2013

Eliminating The Shortage Factor: Modeling The Behavior Of Future Donations Using Forecasting Techniques To Improve The Distribution Efficacy Of A Food Bank

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Eliminating the Shortage Factor:

Modeling the Behavior of Future Donations using Forecasting Techniques to Improve the Distribution Efficacy of a Food Bank

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A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Department: Industrial & Systems Engineering

Major: Industrial & Systems Engineering

Major Professor: Dr. Lauren B. Davis

Greensboro, North Carolina

2013

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School of Graduate Studies
North Carolina Agricultural and Technical State University
This is to certify that the Master's Thesis of

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has met the thesis requirements of
North Carolina Agricultural and Technical State University

Greensboro, North Carolina
2013

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Biographical Sketch

Jessica Rena Terry, born the 9th day of January, graduated Summa Cum Laude from Bennett College for Women in May 2010 with a Bachelor of Science in Mathematics. Ms. Terry is currently a candidate for a Master of Science in Industrial and Systems Engineering. Upon graduation, she plans to pursue a career in Operations Management. After which, she will begin working towards her first doctoral degree at the institution of her choice.

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Dedication

I would like to dedicate this research to God, my immediate family, Gloria, Daniel, Deborah, Christina, Christopher, Brian, and James Terry, the Whorley and Sanford family, and my fiancé Richard Ray Jones Jr. I am forever grateful to each of you for all of the love, support, and prayers. I thank you for all that you have done and appreciate us celebrating this accomplishment together.

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Acknowledgements

I would like to acknowledge the National Science Foundation Graduate Research Fellowship under Grant No. 1000018 for making this research possible.

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Abstract

Food insecurity is defined as the inability to provide food for oneself. As of 2011, more than 14.9% of American households suffered from food insecurity. Many individuals suffering from food insecurity obtain assistance from governmental programs and nonprofit agencies. Food Banks are one of many non-profit organizations assisting in the fight against hunger. They serve communities by distributing food to those in need through charitable agencies. Many of the food distributed by the food bank come from donations. These donations are received from various sources in uncertain quantities at random points in time. Due to this variability, predicting the quantity of future donations is challenging which can negatively impact their ability to properly allocate food. This research utilizes several forecasting techniques to predict future donations. In particular, the effectiveness of moving average, simple exponential smoothing, Holt's and Winter's methods, and Autoregressive Integrated Moving Average (ARIMA) are applied to historical data that is segmented by donation source, type, storage, receiving branch and a combination of variables. The results show that the appropriate technique is largely dependent upon the level analyzed. The resulting forecast is then used in a Supply Level Management Assessment (SLMA) to project equitable distribution. The tool is designed to be easy to manipulate and its applications can be used for all food banks.

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CHAPTER 1

Introduction

1.1 Food Insecurity

Proper nutrition is an essential part of living a healthy lifestyle. However, millions of Americans are unable to provide the proper meals for themselves every day. Whenever the availability of nutritionally adequate and safe foods or the ability to obtain acceptable food in socially conventional means is limited or uncertain for an individual, they are considered food insecure (Haering and Syed, 2009). In 2011, 14.9% of the U.S. population (approximately 17.9 million) households were food insecure. This was an increase of 4% from the prior year (Coleman-Jensen , 2011).

The prevalence of food insecurity can also be viewed at a state level. The number of food insecure households in North Carolina is well above the national percentage at 17.1%. Furthermore, North Carolina has one of the highest percentages of children at risk of hunger in the nation. In 2010, the number of children suffering from food insecurity in North Carolina was 27.6%. Even though hunger negatively affects people of all ages, the effects are more severe for children. They may have a reduction in motor skills, feel isolated and ashamed, and ultimately suffer from chronic health and stressful life conditions (APA, 2012). Fortunately there exists organizations that are actively fighting to end the war against hunger.

1.2 Government Assistance

The United States government has established several public assistance programs for children, low-income adults, and the elderly. One in four Americans participates in at least one of the nation's food assistance programs every year. Three of the most heavily participated

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programs include the Supplemental Nutrition Assistance Program (SNAP), Women, Infants, and Children (WIC) and the Emergency Food Assistance Program (TEFAP).

SNAP, originally established as the Food Stamp Program, has been serving the American population for almost 50 years. SNAP mitigates hunger and enables low-income individuals to purchase nutritious foods for their households. In fiscal year 2011, nearly 45 million Americans, (one in seven), received SNAP benefits which is an increase of 10.9% over the prior year. SNAP is able to quickly adjust to the changes in the economy making it one of the most effective safety net food programs.

WIC is a supplemental food program that provides support to low-income pregnant, postpartum, and breastfeeding women, infants and children under the age of five. Most WIC participants receive a voucher that can be used at one of the 46,000 merchants nationwide. The average monthly participation in the program has been increasing since its implementation in 1974. A total of 40 million women and children received WIC benefits last year in 2011.

TEFAP is a food purchasing and distribution program that is administered at the State level. The eligibility for TEFAP is directly related to the income of the applicant. This program is designed to accommodate short-term, “emergency” food distress. The commodity foods are provided by the U.S. Department of Agriculture and the State deliveries the food to local agencies such as food banks and church pantries. Although food insecurity is an issue that is completely preventable, there are certain conditions that increase one’s likelihood of being affected.

1.3 Poverty and Unemployment

Studies have shown that unemployment and poverty can be strong indicators of those at risk of becoming food insecure. High levels of poverty and unemployment increase the hardships

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of hunger and food insecurity. Barrett (2010) mentions most food insecurity is associated with chronic poverty and temporary unemployment. Figure 1 illustrates the unemployment, poverty, and household food insecurity ratings between the United States and North Carolina. Not only are unemployment and poverty in the state of North Carolina above the national average, the household food insecurity percentage is as well. This emphasizes that unemployment and poverty are correlated to food insecurity and highlights the fact that residents of North Carolina are more at risk of living in a food insecure household. Many of these individuals seek assistance from emergency food programs such as food banks. Tarasuk and Beaton (1999) reported that the number of times a family obtained assistance from an emergency food program in twelve months ranged from 2-72 times. Most of the emergency food organizations providing assistance are overseen by Feeding America.

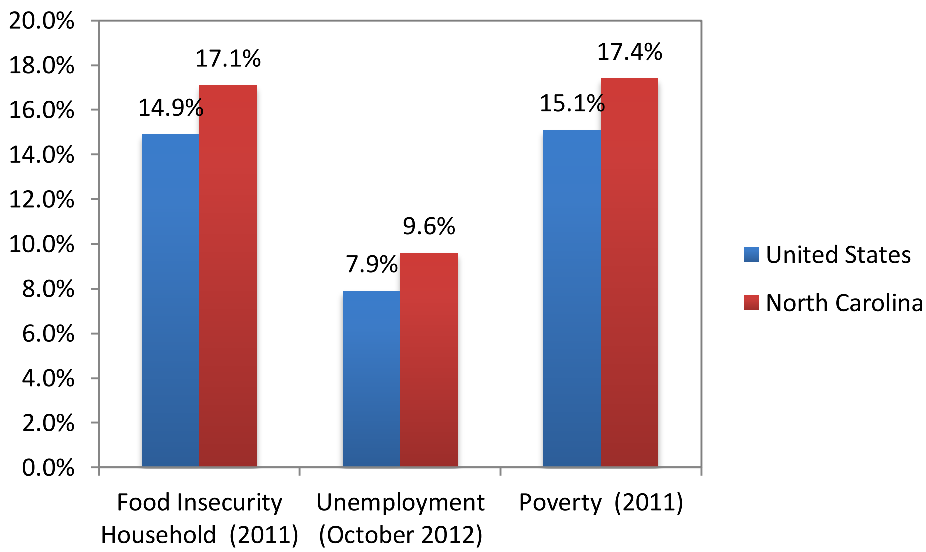

Figure 1. U.S. and North Carolina Comparison of Relevant Statistics.

1.4 Feeding America

Feeding America, formerly known as America's Second Harvest, is the nation's largest hunger-relief charity engaged in the fight to end hunger. Its mission is to feed hungry American's

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through a network of associated food banks. The Feeding America organization assists local food banks in securing and distributing food, raising funds and acquiring more donors, sharing best practices amongst food banks and other agencies, as well as advocating and inspiring individuals and the government to take action in ending hunger. Over 200 food banks under the Feeding America network are serving counties across the country and are supplying food to over 37 million Americans. North Carolina has several food banks that are a part of the Feeding America network.

1.4.1 North carolina association of feeding america food banks. The North Carolina Association of Feeding America Food Banks consists of six food banks and one food shuttle organization: The Food Bank of Albemarle, Food Bank of Central and Eastern North Carolina, Manna Food Bank, Second Harvest Food Bank of Metrolina, Second Harvest Food Bank of Northwest North Carolina, Second Harvest Food Bank of Southeast North Carolina, and the Inter-Faith Food Shuttle. Figure 2 identifies the counties served by each of the six food banks located in North Carolina. The food banks of North Carolina communicate public awareness about hunger issues, initiate fundraising events to collect donations, as well as distribute such food donations statewide.

In 2011, the North Carolina Food Banks distributed over 121 million pounds of food to 10 million North Carolinians in need. The North Carolina Association of Feeding America Food Banks work in all 100 counties in the state and have nearly 2,700 partner agencies. These agencies include church pantries, soup kitchens, shelters for the homeless and abused, child care facilities and programs, and senior meal programs. Practically 170,000 individuals receive assistance from one of those partner agencies every week. The utilization of food banks has been steadily increasing since the early 1980s (Tarasuk & Beaton, 1999). The food bank that is

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the focus of this study is the Food Bank of Central and Eastern North Carolina which serves the largest population in the state.

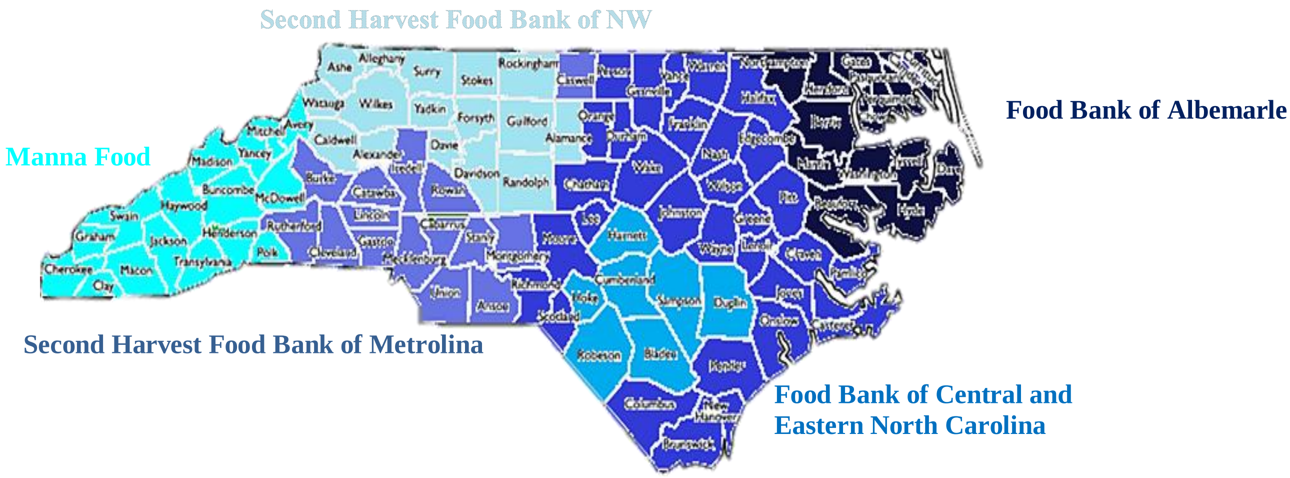

Figure 2. A Map of the Counties Served by Each of the Six Food Banks from www.nc.foodbanks.org

1.4.2 The food bank of central and eastern north carolina. The Food Bank of Central and Eastern North Carolina (FBCENC) serves 34 of the 100 counties in North Carolina and is the largest food bank in the area. The FBCENC is comprised of six branches located in the Wilmington, Durham, Raleigh, Sandhills, Greenville, and New Bern areas. The New Bern branch was recently established within the past two years. Figure 3 displays the specific counties each branch serves. The headquarters of the FBCENC is operated under the Raleigh branch and is located in Wake County. The FBCENC distributes over 150,000 pounds of food to 800 partner agencies. Partner agencies consist of emergency food programs such as soup kitchens, food pantries, homeless shelters, elderly nutrition programs and recognized churches. These partner agencies serve more than 500,000 individuals at risk of hunger across the 34 counties.

