.8867	0.7566	4	-0.1200	
5	0.0578		2.2685	0.8109	5	0.0499	
6	-0.1191		3.9056	0.6895	6	-0.1195	
7	0.0329		4.0320	0.7761	7	0.0329	
8	0.0891		4.9666	0.7611	8	0.0733	
9	0.2170		10.5684	0.3065	9	0.2489	
10	0.0428		10.7886	0.3742	10	0.0306	
11	0.0343		10.9313	0.4490	11	0.0687	
12	0.0309		11.0486	0.5248	12	0.0255	
13	-0.2025		16.1346	0.2419	13	-0.1627	
14	0.0053		16.1381	0.3050	14	-0.0191	
15	-0.0326		16.2726	0.3642	15	0.0104	
16	-0.0985		17.5154	0.3530	16	-0.1161	
17	0.0098		17.5279	0.4192	17	-0.0839	
18	0.0179		17.5699	0.4843	18	-0.0225	
19	0.0244		17.6485	0.5460	19	-0.0501	
20	0.0426		17.8919	0.5945	20	0.0086	
21	-0.0079		17.9004	0.6553	21	0.0279	
22	-0.1476		20.8910	0.5275	22	-0.0953	
23	-0.1508		24.0496	0.4011	23	-0.1771	
24	-0.0748		24.8362	0.4147	24	-0.0552	
25	-0.0751		25.6383	0.4271	25	-0.0363	

Figure 43. Officer's Winter's Method (Additive)—Test for Uncorrelated Residuals

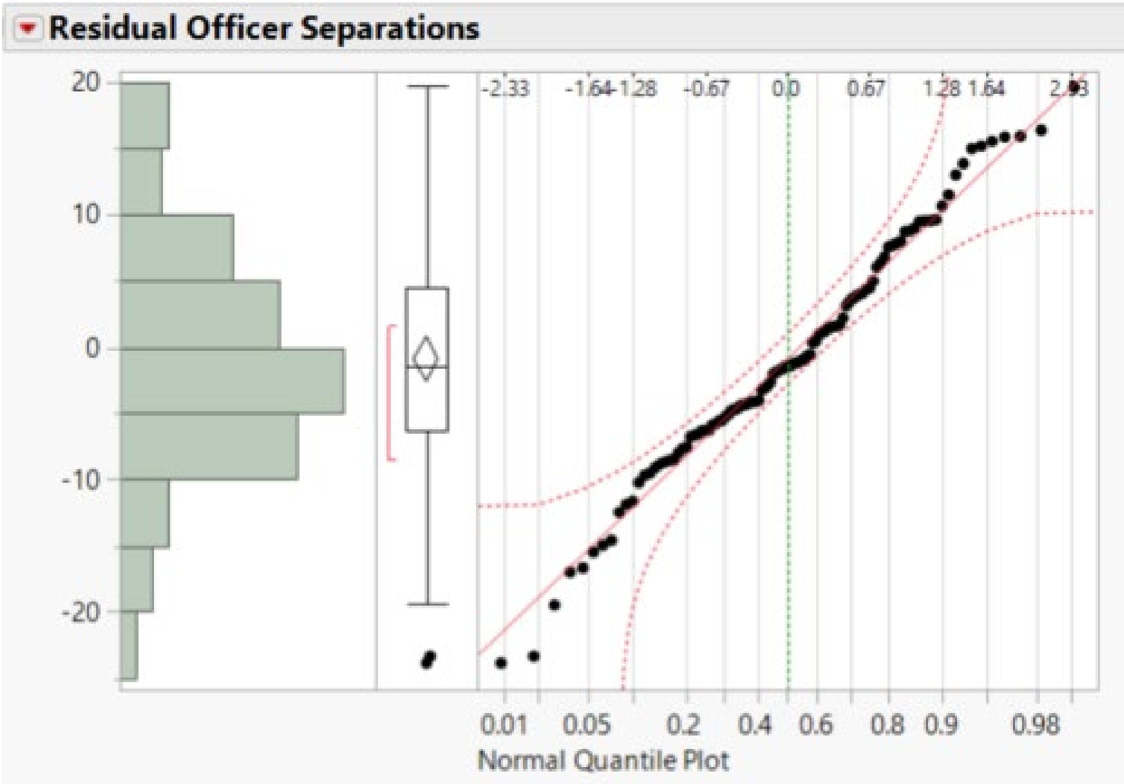


Figure 44. Officers' Winters' Method (Additive)—Test for Normally Distributed Residuals

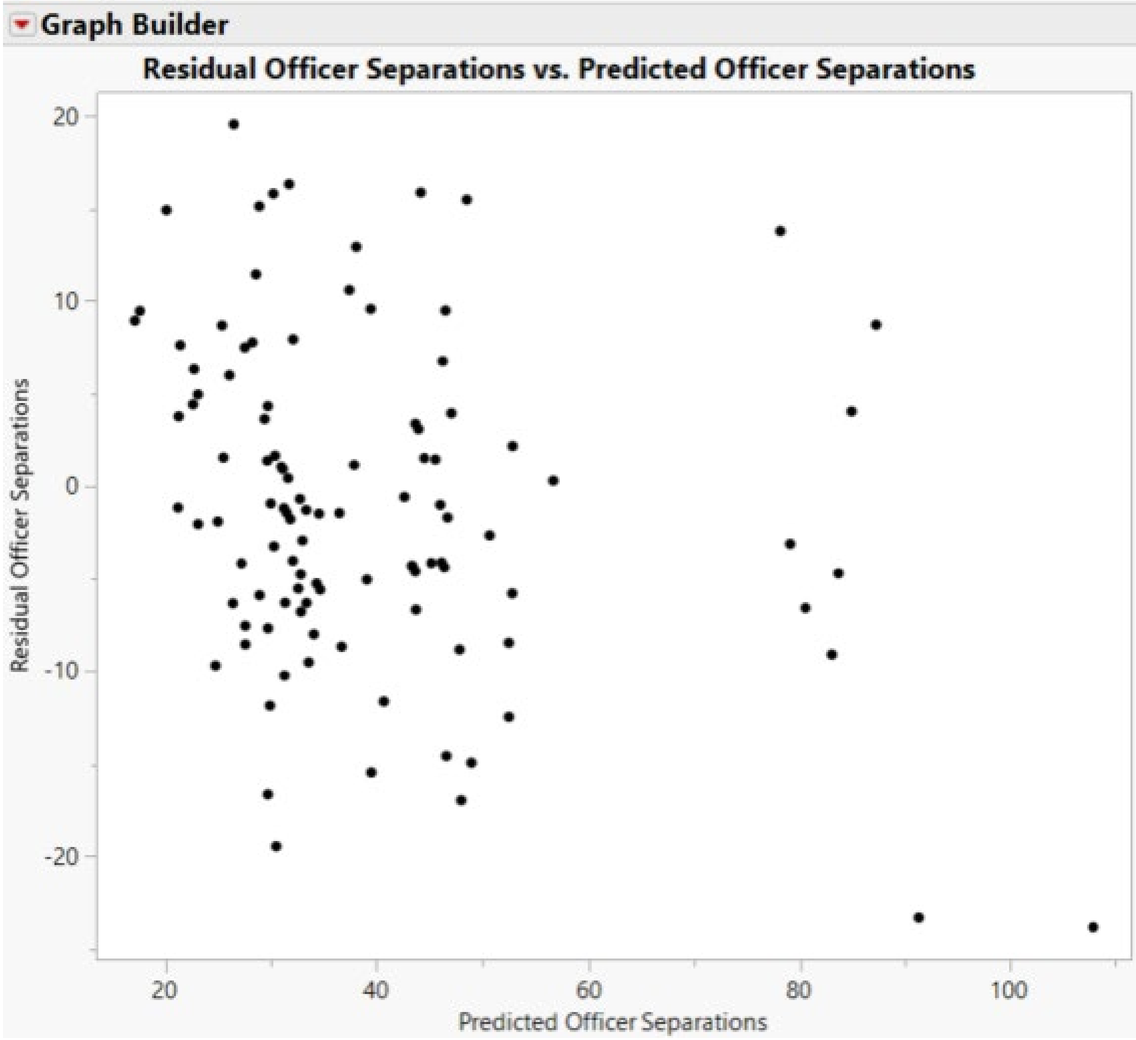


Figure 45. Officer's Winter's Method (Additive)—Test for Constant Variance of Residuals