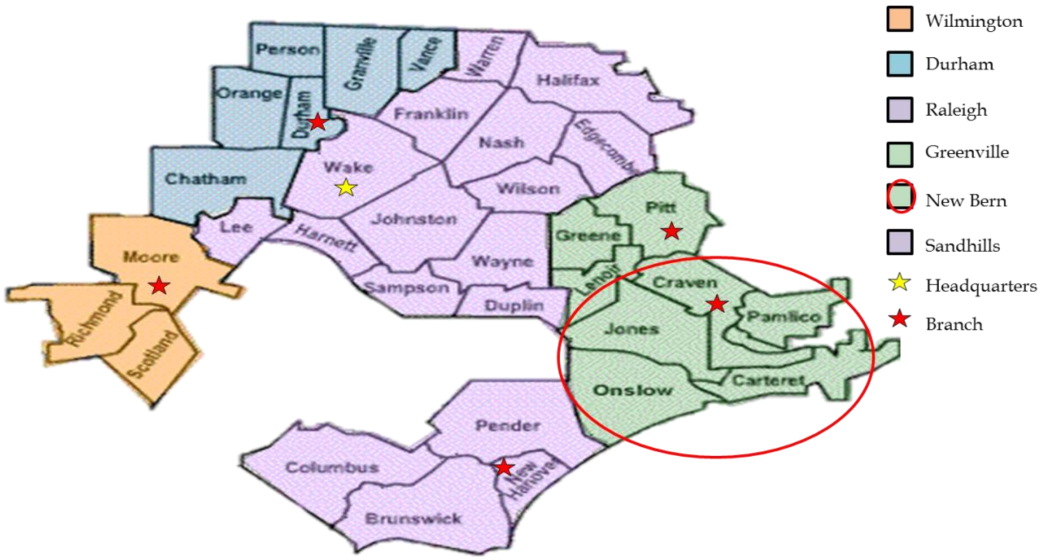

Figure 3. Map of FBCENC Counties by Branch.

The donations received by the food bank are generated from local food drives, deliveries from partner food banks, and individual and business donations. The FBCENC also receives food and monetary donations from the government through the TEFAP and SNAP programs. In addition, the FBCENC will also purchase food to fulfill the unmet demand. Figure 4 demonstrates the Process flow of how the supply is generated and distributed to the demand.

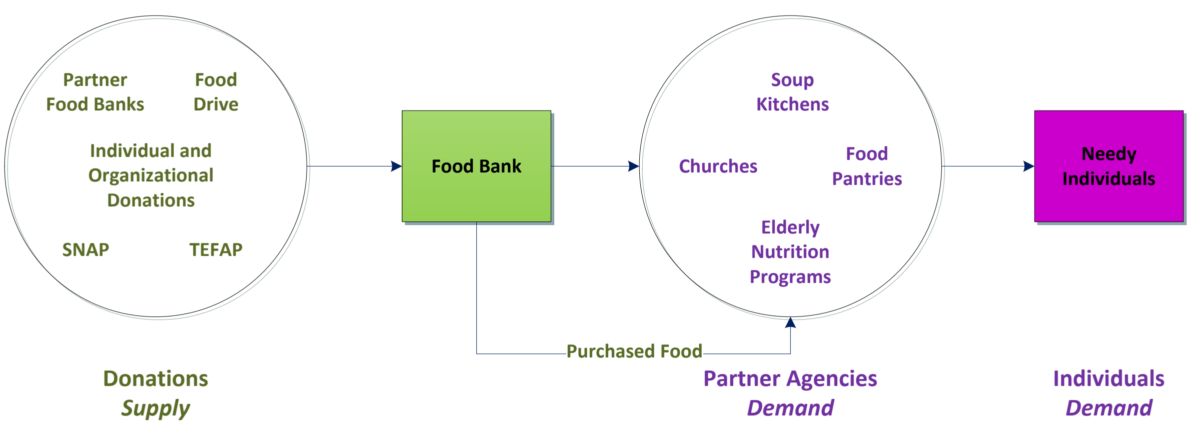

Figure 4. Donated Good Process.

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Although the food bank does receive food from various sources, a majority of them are from donations. Figure 5 displays a partition of the sources from which the food is received.

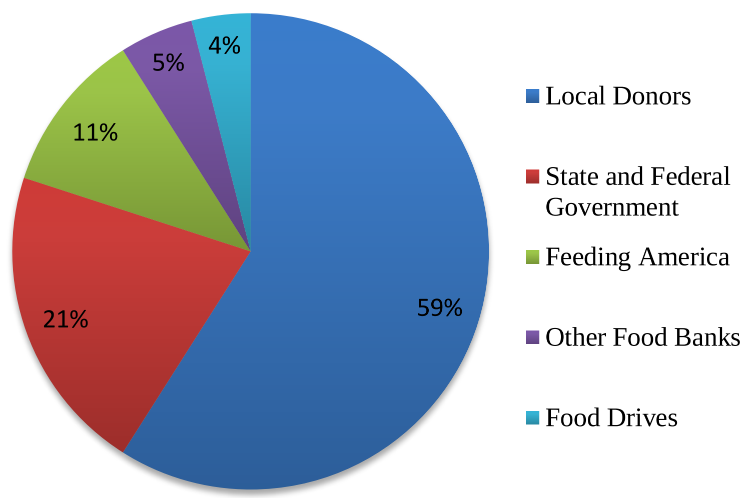

Figure 5. FBCENC Food Sources.

Over 79% of the food received from the food bank is dependent upon donations. Since the donations constitute such a large portion of the food received, the management at the FBCENC need to be able to adequately plan its distribution of supplies to ensure food shortages are avoided. In order to properly manage the distribution of donations, some form of forecasting should be employed. Chu (1998) states that forecasting should be an essential element in the management process; planning for the future must occur in order to minimize the risk of failure, (i.e. food shortages). In this case the desired variable to forecast and analyze would be the amount of food donations received. Several forecasting techniques exist and can be investigated in predicting the food donations. However, certain characteristics of Food Bank donations make the forecasting problem challenging. First, the amount of donations and the type of food received varies with each donation. Second, the donations are received sporadically over the year and in uncertain quantities. This increases the difficulty in choosing a forecasting technique and evaluating the behavior of the donations.

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1.5 Research Objectives

Since the donations contribute significantly to the food donations, understanding their behavior is critical in managing the distribution of food and avoiding food shortages. The Second Harvest Food Bank of Northwest North Carolina has run out of food twice within three years. The stress of economy and the volatile nature of supplies increase the likelihood of shortages. Studying the behavior and trends of donations and using forecasting as a management tool will help reduce the risks of running out of food. Therefore the objectives of this research are as follows:

1. To determine how the data given should be aggregated to construct a forecast.
2. To determine which forecasting technique will produce the most accurate forecast.
3. To develop a logical indicator that will serve as a warning system to alarm management when the inventory levels are low.

The results of this research could be applied to any other food bank affiliated with the Feeding America network.

The remainder of the paper is outlined as follows. Chapter 2 summarizes the related literature. Chapter 3 outlines the methodology employed. Chapter 4 discusses the data and analysis methods. Chapter 5 evaluates the results of the forecasting techniques. Recommendations will be made in Chapter 6. Chapter 7 concludes the research and suggests future work to be explored.

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CHAPTER 2

Literature Review

2.1 Overview of Literature

Forecasting is a systematic tool that produces either statistical results or an opinion about future anticipated events. The types of forecasting methods can be classified into two broad categories: subjective and objective forecasting. Subjective forecasting methods are based on human judgment or intuition and are generally used when either data is lacking or an expert's insight is required. Customer surveys, discussion groups, and the Delphi method are examples of the various methods used. Objective forecasting methods are statistical in nature and utilize existing data to make predictions. Time series and causal models are the two popular types of objective forecasting strategies. Time series forecasting uses time ordered data to generate forecasts and are often referred to as naïve methods as they require minimal information. Causal models explore cause-and-effect relationships and use indicators to predict future events.

Since there is no prior work related to forecasting food donations, the scope of this review is limited to forecasting approaches applied to supply and demand. The articles reviewed provide an in-depth investigation of the various forecasting techniques and the diversity of their applications. The remaining of this chapter will be divided into two sections. The first will review the forecasting techniques used to predict perishable items and other donated items; all other variables will be discussed in the second section.

2.2 Forecasting Techniques Applied to Perishable and Donated Items

Perishable and donated items can be difficult to forecast due to the variability, however, both Miller et al. (1991) and Trent (2009) used prediction models to forecast the demand for food. Miller et al. (1991) modeled the entrée demand for a university dining hall to improve the

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production efficiency of the food and beverage industry. The three forecasting techniques evaluated were the Naïve I, moving average, and exponential smoothing. Trent (2009) studied the pattern of demand for pantry meals to ensure the proper allocation of food was met. After examining the data for trends, seasonality, and cyclical patterns, moving average was selected as the appropriate forecasting model. The performance of the models were assessed by comparing the error percentages and each study produced favorable results.

Another perishable item frequently model is the behavior of blood. Pereira (2004) investigated demand for transfusions of red blood cells to develop the planning for future collection efforts. Autoregressive Integrated Moving Average (ARIMA), Winter's, and a neural-network based model were the three times series models compared. The results showed the forecasts generated by the ARIMA and exponential smoothing were in the tenth percent interval of the actual demand for one year time horizons. In predicting the demand over 2-year time horizons, the exponential smoothing technique greatly outperformed the two other models.

Two studies examined both the supply and demand for blood. Drackley et al. (2012) was interested in forecasting the Canadian blood supply and the number of transfusions required per patient. The forecasts were constructed using percentage projections under the assumption that the donation and demand rates would remain constant over time. Frankfurkter et al. (1974) used exponential smoothing to predict the demand for blood and used the data in a BASIC forecasting model to project the future supply. Neither application measured the performance of the models, rather the purpose of the forecasts was to serve as a planning tool and propose "what-if" scenarios which proved to be very effective.

Lastly, the behavior pattern of donors and monetary donations has also been studied. Britto et al. (1986) used the Poisson distribution to construct a forecasting model to project the

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number of donors, gifts, and cumulative donations for the Berkley Engineering Fund. Whereas, Soukup (1983) created a Markov Chain to model the likelihood of donor behavior for the Tau Beta Pi Association, both analyses reviewed the effects of using different marketing strategies to increase the amount of donations.

2.3 Forecasting Techniques Applied to Other Variables

2.3.1 Tourism volume. Tourist flows have increased exponentially in the past 30 years and the financial gains acquired by tourist contribute largely to the GDP of the United States and foreign countries. In planning for tourism, forecasting plays an essential role in the process and extensive research has been done in this area. Chu (1998) focused on forecasting the tourism volumes into ten Asian-Pacific countries. Six forecasting models were used to include the Naïve I, Naïve II, simple linear regression time series, sine wave time series nonlinear regression, Holt-Winter's, and the seasonsal-nonseasonal ARIMA models. Huang et al.(2011) investigated a similar issue by using the Grey model to forecast the tourism volume to Taiwan from Asia using one year of data. The Grey model considers the uncertainty and integrity of the data and can generate forecasts using small quantities of data. Finally, Chen et al. (2007) investigated the future demand for U.S. National Parks. Several forecasting techniques were compared to determine which resulted in the lowest forecasting error. The forecasting techniques compared were categorized as either basic (Naïve I and II model, simple moving average, simple exponential smoothing) intermediate (Brown's and Holt's methods), or advanced (ARIMA, and two advanced regression procedures). Of the nine prediction models considered, moving average performed the best due to the stationarity of the data.

2.3.2 Miscellaneous variables. Lastly, the behavior of several other volatile variables has been modeled as well. Three such topics include future accidents and welfare caseload volume. Accident forecasting predicts the safety state based upon previous data and observations and is critical for businesses due to the increasing frequency of accidents. Zheng et al. (2009) analyzed seven different forecasting techniques to predict and prevent future accidents in a chemical plant which are scenario analysis, regression method, exponential smoothing, Markov Chain method, grey model, neural networks, and Bayesian networks. Zheng et al. (2009) also considered combining methodologies to see if more accurate results could be achieved.

Predicting welfare caseloads is a complicated process. There has been a large magnitude of fluctuations of the number of welfare cases. If forecasters are unable to predict high upswings for the need of governmental assistance, there may not be enough funding to support those in need. Grogger (2007) created a Markov chain to model the monthly welfare caseload volume for California. The states were defined as the caseload of the present month with transitions to the next month. The model produced a reasonable forecast.

2.3.3 Summary of literature. Although the basic forecasting models are capable of producing highly accurate forecasts, using more advanced forecasting techniques have a high performance rating and can provide a more in depth analysis of the behavior of the interested variable(s). Holt-Winter's exponential smoothing, Autoregressive Integrated Moving Average (ARIMA) , Markov Chains, various versions of the Grey Model, and Neural Networks are a few of the more sophisticated techniques widely used for forecasting purposes. Holt's method is best used in handling trends. Winter's method implies seasonality and trends. The ARIMA model uses present and past data to predict future values (Chen et al. 2008). Markov chains are stochastic processes with defined states that estimate the transition probabilities between them and are suitable in forecasting data with fluctuation. The Grey model is capable of producing a forecast using as little as four data points. Artificial Neural Networks can be a powerful tool in

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forecasting a complex data set that has non-linear relationships between inputs and outputs (Zheng & Liu, 2009).

2.4 Research Contribution

Table 1, summarizes the forecasting techniques reviewed and their many applications. However, Figures 7 and 8 illustrate that the majority of the literature focused on developing a forecasting method to interpret the behavior and trends of the demand, not the supply and evaluated multiple forecasting methods. This paper will focus on 1) analyzing the behavior of the donations (supply) received by a food bank; 2) evaluating and comparing several forecasting techniques; and 3) furnishing a logical management system for the food bank to alarm the administration when the supply is low.

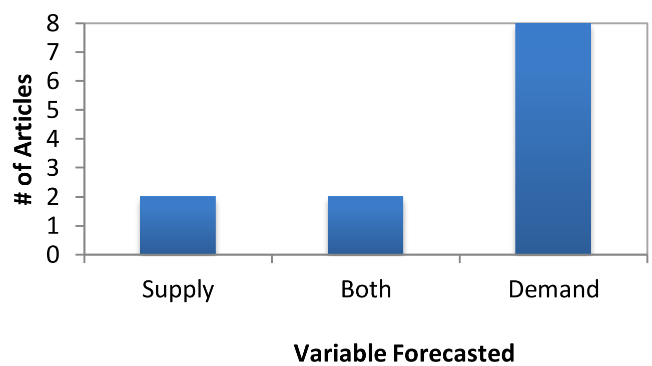

Figure 6. Histogram of the Type of Variable Forecasted.