APPENDIX H. OFFICERS' SEASONAL EXPONENTIAL SMOOTHING

Model: Seasonal Exponential Smoothing(12, Zero to One)

Model Summary

DF	105	Stable	Yes
Sum of Squared Innovations	6594.62526	Invertible	No
Sum of Squared Residuals	8267.7377		
Variance Estimate	62.8059549		
Standard Deviation	7.92502081		
Akaike's 'A' Information Criterion	770.486051		
Schwarz's Bayesian Criterion	775.831709		
RSquare	0.7286639		
RSquare Adj	0.72607975		
MAPE	21.7270781		
MAE	7.00273517		
-2LogLikelihood	766.486051		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.20206227	0.0668207	3.02	0.0031*
Seasonal Smoothing Weight	0.09007308	0.1676620	0.54	0.5922

Figure 46. Officers' Seasonal Exponential Smoothing Model Summary and Parameter Estimates

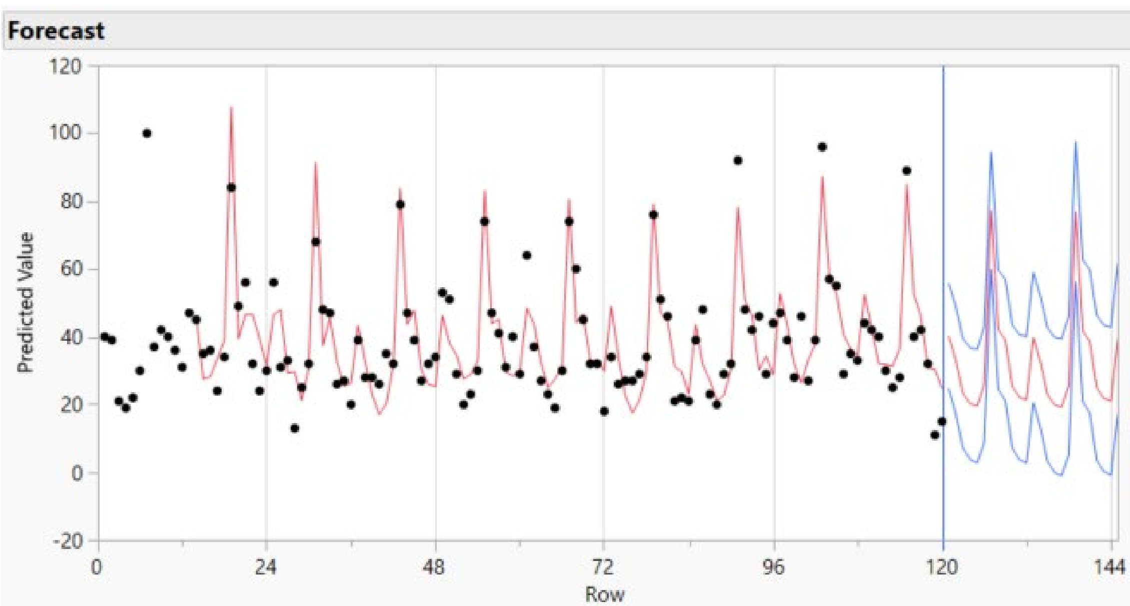


Figure 47. Officers' Seasonal Exponential Smoothing Model Forecast

Acquisition Research Program
Department of Defense Management
Naval Postgraduate School