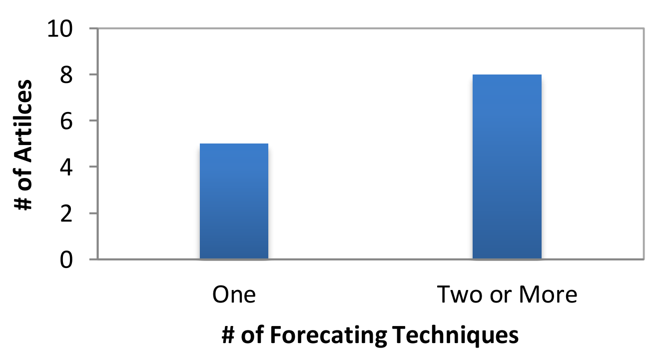

Figure 7. The Number of Forecasting Techniques Applied per Article.

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Table 1

Overview of the Literature Reviewed

Author	**Model**	**Forecasted Variable**	**Demand or Supply Focused**
Britto, Oliver, 1986	Poisson Distribution, Binomial Count	Monetary Donations	Supply
Chen, Bloomfield, Cubbage, 2007	Multiple	Tourism Volume	Demand
Chu, 1998	Naïve, Regression, Holts-Winter, ARIMA	Tourism Volume	Demand
Drackley, Newbold, 2012	Percentage Projections	Blood Transfusions	Both
Frankfurkter, Kendall, 1974	Projections, Exponential Smoothing	Blood Transfusions	Both
Grogger, 2007	Markov Chain	Welfare Caseload Volume	Demand
Huang, Lee, 2011	Grey Model, Fourier Grey Model	Tourism Volume	Demand
Miller, McCahon, Bloss, 1991	Moving Average/ Simple Exponential Smoothing	Entrée Combinations	Demand
Pereira, 2004	ARIMA, Holts-Winters, Neural Networks	Blood Transfusions	Demand
Soukup, 1983	Markov Chain	Monetary Donations	Supply
Trent, 2009	Moving Average	Meals	Demand
Zheng, Liu, 2009	Multiple	Accidents	Demand

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CHAPTER 3

Methodology

3.1 Methodology

The methodology is subdivided into three sections. The first highlights the key material used from the data set. A description of the forecasting models selected is described in section two, and the final segment summarizes how the models will be validated.

3.2 Data Analysis

3.2.1 Summarization of the data. The data used in this study was provided by the Food Bank of Central and Eastern North Carolina. It contains 88,133 records of the food received by the Food Bank for the fiscal years of July 2006-07 to June 2010-11. Table 2 identifies the key fields that were used from the data set. To ensure only the donated records were used, the data was filtered to remove the purchased records from the set. This decreased the records of food donations to 87, 604.

Table 2

Key Fields in Data Set

Key Fields	Description
Posting Date	Date item received
Donor Name	Name or title of source
Gross Weight	Total mass of item
UNC_Product_Category_Code	Donor classification
UNC_Storage_Requirements_Code	Storage classification
FBC_Product_Type_Code	Food classification
Branch_Code	Branch
FBC_Product_Category_Code	Classification of receipt

Four specific fields were selected for analysis: UNC_Product_Category_Code, UNC_Storage_Requirements_Code, FBC_Product_Type_Code, and Branch_Code. Each field is

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complete for each product and provides a level of diversity in aggregating the data to construct forecasts. To increase the flexibility in categorizing the given data two additional fields were created, Year:Month Code and Year:Week Code. These two fields were constructed using the posting date and extracting the associated week and month (Week 35-March) or week and year (Week 35 – 2009) associated with each product. This will allow the data to be forecasted by week, month, or year.

3.2.2 Construction of aggregation levels. Each of the four fields can be dissolved into more detailed categories. UNC_Product_Category_Code (Donor Type) has 11 different subgroups, UNC_Storage_Requirements_Code, (Storage Type) has 6 subgroups, FBC_Product_Type_Code, (Food Type) has 22 subgroups, and Branch_Code (Branch) had 6 subgroups.

Table 3

Key Subgroups by Type

Type	Subgroup		
Donor type	Affiliate	Bonus/Oth	FoodDrive
	Miscellany	OtherPurch	Produce
	Ret/Whlsle	Salvage	TEFAP
	GrantPurch	MFGD	
Storage type	Dry	Frozen	Produce
	Refrigerated	Salvage	Prepared
Food type	Beverages	Fruit	Pet
	Cereal	Grains	Prepared
	Clean	Hygiene	Produce
	Condiments	Juice	Protein
	Dairy	Meals	Salvage
	Dessert	Meats	Snacks
	MixFood	Paper	Vegetable
	NonFood	Pasta	
Branch	R (Raleigh)	W (Wilmington)	G (Greenville)
	D (Durham)	S (Sandhills)	N (New Bern)

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3.2.3 Descriptive analysis. To begin analyzing the data, the mean, standard deviation, and coefficient of variation are determined for the donation frequency and quantity. The coefficient of variation (CV) is the statistical measure of the distribution of data of the values around the mean. The CV characterizes the relative variability and interprets the comparative magnitude of the standard deviation. The equation for the coefficient of variation is the ratio of the standard deviation and the mean; the ratio is often multiplied by 100 to be depicted as a percentage. If the CV is measured to be 19%, then the standard deviation is considered to be 19% of the mean.

$$CV = \frac{\sigma}{\mu} \times 100 \tag{1}$$

The data is summarized by the monthly quantity received over each fiscal year. Although several forecasting techniques have already been selected to assess the data set, this analysis should furnish a comprehensive insight in determining other forecasting methods that should be considered.

3.2.4 Paired t-test analysis. In analyzing multiple sets of data, one must consider if there exists similarities amongst the samples. Knowing that the amount of donations fluctuates over the years due to several uncontrollable factors (economy), certain fiscal years may be more similar in comparison to others. Understanding and identifying any similarity amongst the groupings may assist in producing a more accurate forecast (Montgomery, 2008). The paired t-test is popular technique and compares two population means, μ, to determine if any similarities are present. The null hypothesis, H_0, is tested to decipher if the difference between the means is zero and is equivalent to testing:

$$H_0 : \mu_1 = \mu_2 \tag{2}$$

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$$H_1 : \mu_1 \neq \mu_2 \tag{3}$$

The test statistic for the hypothesis is given by EQ (4), with

$$t_0 = \frac{\bar{d}}{\frac{s_d}{\sqrt{n}}} \tag{4}$$

The sample mean of the differences given by EQ (5)

$$\bar{d} = \frac{1}{n}\sum_{j=1}^{n} d_j \tag{5}$$

and the sample standard deviation of the differences given by EQ (6)

$$S_d = \left[\frac{\sum_{j=1}^{n}(d_j - \bar{d})^2}{n-1}\right]^{1/2} \tag{6}$$

3.3 Application of Forecast Model Selection

Two of the fundamental forecasting procedures utilized in this work are moving average and exponential smoothing. These methods are known to work well if the data is stationary.

3.3.1 Moving average. Moving Average is a simple forecasting method and is determined by summing the previous values together and dividing by the number of values, *N*. Moving Average assumes that all of the previous selected observations have equal weight on the forecast value. The mathematical equation and parameters for moving average are Table 4.

$$F_t = \frac{\sum_{i=t-N}^{t-1} D_i}{N} \tag{7}$$

3.3.2 Exponential smoothing. Exponential smoothing forecasts use the weighted average of the previous forecast and the value of the current demand. The smoothing constant (α), is chosen by the forecaster and must be a value between 0 and 1. If the α level is closer to 1, more emphasis is applied to the current observations of the variable and therefore the forecast reacts quickly to changes in the data time series. If α is closer to 0, more weight is given to past

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observations and results in forecasts that are more stable. The mathematical model and the related parameters are defined in equation (8) and Table 5, respectively.

$$F_t = \propto D_{t-1} + (1-\propto)F_{t-1} \tag{8}$$

$$0 \leq \propto \leq 1$$

Table 4

Parameters for Moving Average

Variable	**Definition**
N	Number of Periods
D_i	Demand in Period *i*
F_t	New Forecast

Table 5

Parameters for Exponential Smoothing

Variable	**Definition**
F_t	New Forecast
F_{t-1}	Previous Forecast
D_{t-1}	Previous Actual Demand
$\propto$	Smoothing Constant

3.3.3 Holt's and winter's method. Holt's method focuses on tracking linear trends in a time series data set. It is form of double exponential smoothing and requires two smoothing constants, α and β, and uses two smoothing equations as defined below.

$$S_t = \alpha D_t + (1-\alpha)(S_{t-1} + G_{t-1}) \tag{9}$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1} \tag{10}$$

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The τ-step-ahead forecast made in period *t*, denoted by $F_{t,t+\tau}$ is

$$F_{t,t+\tau} = S_t + \tau G_t \tag{11}$$

Table 6

Parameters for Holt's Method

Variable	**Definition**
$F_{t,t+\tau}$	T Step-Ahead Forecast
S_t	Intercept
G_t	Slope
S_{t-1}	Previous Intercept
G_{t-1}	Previous Slope
$\propto$, β	Smoothing Constants

Winter's method is specifically applied to time series that display seasonality. This method is considered to be a type of triple exponential smoothing and has the capability to integrate new data as it is received. The demand follows the following assumption of equation (12).

$$D_t = (\mu + G_t)c_t + \epsilon_t \tag{12}$$

There are a total of three equations used to compute the final forecast. Equation (13) is the current level of the deseasonalized data, (14) updates the trend similar to that of the Holt's method, and (15) incorporates the seasonal factors required to produce the final prediction. The forecast is then calculated by equation 16 and the parameters for Winter's method are defined in Appendix A.

$$S_t = \alpha\left(\frac{D_t}{c_{t-N}}\right) + (1-\alpha)(S_{t-1} + G_{t-1}) \tag{13}$$

$$G_t = \beta[S_t - S_{t-1}] + (1-\beta)G_{t-1} \tag{14}$$

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$$c_t = \gamma\left(\frac{D_t}{S_t}\right) + (1-\gamma)c_{t-N} \tag{15}$$

$$F_{t,t+\tau} = (S_t + \tau G_t)c_{t+\tau-N} \tag{16}$$

3.3.4 Auto regressive integrated moving average (ARIMA). Box, Jenkins and Reinsel(1997) developed some of the most well-known time series forecasting approaches. Autoregressive integrated moving average (ARIMA) attempts to solve two problems. The first is to analyze the stochastic, stationary, or seasonal properties of the time series and the other is model selection. The model selection is defined by three variables *p*, *d*, and *q*. The auto-regressive element, *p*, denotes the effects the past data points may have had. The second parameter, *d*, is the integrated variable and considers the trends in the data. The final element *q*, is the moving average variable that depicts the effects of previous random shocks. Only the nonseasonal mixed autoregressive moving average model will be used for this study.

$$z_t = \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} \dots + \phi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \tag{17}$$

The first step for the ARIMA process is to determine if the data series is stationary and has a constant mean and variance. If it is not, differencing must be performed until the series meets the criteria. Secondly, the autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) must be calculated to determine which model parameters should be used. The ACF and PACF is usually computed using standard software and the results are plotted. The interpretation of these graphs determines the parameters used for the model. The value of the lags is equally important. A lag, *k*, is a period of time between one observation and another. The following recommendations can be used to identify which of model is depicted:

1. If the ACF cuts off after lag *q* and the PACF dies down, a moving average parameter of order *q* should be used.

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2. If the ACF dies down and the PACF cuts off after lag *p*, an autoregressive parameter of order *p* should be used.

3. If both the ACF and PACF die down, a mixed autoregressive-moving average of order (*p*, *q*) should be used.

Once the correct parameters have been identified, the next step is to estimate the value of the parameters. Although statistical methods can be used to estimate the model parameter such as calculating the least square errors or using the maximum likelihood method, the parameters can be identified graphically. The value for the parameters is equal to lag *k*. After these values have been decided, the forecast can be produced using the selected ARIMA model and the new values can be evaluated.

3.4 Forecast Model Evaluation

To gauge the performance of the forecast, the forecasting error and level of variability is being analyzed. The forecasting error is assessed by calculating the Mean Absolute Percentage Error (MAPE). Equations 18 and 19 demonstrate how the forecasting error is determined. The advantage of using the mean absolute percentage error is errors are measured as a percentage and therefore are not dependent on the magnitude of the demand. Chen et al. (2008) suggests that a technique producing a mean absolute percentage error value less than 10% has a highly accurate forecast, 10% to 20% has a good forecast, 20% to 50% has a reasonable forecast, and 50% or more has an inaccurate forecast. The parameters for the error equations are highlighted in Table 7.

$$e_t = D_t - F_t \tag{18}$$

$$MAPE = \frac{\sum_{T=1}^{N}(|e_t|/D_t) * 100}{N} \tag{19}$$

`

Table 7

Parameters of Error Equations

Variable	Definition
N	Number of Periods
D_t	Demand in Period *t*
e_t	Error in Period *t*
F_t	Forecast in Period *t*

`

CHAPTER 4

Data Analysis

4.1 Data

Over the duration of five fiscal years 194,424,451 pounds of food were donated. Figure 8 displays the amount of donations received each fiscal year. Despite the economic hardships North Carolina faced, the quantity of donations increased each year. The amount of donations received per month is illustrated in Figure 9. Three speculations are evident from this graph. First, there appears to be a trend. Second, all the fiscal years display a decrease in donations in February and in September. Lastly fiscal years 2008-2009, 2009-2010, and 2010-2011 also appear to demonstrate similar behavior. The remaining two fiscal years (2006-2007 and 2007-2008) do not appear to have the identical pattern, nor do the fiscal years demonstrate a trend amongst comparatively.

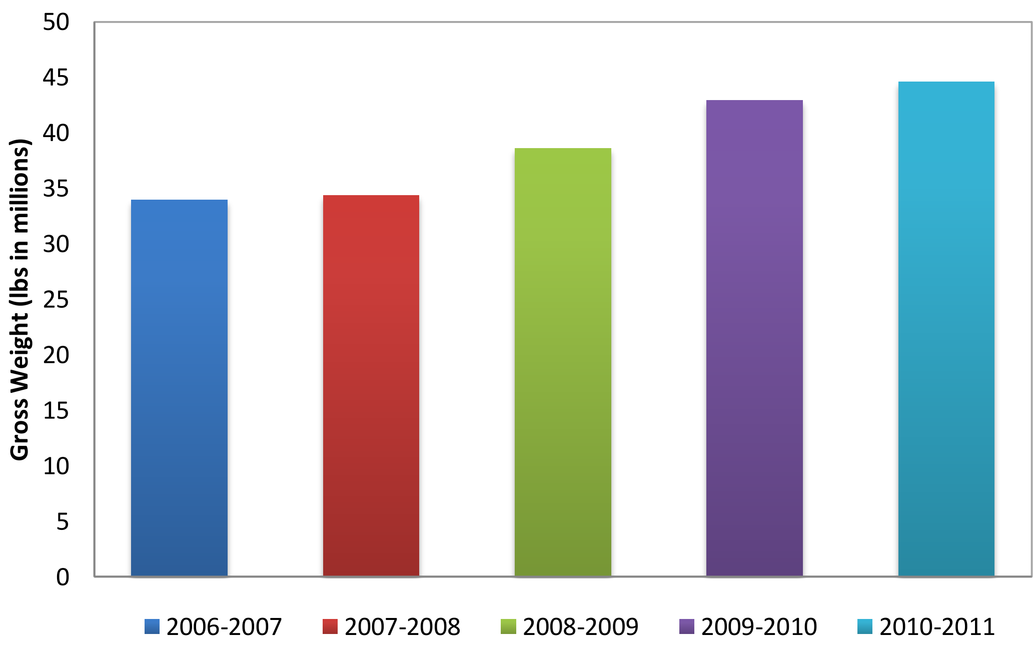

Figure 8. Total Donations by Fiscal Year.

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In order to confirm whether the third claim is true, a paired t-test is conducted. Using all five of the fiscal years testing was performed by year and compared the weekly donations of each fiscal year combination (ex. FY067&FY0708). Table 8 summarizes the resulting variable P values.

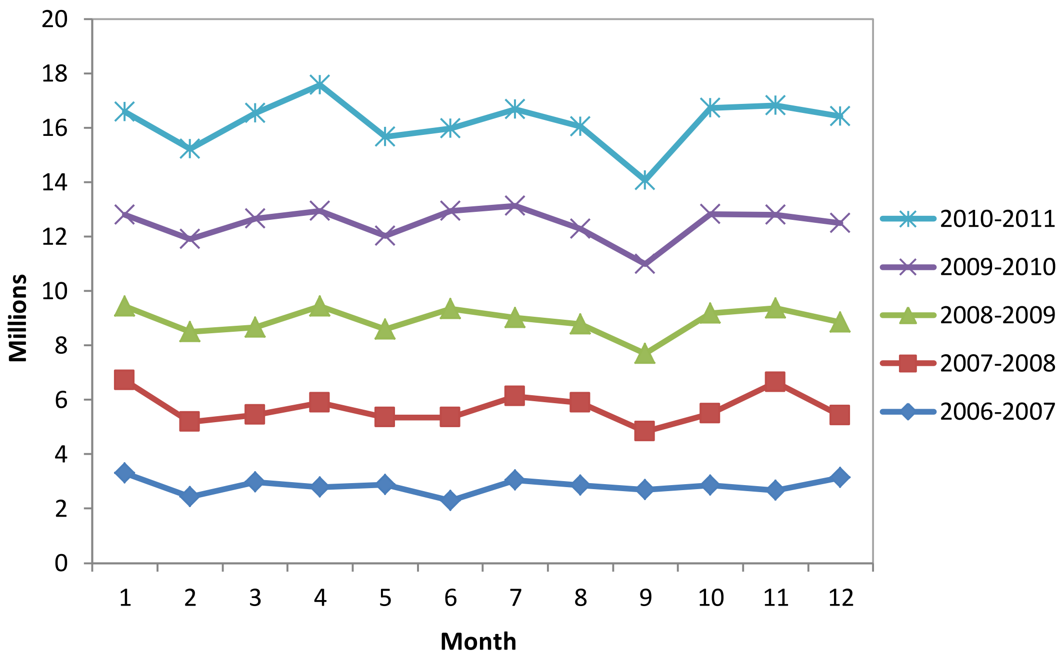

Figure 9. Monthly Donations by Fiscal Year.

Table 8

Paired T-Test P Values

	FY0607	**FY0708**	**FY0809**	**FY0910**	**FY1011**
FY0607	*	0.8214	0.0894	0.0099	0.0035
FY0708	*	*	0.09	0.01	0.0145
FY0809	*	*	*	**0.0961**	**0.134**
FY0910	*	*	*	*	**0.7072**
FY1011	*	*	*	*	*

Note: An alpha level of 0.05 was used.

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The results of the test indicate FY0607 should be removed as it is least similar to the remaining fiscal years. Although FY0708 is similar to FY0809, FY0910, and FY1011, p-values for the latter two combinations are very conservative. Furthermore FY0708 should not be used during analysis as well. Fiscal years FY0809, FY0910, and FY1011 displayed the greatest similarity among the data sets and should therefore be used for the remaining analysis.

4.2 Evaluating the Supply by Aggregate Levels

To attempt to build a more accurate forecast, only Food, Donor, Storage Type, and Branch and a combination of these subgroups are evaluated. Due to the significant amount of subgroups, only the three levels with the overall largest percentage by gross weight are selected, excluding Branch. For the combined levels, the combinations that have a value of 33% and greater are selected for analysis. After the subgroups have been identified, the mean, standard deviation, and coefficient of variation is calculated and each sublevel is graphed to determine the forecasting technique that should be applied to each sublevel.

4.2.1 Food type. There are a total of 22 different food types that classifies the various types of food donations received. Table 9 summarizes the percentage of each food type given per fiscal year and the total percentage received for all three fiscal years. The Food Bank indicated having a very extensive fresh produce and retail recovery program that focuses on acquiring fresh produce, meats, deli foods, and baked goods. This may help to explain as to why *Produce* is the largest type of donated food item. Table 10 summarizes the descriptive statistics for the *Beverages*, *Mixfood*, and *Produce*. Each food type has nearly an equal amount of variability within the data series, however the averages and standard deviations vary amongst the different groups. *Produce* has the largest mean and standard deviation and *Beverages* has the smallest for both.

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Table 9

Percentage of Each Food Type by Fiscal Year

Food Type	2008-2009	2009-2010	2010-2011	Grand Total
PRODUCE	**26.18%**	**23.03%**	**20.76%**	**23.20%**
MIXFOOD	**16.15%**	**13.83%**	**16.72%**	**15.56%**
BEVERAGES	**13.05%**	**10.52%**	9.89%	**11.08%**
GRAINS	10.31%	9.85%	**12.02%**	10.76%
MEATS	8.10%	8.24%	7.55%	7.96%
VEGETABLE	3.49%	5.75%	7.46%	5.65%
DAIRY	3.54%	7.30%	5.62%	5.55%
JUICE	5.24%	4.67%	4.27%	4.71%
FRUIT	2.20%	2.60%	5.61%	3.54%
CONDIMENTS	3.66%	3.50%	2.24%	3.11%
PROTEIN	1.27%	2.28%	2.59%	2.08%
PREPARED	1.56%	3.08%	1.36%	2.01%
PASTA	1.12%	1.39%	1.05%	1.19%
SNACKS	1.61%	1.00%	0.71%	1.09%
MEALS	0.55%	1.28%	0.13%	0.65%
NON FOOD	0.41%	0.85%	0.31%	0.52%
CERERAL	0.47%	0.35%	0.27%	0.36%
SALVAGE	0.00%	0.00%	0.97%	0.34%
HYGIENE	0.38%	0.23%	0.32%	0.31%
CLEAN	0.37%	0.06%	0.07%	0.16%
DESSERT	0.25%	0.03%	0.02%	0.09%
PET	0.01%	0.08%	0.06%	0.05%
PAPER	0.07%	0.07%	0.00%	0.05%

Note: **Bold** indicates top three subgroups.

Table 10

Descriptive Statistics - Food Type

	Mean(lbs)	Standard Deviation(lbs)	CV
Beverages	377,723	130,661	34.59%
MixFood	530,710	176,818	33.32%
Produce	791,354	241,252	30.49%

4.2.2 Donor type. There are a total of 11 donor types. Table 11 indicates that donor types *Manufactured Goods* and *Retail /Wholesale* comprised the largest and second largest percentage

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of the total donations given respectively for fiscal years 2008-2009 and 2009-2010. In fiscal year 2010-2011, *Manufactured Goods* and *Retail/Wholesale* traded positioning resulting in *Retail/Wholesale* giving the largest quantity of donations. The third largest donor type alternates between Produce and Miscellany for the first two fiscal years; *TEFAP* was the third largest donor for the remaining three fiscal years. Therefore, the top three donor types by gross weight are *MFGD*, *RET/WHLSLE*, and *TEFAP*. Table 12 outlines the descriptive statistics for the selected donors. Both means for RET/WHLSLE and MFGD are significantly high. The average for TEFAP, conversely, is half that of RET/WHLSLE and had the greatest amount of variability within its data set.

Table 11

Percentage of Donations per Donor Type by Fiscal Year

	2008-2009	**2009-2010**	**2010-2011**	**Grand Total**
MFGD	**39.96%**	**31.78%**	**25.25%**	**32.01%**
RET/WHLSLE	**26.79%**	**29.11%**	**34.99%**	**30.46%**
TEFAP	**13.79%**	**18.92%**	**22.05%**	**18.44%**
MISCELLANY	8.39%	9.06%	7.88%	8.44%
AFFILIATE	6.07%	6.48%	4.96%	5.82%
FOODDRIVE	2.84%	2.76%	3.65%	3.10%
PRODUCE	2.15%	1.77%	1.16%	1.67%
SALVAGE	0.00%	0.13%	0.05%	0.06%
BONUS/OTH	0.00%	0.00%	0.00%	0.00%

Table 12

Descriptive Statistics of the Donor Types

	Mean(lbs)	**Standard Deviation(lbs)**	**CV**
RET/WHLSLE	1,038,806	187,800	18.08%
TEFAP	621,997	283,238	45.54%
MFGD	1,091,660	272,720	24.98%

`

4.2.3 Storage type. Table 13 summarizes the percentage of each storage type given over the three fiscal years and overall. Storage types *Dry* and *Produce* are the highest and second highest amount given for all three fiscal years. Donated goods which were classified under the *Frozen* storage type was the third largest amount received. Therefore, the top three storages types are *Dry*, *Produce*, and *Frozen*. Table 14 summarizes the mean, standard deviation, and CV for the top three storage types. Comparatively, Produce had the greatest variability within the data.

Table 13

Percentage of Donations per Storage Type by Fiscal Year

	2008-2009	**2009-2010**	**2010-2011**	**Grand Total**
DRY	**48.43%**	**54.36%**	**55.57%**	**52.96%**
PRODUCE	**26.02%**	**22.71%**	**20.64%**	**23.00%**
FROZEN	**13.84%**	**12.67%**	**13.45%**	**13.31%**
REF	10.29%	10.27%	10.32%	10.29%
SALVAGE	1.42%	0.00%	0.02%	0.44%

Table 14

Descriptive Statistics of Storage Types

	Mean(lbs)	**Standard Deviation(lbs)**	**CV**
Dry	1,806,088	391,992	21.70%
Frozen	453,783	70,440	15.52%
Produce	784,476	232,405	29.63%

4.2.4 Branch. The Food Bank of Central and Eastern North Carolina has a total of 6 branches. New Bern is a newly added branch and is not used in the study. Evaluating the data on a branch level will allow the Food Bank to understand if any patterns or trends may exist for a specific branch. Being that *Raleigh* is the headquarters, it is very feasible that *Raleigh* received the largest amount of donations compared to the other branches. Table 15 indicates that not only did *Raleigh* receive the largest amount of donations total, the branch received the largest

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percentage of donations for each fiscal year as well. Table 16 highlights the descriptive statistics for the branches. *Raleigh* had the largest mean and the smallest CV. In contrast, *Durham* had the smallest average and the largest CV.