Lag	AutoCorr	-.8-.6-.4-.2 0 .2 .4 .6 .8	Ljung-Box Q	p-Value	Lag	Partial	-.8-.6-.4-.2 0 .2 .4 .6 .8
0	1.0000		.	.	0	1.0000	
1	-0.0384		0.1619	0.6874	1	-0.0384	
2	-0.0050		0.1647	0.9209	2	-0.0065	
3	0.0218		0.2180	0.9746	3	0.0214	
4	-0.1214		1.8861	0.7567	4	-0.1200	
5	0.0578		2.2676	0.8110	5	0.0498	
6	-0.1191		3.9049	0.6895	6	-0.1195	
7	0.0329		4.0313	0.7762	7	0.0329	
8	0.0891		4.9663	0.7612	8	0.0733	
9	0.2170		10.5695	0.3064	9	0.2489	
10	0.0428		10.7900	0.3741	10	0.0307	
11	0.0343		10.9329	0.4489	11	0.0687	
12	0.0310		11.0508	0.5246	12	0.0256	
13	-0.2025		16.1408	0.2416	13	-0.1628	
14	0.0052		16.1443	0.3046	14	-0.0191	
15	-0.0326		16.2790	0.3638	15	0.0103	
16	-0.0985		17.5226	0.3526	16	-0.1161	
17	0.0098		17.5351	0.4187	17	-0.0839	
18	0.0179		17.5769	0.4838	18	-0.0226	
19	0.0244		17.6556	0.5455	19	-0.0501	
20	0.0426		17.8992	0.5940	20	0.0086	
21	-0.0079		17.9077	0.6548	21	0.0278	
22	-0.1477		20.8992	0.5270	22	-0.0952	
23	-0.1508		24.0573	0.4006	23	-0.1770	
24	-0.0748		24.8436	0.4143	24	-0.0552	
25	-0.0752		25.6471	0.4266	25	-0.0363	

Figure 48. Officers' Seasonal Exponential Smoothing Model—Test for Uncorrelated Residuals

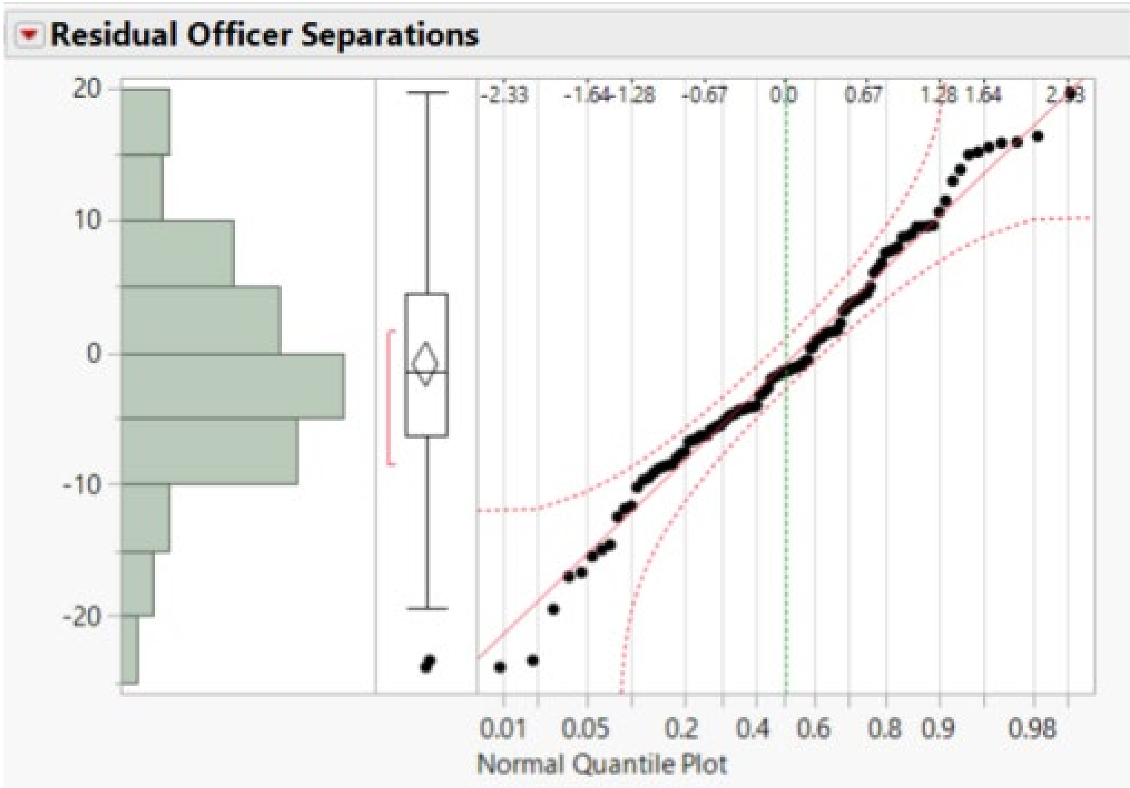


Figure 49. Officers' Seasonal Exponential Smoothing Model—Test for Normally Distributed Residuals