Table 15

Total Percentage Received Per Branch by Fiscal Year

	2008-2009	**2009-2010**	**2010-2011**	**Grand Total**
Raleigh	67.05%	69.44%	68.20%	68.27%
Greenville	12.54%	11.35%	11.46%	11.76%
Wilmington	6.28%	7.18%	7.50%	7.01%
Sandhills	7.31%	6.60%	7.07%	6.99%
Durham	6.82%	5.43%	5.76%	5.97%

Table 16

Descriptive Statistics for Branch

	Mean(lbs)	**Standard Deviation(lbs)**	**CV**
Raleigh	2,327,842	336,476	14.45%
Greenville	400,933	71,270	17.78%
Wilmington	239,182	59,011	24.67%
Sandhills	238,192	50,114	21.04%
Durham	203,716	56,351	27.66%

4.2.5 Branch vs. donor type. Table 17 highlights the percentage of donors that gave to each branch. The *Raleigh*, branch received the largest amount of its donations from *MFGD*. *RET/WHLSLE* gave the most to both the *Wilmington* and *Sandhills* branches. *Durham* and *Greenville* received a significant quantity of donations from both *MFGD* and *RET/WHLSLE*. The descriptive statistics for the significant Branch vs Donor type selections are summarized in table 18. *Greenville*/*RETWHLSLE* has the largest average for the group and the smallest coefficient of variation. *Durham*/*MFGD* has the smallest mean and the largest coefficient of variation. The remaining groups had similar averages and CVs.

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Table 17

Branch vs Donor type Percentages

	MFGD	RET/WHLSLE	TEFAP
Raleigh	**44.29%**	23.48%	32.23%
Greenville	**42.53%**	**57.16%**	0.31%
Wilmington	11.62%	**88.38%**	0.00%
Sandhills	25.12%	**58.69%**	16.19%
Durham	**34.89%**	**65.11%**	0.00%

Table 18

Descriptive Statistics - Branch vs. Donor type

	Mean(lbs)	Standard Deviation(lbs)	CV
Durham vs MFGD	54,611	41,213	75.47%
Durham vs RET/WHLSLE	101,900	21,823	21.42%
Greenville vs MFGD	142,775	60,599	42.44%
Greenville vs RET/WHLSLE	191,895	36,492	19.02%
Raleigh vs MFGD	819,323	182,825	22.31%
Sandhills vs RET/WHLSLE	114,763	38,784	33.79%
Wilmington vs RET/WHLSLE	195,675	49,220	25.15%

4.2.6 Branch vs. food type. Table 19 displays the percentage which food types were donated to each branch. All five of the branches received an equally substantial quantity of *Produce* donations. The *Greenville*, *Wilmington*, and *Durham* also received a large amount of *MixFood* as well. *Beverages*, however, did not account for 35% or more of the percentage of donations received for neither of the branches. The mean, standard deviation, and coefficient of variation for the Branch vs Food type segmentation is depicted in table 20. Both of the *Raleigh* combinations have the two largest averages and standard deviations. The coefficient of variation for *Durham*/*Produce* is almost twice that of the other groupings. The other groupings have both similar means and coefficient of variations.

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Table 19

Branch vs Food type Percentages

	Produce	MixFood	Beverages
Raleigh	**52.40%**	28.50%	19.09%
Greenville	**35.93%**	**36.04%**	28.03%
Wilmington	**38.42%**	**44.76%**	16.82%
Sandhills	**44.70%**	23.97%	31.33%
Durham	**33.94%**	**34.24%**	31.82%

Table 20

Descriptive Statistics - Branch vs Food type

	Mean(lbs)	Standard Deviation(lbs)	CV
Durham vs MixFood	43,727	21,036	48.11%
Durham vs Produce	46,277	48,963	105.80%
Greenville vs MixFood	91,426	22,503	24.61%
Greenville vs Produce	86,386	51,151	59.21%
Raleigh vs. MixFood	288,354	141,417	49.04%
Raleigh vs. Produce	527,586	160,511	30.42%
Sandhills vs Produce	64,543	36,254	56.17%
Wilmington vs MixFood	72,716	21,471	29.53%
Wilmington vs Produce	62,282	18,098	29.06%

4.2.7 Donor type vs. food type. Table 21 summarizes the percentage of food types that are given the most by the donor types. *Produce* was considerably donated for each of the donor types. *RET/WHLSLE* gave a significant amount of *MixFood*, and *MFGD* gave a large percentage of *Beverages*. Table 22 describes the descriptive statistics for the relevant Donor vs Food type combinations. The averages for all four groupings are fairly similar, however coefficient of variation values vary significantly. The *MFGD* groupings also have a relatively large standard deviation as well as a high coefficient of variation. This may indicate this subgroup has a substantial amount of variability within its data set.

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Table 21

Donor type vs Food type Percentages

	Produce	MixFood	Beverages
MFGD	**39.01%**	10.12%	**50.87%**
RET/WHLSLE	**47.48%**	**49.59%**	2.93%
TEFAP	**95.14%**	4.86%	0.00%

Note: There was not enough data to perform an y further analysis for TEFAP vs Produce.

Table 22

Descriptive Statistics - Donor type vs Food type

	Mean(lbs)	Standard Deviation(lbs)	CV
MFGD vs Beverages	298,389	132,209	44.31%
MFGD vs Produce	228,926	168,910	73.78%
RET/WHLSLE vs MixFood	278,851	41,226	14.78%
RET/WHLSLE vs Produce	266,950	78,600	29.44%

4.3 Forecasting Model Selection and Validation

Appendix C and D displays the results of the visual analysis performed to check for trends and seasonality. While majority of the groupings did not display any patterns, five subgroups indicated trending and four levels displayed seasonality. The Branch vs Donor type group had the most cases of trending. Neither the Branch nor Donor vs Food type levels displayed any noticeable patterns. Appendix E summarizes the forecasting methods that are used for each classification. Moving Average and Exponential Smoothing are applied to all of the levels. The *Aggregate Total* (*AT*) serves as the model set, therefore each method is exercised regardless of donation patterns. After graphing the donations by month and conducting the paired t-test, signs of a potential trend became evident for fiscal years 2008-2009, 2009-2010, and 2010-2011. Also, some of the fiscal years appeared to have similar behavior. The top three

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subgroups were chosen by analyzing the total volume given in which each subtype was received. A total of 35 groups are modeled.

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CHAPTER 5

Forecasting Results

5.1 Forecasting Analysis

MiniTab is used to construct the exponential smoothing and moving average forecasts for each of the 35 aggregate levels. The forecasts are constructed using the total gross weight donated monthly for the three fiscal years selected and each data set had 36 observations. StatTools is used to calculate the Holt's and Winter's forecast. The ARIMA analysis is performed using JMP. The model parameter (N) and smoothing constant (α) are selected by the software and the optimal value is chosen. The forecasts are then evaluated by calculating the Mean Absolute Percentage Error to further measure the performance of the forecasts. The calculated forecasting parameters are then used to build a prediction using data from fiscal year 2011-2012. The newly produced forecasting errors are categorized as the validation error set. Only the validation MAPE will be compared and assessed.

5.2 Performance of Simple Forecasting Techniques

5.2.1 Aggregate total. To capture an overall assessment of the performance of the forecasting methodologies, a model set representing the total amount of food donated over the three fiscal years independent of sublevels is established. This data is referred to as Aggregate Total (AT). Table 23 illustrates the results of exponential smoothing and moving average for AT. Comparably, moving average produced the lowest error for both the original and validation MAPE using less than half of the data.

5.2.2 Food type. Table 24 depicts that *MixFood* and *Beverages* had alpha levels below 0.500, and is considered to have more stable forecasts. *Produce*, *MixFood*, and *Beverages* all have reasonable forecasts. Unfortunately, all three food types required nearly the entire data set

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to produce the best forecast for moving average. Exponential smoothing produced the lowest error for *Beverages*, and moving average generated the smallest MAPE for both *MixFood* and *Produce*.

Table 23

Results for Exponential Smoothing and Moving Average- Aggregate Total

Forecasting Technique	**Time Period**	**Alpha**	**Model Parameter**	**MAPE**	**Validation MAPE**
Exponential Smoothing	Monthly	0.188	-	8.90%	**9.78%**
Moving Average	Monthly	-	14	7.24%	**9.34%**

Table 24

Results for Exponential Smoothing and Moving Average- Food Type

Model	**Food Type**	**Time Period**	**Alpha**	**MAPE**	**Validation MAPE**
Exponential Smoothing	Produce	Monthly	1.000	20.36%	**24.33%**
	MixFood	Monthly	0.130	26.45%	**32.98%**
	Beverages	Monthly	0.030	50.80%	**40.29%**
Moving Average	Produce	Monthly	33.00	11.00%	**23.11%**
	Mixfood	Monthly	35.00	6.00%	**32.41%**
	Beverages	Monthly	29.00	15.76%	**46.25%**

Note: Bold Red text indicates loweset MAPE for aggregate level.

5.2.3 Donor type. Table 25 demonstrates that *MFGD* and *RET/WHLSLE* had alpha levels below 0.500 for exponential smoothing. This means the more weight was placed on the more historical data points over time and is a more stable forecast. *TEFAP* had a smoothing constant above 0.500, meaning the forecast will respond quicker to changes within the data set. Both *RET/WHLSLE* and *MFGD* donor types had relatively small model parameters and required few data points to produce a forecast. *TEFAP* required a majority of the data set to produce a forecast. Exponential smoothing produced the lowest forecasting error for *MFGD* and *TEFAP*. Moving average generated the lowest errors for *RET/WHLSLE*.

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Table 25

Results for Exponential Smoothing and Moving Average - Donor Type

Model	Donor Type	Time Period	Alpha	MAPE	Validation MAPE
Exponential Smoothing	MFGD	Monthly	0.241	20.24%	**12.38%**
	RETWHLSE	Monthly	0.452	6.96%	**11.52%**
	TEFAP	Monthly	0.505	29.33%	**59.21%**
Moving Average	MFGD	Monthly	4.00	21.31%	**14.92%**
	RETWHLSE	Monthly	3.00	6.85%	**11.21%**
	TEFAP	Monthly	35.00	27.70%	**61.78%**

5.2.4 Storage type. Table 26 summarizes the effectiveness of the simple exponential smoothing and moving average forecasts. *Dry* and *Frozen* have low alpha levels compared to *Produce*. *Frozen* and *Produce* had fairly high model parameters and needed over 75% of the data to exhibit the best results. Once again, the validation error percentages increased for all three storage types. Overall, moving average provided the lowest error percentages. Although both techniques had arguably equal error percentages, moving average performed best for *Produce* and *Frozen*. Exponential smoothing executed best for *Dry*.

Table 26

Results of Exponential Smoothing and Moving Average- Storage Type

Model	Storage Type	Time Period	Alpha	MAPE	Validation MAPE
Exponential Smoothing	Dry	Monthly	0.335	14.97%	**16.67%**
	Produce	Monthly	1.000	19.91%	**24.27%**
	Frozen	Monthly	0.192	10.00%	**24.99%**
Moving Average	Dry	Monthly	5.00	14.82%	**16.75%**
	Produce	Monthly	33.00	10.00%	**23.47%**
	Frozen	Monthly	35.00	2.00%	**20.87%**

5.2.5 Branch. Table 27 indicates all 5 of the branches had smoothing constants below 0.500 indicating each forecast was constructed using primarily the least recent data points. The

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model parameters for *Durham*, *Sandhills*, and *Wilmington* were all significantly high. The validation errors for all five of the branches increased tremendously. Exponential smoothing performed best in modeling *Raleigh*, *Wilmington*, and *Sandhills*. Moving average generated the lowest errors for *Greenville* and *Durham.*

Table 27

Results for Exponential Smoothing and Moving Average - Branch

Model	Branch	Time Period	Alpha	MAPE	Validation MAPE
Exponential Smoothing	Raleigh	Monthly	0.221	10.28%	**14.21%**
	Greenville	Monthly	0.200	15.00%	**11.90%**
	Sandhills	Monthly	0.200	19.00%	**27.71%**
	Wilmington	Monthly	0.217	18.00%	**15.26%**
	Durham	Monthly	0.200	23.00%	**20.54%**
Moving Average	Raleigh	Monthly	4	10.52%	**41.59%**
	Greenville	Monthly	18	9.00%	**11.32%**
	Sandhills	Monthly	34	1.00%	**30.39%**
	Wilmington	Monthly	35	5.00%	**15.36%**
	Durham	Monthly	33	2.00%	**16.60%**

5.2.6 Branch vs. donor type. The alpha level for each of the sets was below 0.500 for exponential smoothing in Table 28. All of the combinations required 60% or more of the data to produce a forecast for moving average except *Raleigh*/*MFGD*. Exponential smoothing outperformed moving average for each aggregate level.

5.2.7 Donor type vs. food type. Table 29 depicts *MFGD/Beverages*, *RW/Mixfood* and *RW/Produce* all had smoothing constants below 0.500 and more stable forecasts. *MFGD* by *Produce* had an alpha level of 1.000 and the forecast was constructed using more of the current observations. Three of the four sets had very high model parameters for moving average. *RW*/*Produce* is modeled best using moving average. The other three sublevels performed slightly better with exponential smoothing.

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5.2.8 Branch vs. food type. Table 30 shows *Raleigh vs. Produce* is the only level that had a smoothing constant above 0.500. Subgroups *Greenville/Produce* and *Wilmington/Produce* were best modeled using exponential smoothing. Moving average generated the best results for the remaining aggregate levels.

Table 28

Results for Exponential Smoothing and Moving Average-Branch vs Donor Type

Model	Branch	Donor Type	Model Parameter	MAPE	Validation MAPE
Exponential Smoothing	Durham	MFGD	0.471	109.00%	-
	Durham	RW	0.112	18.00%	**14.75%**
	Greenville	MFGD	0.022	61.00%	**42.92%**
	Greenville	RW	0.160	14.00%	**7.44%**
	Raleigh	MFGD	0.187	17.42%	**12.91%**
	Sandhills	RW	0.380	19.00%	**12.42%**
	Wilmington	RW	0.270	16.00%	**4.03%**
Moving Average	Durham	MFGD	30	52.00%	-
	Durham	RW	30	10.00%	**21.72%**
	Greenville	MFGD	25	40.00%	**48.70%**
	Greenville	RW	34	40.00%	**17.13%**
	Raleigh	MFGD	5	18.00%	**15.68%**
	Sandhills	RW	35	17.00%	**17.44%**
	Wilmington	RW	31	11.00%	**9.97%**

Note: Time period is monthly; Validation MAPE could not be calculated for Durham vs MFGD

Table 29

Results of Exponential Smoothing and Moving Average- Donor vs Food Type

Model	Donor Type	Food Type	Parameter	MAPE	Validation MAPE
Exponential Smoothing	MFGD	Beverages	0.071	75.91%	**167.26%**
	MFGD	Produce	0.878	71.52%	**42.49%**
	RET/WHLSLE	Mixfood	0.166	11.00%	**10.02%**
	RET/WHLSLE	Produce	0.264	16.00%	**18.32%**
Moving Average	MFGD	Beverages	27	42.41%	**168.38%**
	MFGD	Produce	35	28.00%	**51.34%**
	RET/WHLSLE	Mixfood	35	2.00%	**11.64%**
	RET/WHLSLE	Produce	5	17.00%	**18.03%**

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Table 30

Results for Exponential Smoothing and Moving Average - Branch vs Food Type

Model	Branch	Food Type	Model Parameter	MAPE	Validation MAPE
Exponential Smoothing	Durham	Produce	0.040	136.00%	**25.93%**
	Durham	MixFood	0.066	52.00%	**25.24%**
	Greenville	MixFood	0.065	21.00%	**34.08%**
	Greenville	Produce	0.175	64.00%	**21.46%**
	Raleigh	MixFood	0.213	39.54%	**46.97%**
	Raleigh	Produce	0.939	21.65%	**29.64%**
	Sandhills	Produce	-	-	-
	Wilmington	MixFood	0.079	23.00%	**16.14%**
	Wilmington	Produce	0.180	20.00%	**18.64%**
Moving Average	Durham	Produce	35	50.00%	**25.03%**
	Durham	MixFood	35	0.40%	**24.68%**
	Greenville	MixFood	35	11.00%	**31.70%**
	Greenville	Produce	35	21.00%	**25.28%**
	Raleigh	MixFood	35	13.00%	**45.47%**
	Raleigh	Produce	35	1.00%	**22.84%**
	Sandhills	Produce	26	16.00%	**22.96%**
	Wilmington	MixFood	29	16.00%	**14.94%**
	Wilmington	Produce	13	14.00%	**28.28%**

Note: MAPE could not be calculated for *Sandhills* vs *Produce*

5.3 Performance of Intermediate Forecasting Techniques

The next section will gauge the performance for the moderately advanced techniques, Holt's and Winter's methods. To establish which groups should be evaluated by the following methods, each of the sets were plotted and a visual analysis was performed to check for trends, seasonality, and patterns. The software package StatTools was used to perform all of the analysis.

5.3.1 Holt's method. Holt's method, also known as Double Exponential Smoothing, tracks data series for linear trends. The two smoothing constants required for this approach are alpha (α) and beta (β). Table 31 demonstrates each of the alpha levels is all below 0.500. A beta

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smoothing constant of 0 denotes that a trend did not exist. Since *RET/WHLSLE*, and *MFGD* had a beta of zero, Holt's method is not the best approach for these groupings. The performances of the other forecasting techniques need to be compared to determine which method is best.

Table 31

Results of Holt's Method

Donor Type	Food Type	Branch	Alpha	Beta	MAPE	Validation MAPE
-	AT	-	0.161	0.027	8.83%	**9.09%**
RET/WHLSLE	-	-	0.311	0.000	6.76%	**134.30%**
MFGD	-	-	0.207	0.000	18.89%	**13.47%**
RET/WHLSLE		Wilmington	0.369	0.090	17.00%	**12.41%**
RET/WHLSLE		Sandhills	0.496	0.088	20.00%	**21.94%**
RET/WHLSLE	-	Raleigh	0.002	1.000	11.68%	**16.06%**

Note: Time period is monthly.

5.3.2 Winter's method. Winter's method is a type of triple exponential smoothing that is easily adaptable to updates within a data series. Winter's method is appropriate to be applied to a series that exhibits a seasonal trend. Table 32 highlights that the alpha levels for all five groupings were less than 0.500. The beta and gamma smoothing constants for both *Produce* storage type and *Produce* food type were zero. This means the procedure did not detect neither a trend nor any seasonality for the data sets. *Raleigh/Produce* had a high level of seasonality within the data.

Table 32

Results of Winter's Method

Branch	Storage Type	Food Type	Alpha	Beta	Gamma	MAPE	Validation MAPE
-	-	Produce	1	0	0	20.16%	**25.92%**
AT	AT	AT	0.017	0.252	0.437	8.54%	**9.50%**
-	Produce	-	1	0	0	20.03%	**25.57%**
Durham		MixFood	0.006	1	0	49.39%	**34.73%**
Raleigh	-	Produce	1.000	0	0.876	20.54%	**32.57%**

Note: Time period is quarterly.

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5.4 Performance of the Advanced Forecasting Method

The final forecasting method evaluated is ARIMA. Due to the complexity of this modeling technique, only the Aggregate Total data set will be analyzed using ARIMA. Autoregressive Integrated Moving Average is a sophisticated Box-Jenkins procedure that uses the autocorrelation function to develop a forecast. The analysis was performed using JMP software. The first step of the process is to check for stationarity. A series is considered to be stationary if the mean and standard deviation are constant overtime. Stationarity can be tested by plotting the autocorrelation function (ACF) and partial autocorrelation function (PACF) for the series. The ACF gives the correlations between the series and the lagged values k of the series. The PACF at lag k is the autocorrelation between the series the is not accounted for by lags 1 through k-1. The ACF for the Aggregate Total model can be seen in figure 10. According to Bowerman (1987) for a data series to be classified as stationary, the value of the ACF either cuts off fairly quickly or dies down fairly quickly. Table 33 summarizes the rules that should be used when studying these nonseasonal plots. The ACF pattern for the Aggregate Total model falls under the second category of dying down quickly and is thus considered stationary. That being said, the next step is to identify which model should be used for the forecast. To determine which model is appropriate, both the ACF and PACF are examined.

Table 33

General Nonseasonal Models

ACF	**PACF**	**Model**
Cuts off after lag q	Dies down	$(0, q, 0)$
Dies down	Cuts off after lag p	$(p, 0, 0)$
Dies down	Dies down	$(p, q, 0)$

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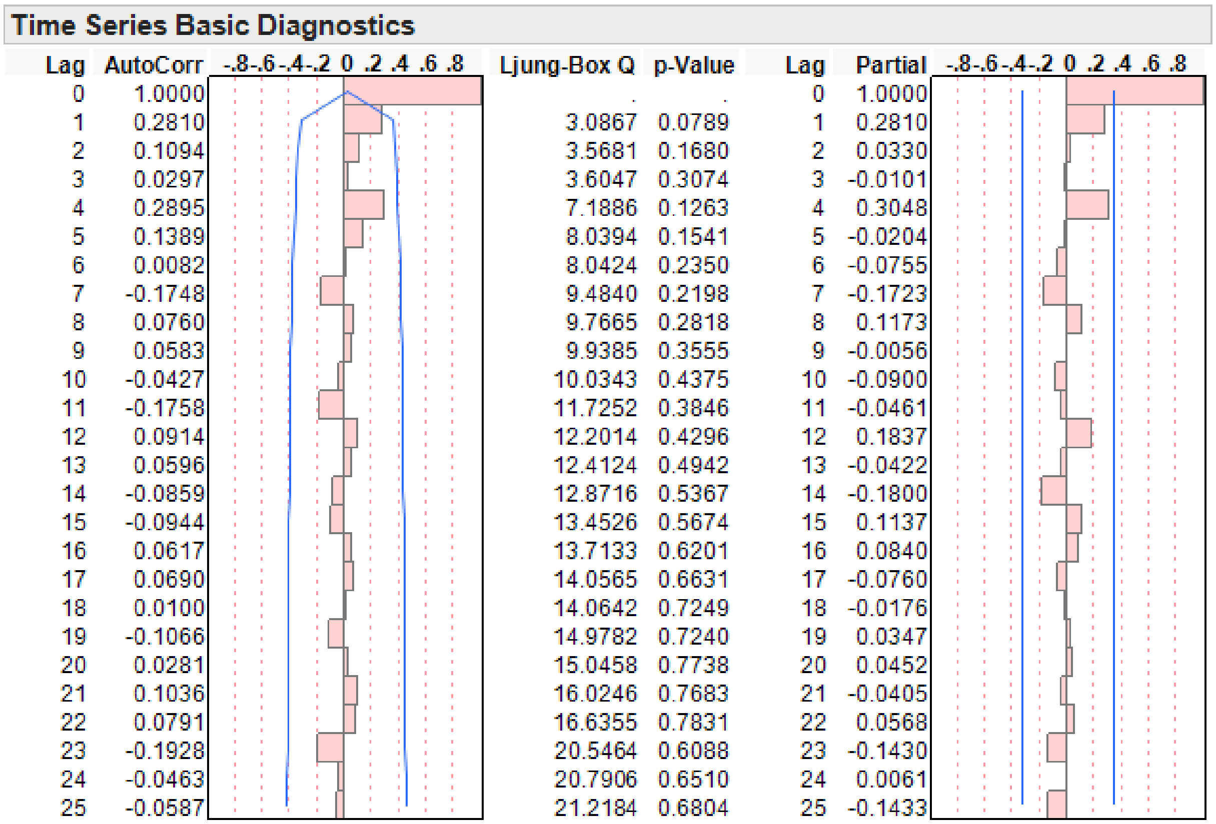
The ACF and PACF both appear to die down after lag 1 and are therefore considered to be a mixed model of order (0,1,0). The *p* value is equal to 0 because lag k cuts off at 0. The last step of the analysis is to perform and evaluate the forecast. The MAPE produced using this model was 11.47%.



Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.2810	3.0867	0.0789	1	0.2810
2	0.1094	3.5681	0.1680	2	0.0330
3	0.0297	3.6047	0.3074	3	-0.0101
4	0.2895	7.1886	0.1263	4	0.3048
5	0.1389	8.0394	0.1541	5	-0.0204
6	0.0082	8.0424	0.2350	6	-0.0755
7	-0.1748	9.4840	0.2198	7	-0.1723
8	0.0760	9.7665	0.2818	8	0.1173
9	0.0583	9.9385	0.3555	9	-0.0056
10	-0.0427	10.0343	0.4375	10	-0.0900
11	-0.1758	11.7252	0.3846	11	-0.0461
12	0.0914	12.2014	0.4296	12	0.1837
13	0.0596	12.4124	0.4942	13	-0.0422
14	-0.0859	12.8716	0.5367	14	-0.1800
15	-0.0944	13.4526	0.5674	15	0.1137
16	0.0617	13.7133	0.6201	16	0.0840
17	0.0690	14.0565	0.6631	17	-0.0760
18	0.0100	14.0642	0.7249	18	-0.0176
19	-0.1066	14.9782	0.7240	19	0.0347
20	0.0281	15.0458	0.7738	20	0.0452
21	0.1036	16.0246	0.7683	21	-0.0405
22	0.0791	16.6355	0.7831	22	0.0568
23	-0.1928	20.5464	0.6088	23	-0.1430
24	-0.0463	20.7906	0.6510	24	0.0061
25	-0.0587	21.2184	0.6804	25	-0.1433

Figure 10. ACF and PACF for Aggregate Total Data Set.

5.5 Comparison of Aggregate Levels and Models

5.5.1 Coefficient of variation. Figure 11 highlights the CV values for each aggregation level and the *Aggregate Total* subgroup. As the variability within the data set increases, the mean absolute percentage error increases as well. The *AT* had the smallest coefficient of variation and mean absolute percentage error overall. The *Raleigh* branch and *AT* had the least variability amongst the different groupings. This may suggest the *Raleigh* branch receives food consistently and the food which must be stored as *Frozen* is given consistently.

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All food types had relatively similar coefficient of variation and mean absolute percentage values. This could indicate that these types of foods are given with the same level of variation. Donor type *TEFAP* had the greatest amount of variability within its data set and error percentage which is understandable as the food bank can adjust when requests for food are asked of the donor. Produce had the smallest CV and MAPE for the food types, Dry had the smallest CV and MAPE for the storage types, and RETWHLSE had the smallest CV and MAPE for the donor types.