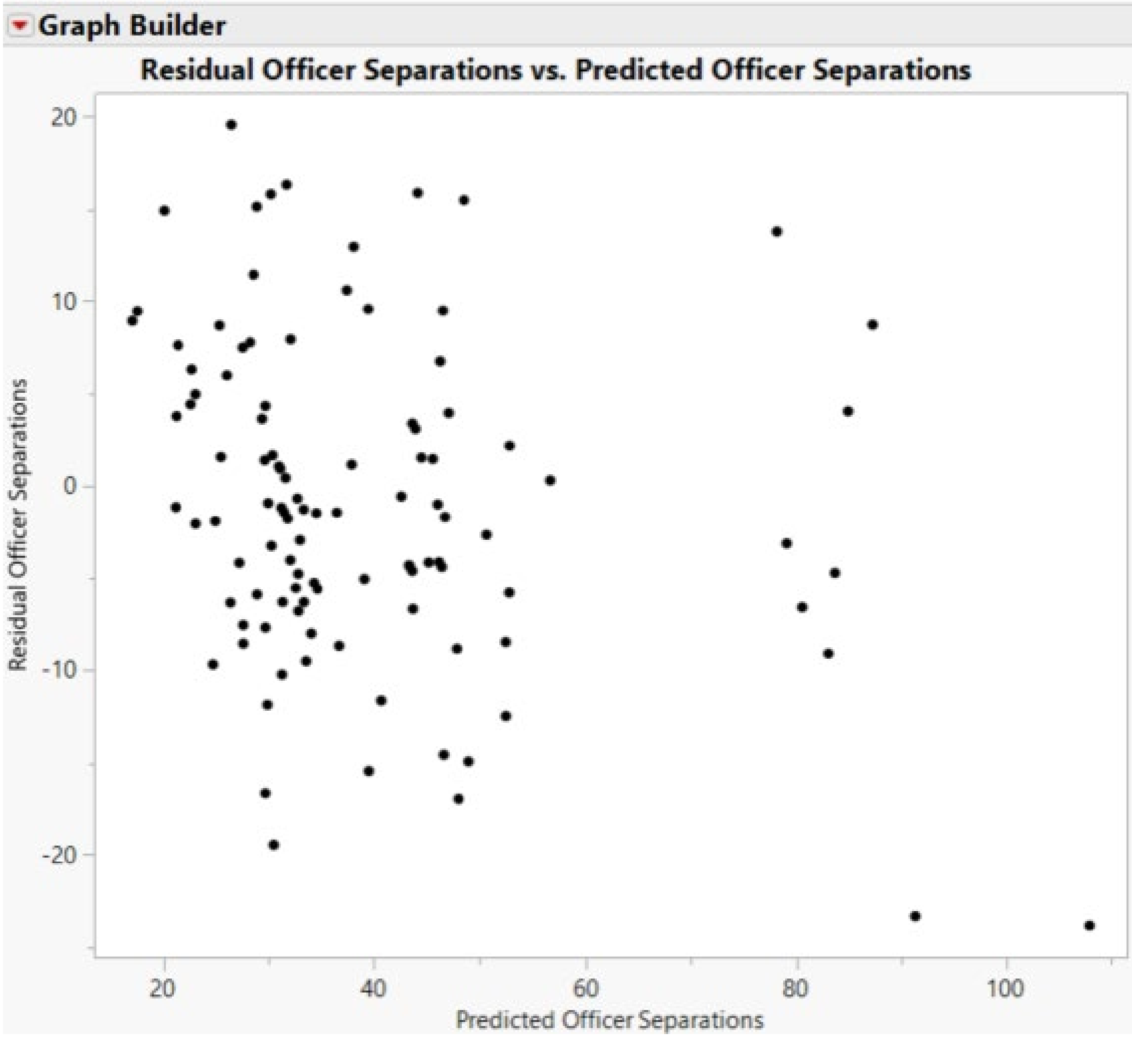


Figure 50. Officers’ Seasonal Exponential Smoothing Model—Test for Constant Variance of Residuals

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