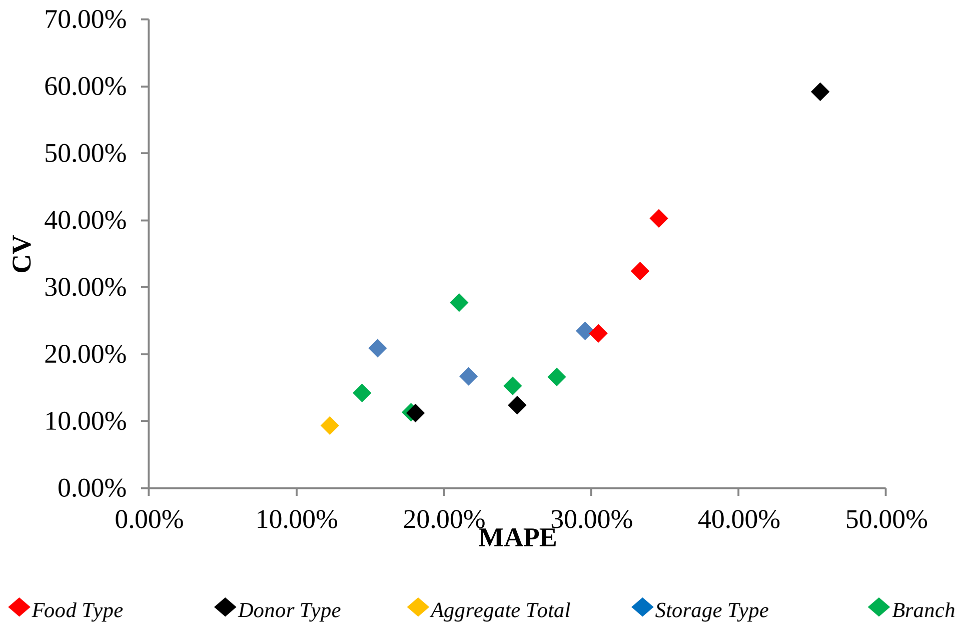

Figure 11. Coefficient of Variance by Individual Aggregation Level.

Figure 12 displays a coefficient of variation values for the coupled aggregation sets. The *AT* group had the smallest amount of variability within the data set while *MFGD vs. Produce* had the greatest amount of variability. The donor type vs food type data sets had the widest range of variability within a group. The graphs also demonstrate that as the coefficient of variation and mean absolute percentage error increase directly. Outliers were discovered for each graph and are marked as such.

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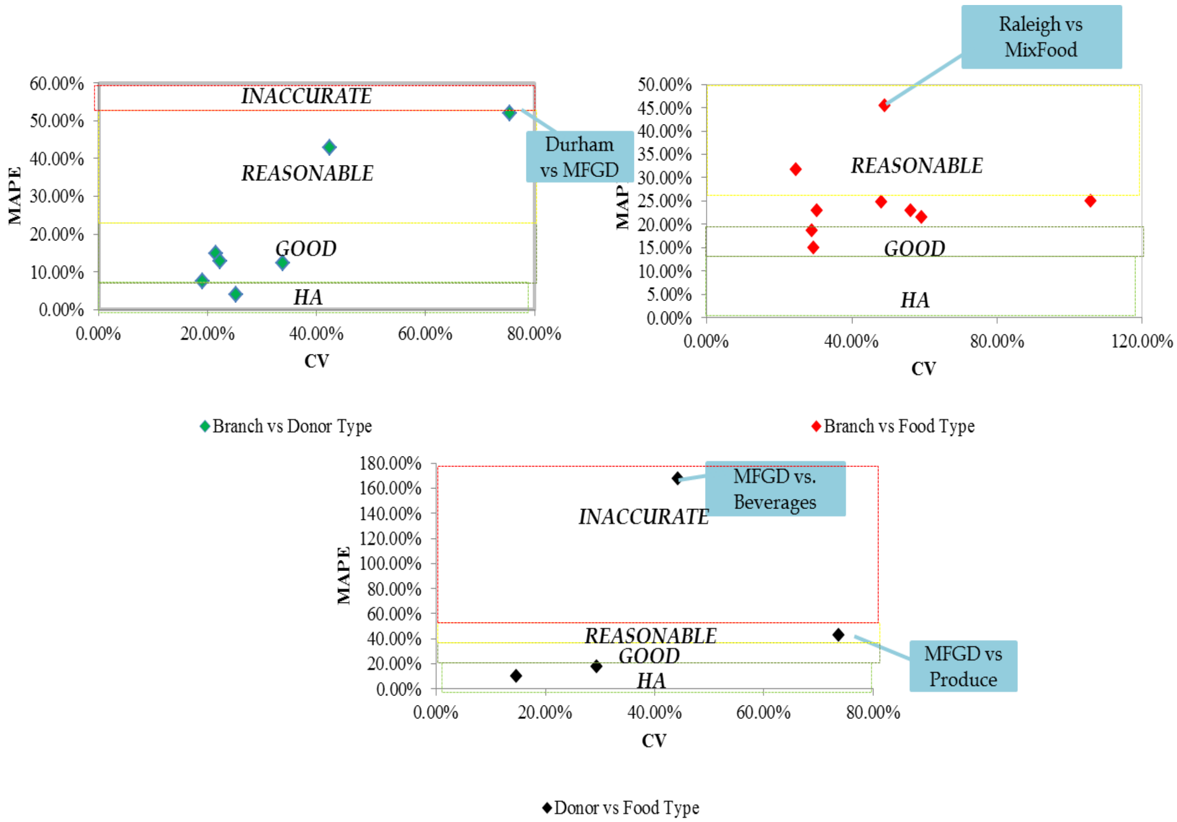

Figure 12. Coefficient of Variation – Combination

5.5.2 Forecasting accuracy for model set. Table 34 illustrates the performance of each of the forecasting techniques against the *AT* subgroup. Comparatively, exponential smoothing generated the lowest forecasting error and ARIMA produced the largest. The Holt's and exponential smoothing techniques produced fairly close error percentages. Overall, all four of the five forecasting techniques were able to produce a highly accurate forecasting technique against the *AT* group.

5.5.3 Overall forecasting accuracy. Figure 13 outlines the overall forecasting accuracy for moving average and exponential smoothing. Exponential smoothing, moving average, and Holt's and Winter's method were all capable of producing a highly accurate forecast. Conversely, exponential smoothing, moving average, and Holt's also produced inaccurate forecasts. Therefore, the models performed equally the same depending on the level investigated.

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Table 34

Overall Results for Aggregate Total

Forecasting Model	MAPE
Holt's	9.09%
Moving Average	9.34%
Winter's	9.50%
Exponential Smoothing	9.78%
ARIMA	11.47%

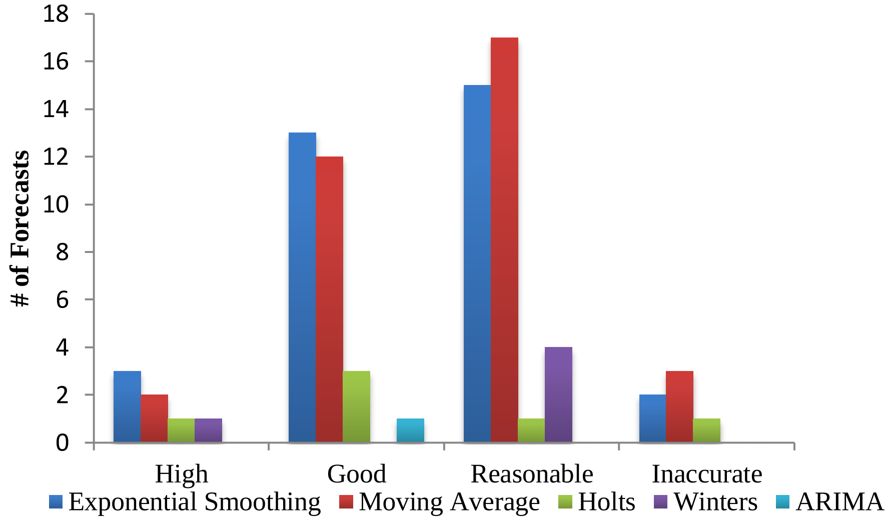

Figure 13. Forecasting Accuracy of All Techniques.

5.6 Summary

Currently, the forecasting methods furnish highly accurate to inaccurate forecasts. Table 35 summarizes which forecasting technique provided the best projection for each subgroup and the classification of accuracy. Therefore, the forecasting technique that should be selected to produce a robust forecast depends significantly upon the segmentation level of interest. Although exponential smoothing generated the lowest forecasting error for TEFAP and MFGD/Beverages, the models are still considered to be inadequate. Further exploration is required to address this issue.

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Table 35

Recommended Forecasting Methods and the Resulting Accuracy

	Moving Average	**Exponential Smoothing**	**Holt's**
Aggregate Total			*Highly Accurate*
Beverages		*Reasonable*	
MixFood	*Reasonable*		
Produce	*Reasonable*		
MFGD		*Good*	
RET/WHLSLE	*Good*		
TEFAP		*Inaccurate*	
Dry		*Good*	
Produce	*Reasonable*		
Frozen	*Reasonable*		
Raleigh		*Good*	
Durham	*Good*		
Sandhills		*Reasonable*	
Wilmington		*Good*	
Greenville	*Good*		
Durham vs MixFood	*Reasonable*		
Durham vs Produce	*Reasonable*		
Greenville vs MixFood	*Reasonable*		
Greenville vs Produce		*Reasonable*	
Raleigh by MixFood	*Reasonable*		
Raleigh by Produce	*Reasonable*		
Sandhills vs Produce			
Wilmington vs MixFood	*Good*		
Wilmington vs Produce		*Good*	
Durham vs MFGD			
Durham vs RET/WHLSLE		*Good*	
Greenville vs MFGD		*Reasonable*	
Greenville vs RET/WHLSLE		*Highly Accurate*	
Raleigh vs MFGD		*Good*	
Sandhills vs RET/WHLSLE		*Good*	
Wilmington vs RET/WHLSLE		*Highly Accurate*	
MFGD vs Beverages		*Inaccurate*	
MFGD vs Produce		*Reasonable*	
RET/WHLSLE vs MixFood		*Good*	
RET/WHLSLE vs Produce	*Good*		

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CHAPTER 6

Supply Level Management Assessment

6.1 Fair Share Analysis

The fair share distribution is an analysis performed monthly to determine the amount of food each branch and county should receive relative to the amount of food donated each month. This is referred to as the theoretical fairshare and is determined as follows: First, the number of people living in poverty, (both 185% above and below the poverty line) and unemployment for each county per year is determined. The amount of food needed per county is determined by multiplying the total amount of food distributed by the fairshare percentage. Finally, the pounds per person in poverty (PPIP) are calculated by dividing the amount of food actually distributed to the people in poverty. Feeding America has recommended that the PPIP should always be 75 or above for each county.

6.2 Supply Level Management Assessment (SLMA)

Currently, the fairshare analysis is used as a reactive tool and only allows the food bank to make adjustments after the event has occurred. This research proposes using the predicted forecasts in place of the theoretical fairshare and then measuring the PPIP. If this number falls below the recommended Feeding America standards then action is required.

To construct the SLMA, the food bank will need the forecasted values for the fiscal year in consideration. For this example, fiscal year 2010-2011 will be examined. Using the data provided by the food bank, table 36 demonstrates the predetermined fairshare percentages for fiscal year 2010-2011 for each branch; the fairshare percentage for each county is used in the appendix.

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Table 36

Fairshare Percentages

	Fairshare %	
	2009	**2010**
Wilmington	12.35%	12.19%
Greenville	17.44%	17.61%
Durham	16.76%	16.94%
Raleigh	40.60%	40.59%
Sandhills	5.66%	5.62%
Shared Counties	7.18%	7.04%

The slight change in the fairshare percentages is due to the decrease in unemployment in 2010. The fairshare percentages hold true in 2009 for the months of July-December, and the fairshare percentages for 2010 are applicable from January-June. To coincide with the annual poverty and unemployment statistics measured, FBCENC calculates a running annual total of the pounds of food received. Since the food bank performs this analysis monthly, the forecasted values that will be used for the SLMA will also be calculated monthly. The historical data from the prior August-June and the forecasted value for July are summed to produce an annual forecasted amount. Using table 35, the recommended technique is applied to the associated branch. Table 37 illustrates the results of the forecasts for the projected fairshare analysis for 2011-2012. The projected donations were within 6.45% of the actual donations distributed.

Using the fairshare percentages, the PPIP are calculated for each county and branch. The SLMA indicated that counties Lenoir, Pitt, Vance, Duplin, Richmond, and Scotland consistently

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fall below the PPIP standard. Although the food bank may reactively adjust its allocation of donations for subsequent months to address the issue, the SLMA provides insight to circulation patterns and encourages the Food Bank to proactively plan allocation of donations to prevent inequitable distributions.

Table 37

Results of SLMA Forecast for Fair Share Analysis 2011-2012

	Forecasted Total	Actual
July	43,227,044	41,207,873
August	43,601,609	41,118,292
September	44,647,083	41,757,749
October	44,666,463	41,655,469
November	43,964,556	41,373,733
December	44,190,496	41,080,444
January	44,140,931	41,465,032
February	44,895,213	42,091,079
March	44,908,687	42,309,429
April	44,322,814	41,690,017
	MAPE	6.45%

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CHAPTER 7

Summary and Future Work

7.1 Conclusion

Food insecurity and hunger are critical issues among the communities of the United States. Food banks such as the Food Bank of Central and Eastern North Carolina, aid the communities by providing food and other necessities to partner agencies whom then distribute to those in need. The survival of most food banks, including the FBCENC, rely heavily on receiving donations from the community. Therefore the amount of donations received fluctuates over time and can be difficult to predict. This instability increases the difficulty for a food bank to properly plan, distribute, and ration donations to the partner agencies. The purpose of this study was to evaluate several different forecasting methodologies and aggregate levels to assess which technique and level produced the lowest errors. The data was evaluated on 5 individual and three dual aggregate levels. The forecasting techniques explored were simple moving average, simple exponential smoothing, Holt's method, Winter's method, and ARIMA. To compare the accuracy of each approach, the mean absolute error percentages were calculated for each test. Overall, the simple moving average technique performed the best. A warning system, Supply Level Management Tool, was proposed to benefit the FBCENC in the planning process.

7.2 Future Work

Although many of the techniques produced robust forecasts, donor type *TEFAP* and *MFGD*/*Beverages* both had inaccurate forecasts. Therefore, more investigation is required to determine how to better predict the donation pattern. One recommendation is to perform the forecasting analysis on all of the sublevels regardless of the gross weight total. This will capture the entire data set and may provide a more accurate representation of the behavior of the

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donations received. Secondly, one should consider possibly removing the donor type *TEFAP* from the data set. *TEFAP*, although a donated item, is a government donor and is mandated to give to the food banks. Also, the food bank decides when and how much of their allotment it receives over the year. Thus, the *TEFAP* donations can be viewed “purchased” donations with predicted fluctuations. Another recommendation is exploring ensemble type forecasting to determine if combining approaches will results in a better forecasting accuracy. Lastly, the SLMA can be an excellent proactive instrument for the food bank to use in conjunction with the fairshare analysis. Further investigation is recommended to explore the potential applications thereof.

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Appendix A

Table 38

Description of Donor Types

Donor Types	**Description**	**Donor Group**
AFFILIATE	Affiliated	Food Banks Transfers
BONUS/OTH	Bonus/Other	United States Department of Agriculture
FOODDRIVE	Food Drive	Individual and Community Food Drives
GRANTPURCH	Grant Purchase	Items Purchased Using Grant Money
MFGD	Manufactured Goods	Major Business and Corporations
MISCELLANY	Miscellanies	Miscellaneous Donors
OTHERPURCH	Other Purchase	Items Purchased for Stores
PRODUCE	Produce	Local Farmers and Companies
RET/WHLSLE	Retail/ Wholesale	Local Retail and Wholesale Stores
SALVAGE	Salvage	Salvage Items
TEFAP	TEFAP	North Carolina Department of Agriculture

Table 39

Description of Storage Type

Storage Type	Description
DRY	Donations stored at room temperature
PRODUCE	Fruits, Vegetables and other Perishables
FROZEN	Donations stored at or below 0°
REF	Donations stored between 40° and 0°
SALVAGE	Stored cans and dented boxes
PREPARED	Food that is prepared

Table 40

Branch Code Names

Branch_Code	**Branch Name**
R	Raleigh
D	Durham
S	Sandhills
W	Wilmington
G	Greenville
N	New Bern

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Appendix B

Table 41

Parameters for Winter's Method

Variable	Definition
β	Smoothing Constant
α	Smoothing Constant
S_t	Intercept at time *t*
G_t	Value of the Slope at time *t*
S_{t-1}	Previous Intercept
G_{t-1}	Previous Slope
D_t	Current Observation of Demand
$F_{t,t+1}$	The τ-step-ahead forecast made in period *t*
Υ	Smoothing Constant
c_t	Current Seasonal Factor
c_{t-N}	Pervious Seasonal Factor
$c_{t+\tau-N}$	Seasonal Factor at future periods

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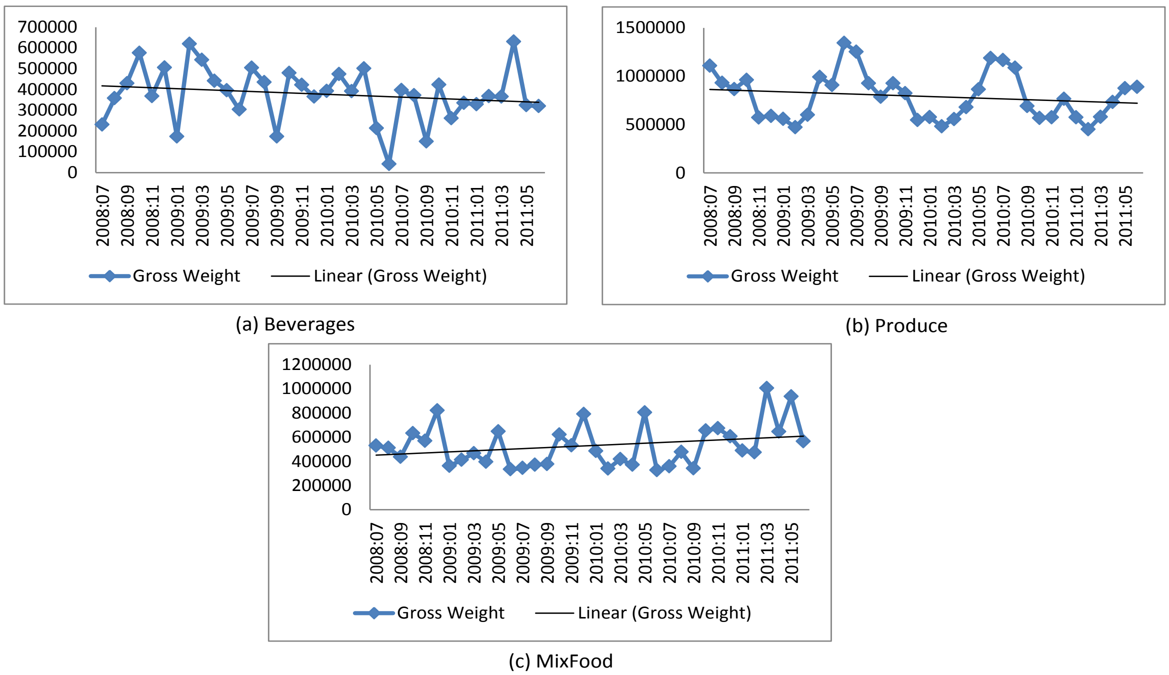
Appendix C

Figure 14. Time Series Plots - Food Type

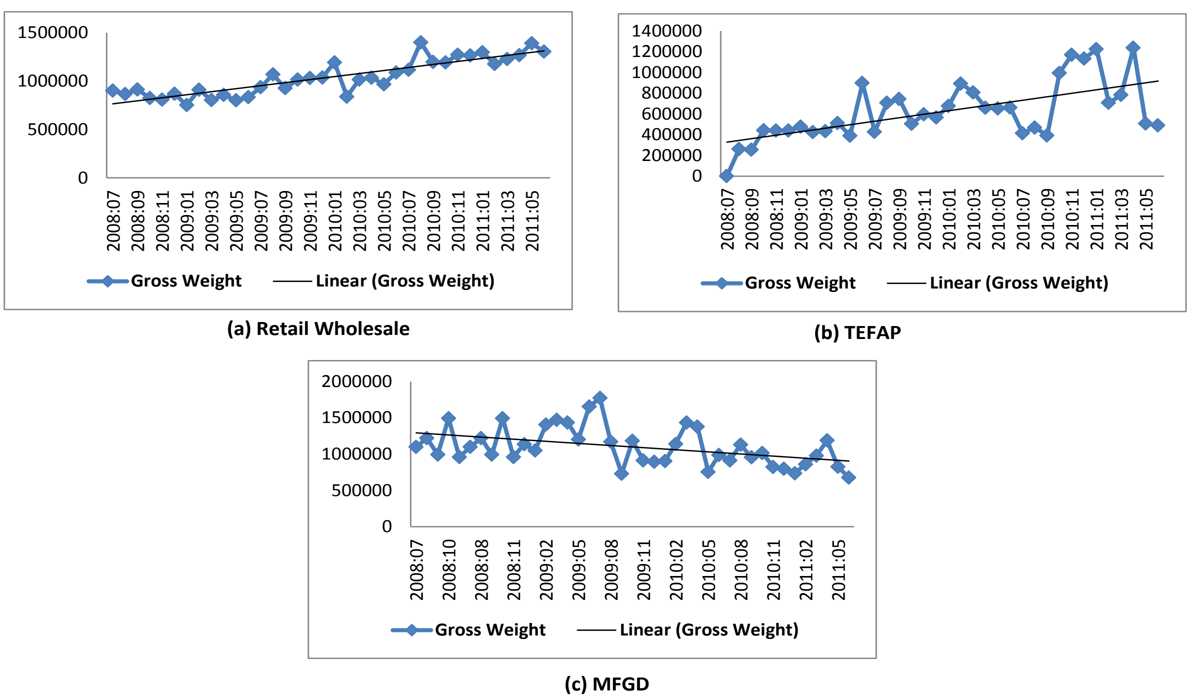


(a) Beverages

(b) Produce

(c) MixFood

Figure 15. Time Series Plots - Donor Type



(a) Retail Wholesale

(b) TEFAP

(c) MFGD

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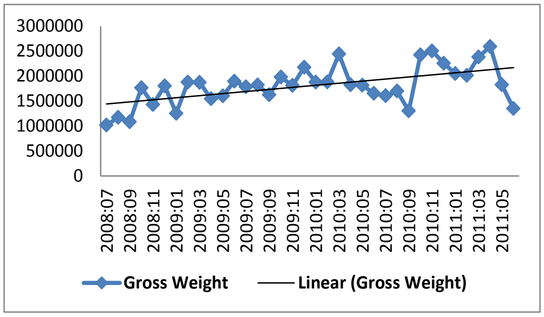
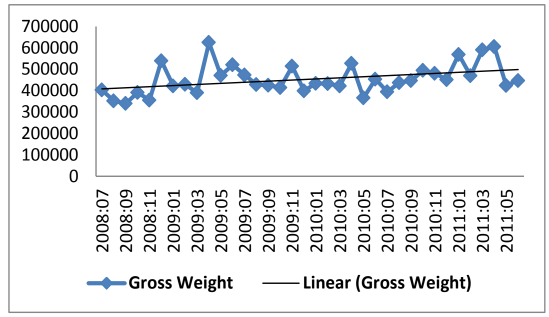
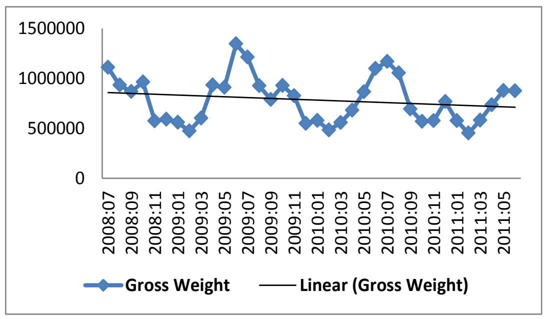
Figure 16. Time Series Plots - Storage Type



(a) Dry



(b) Frozen



(c) Produce

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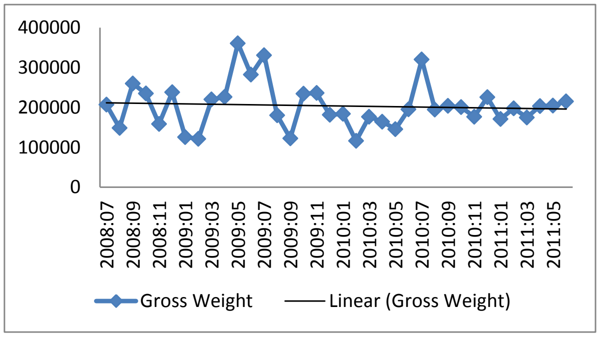
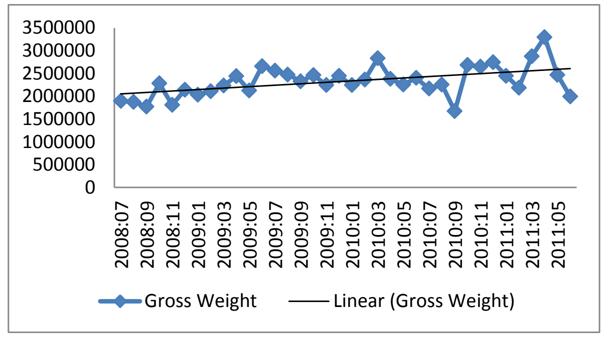
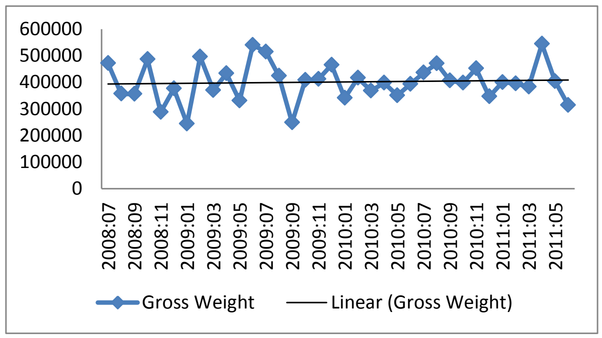
Figure 17. Time Series Plots - Branch



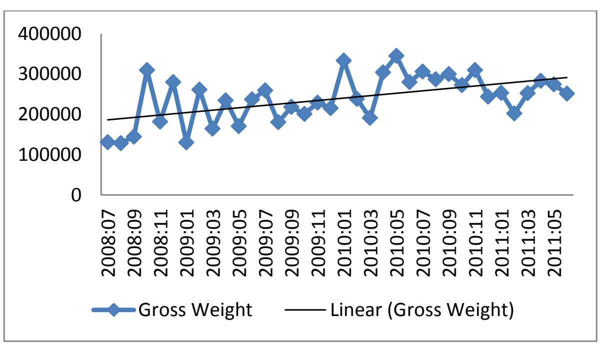
(a) Durham



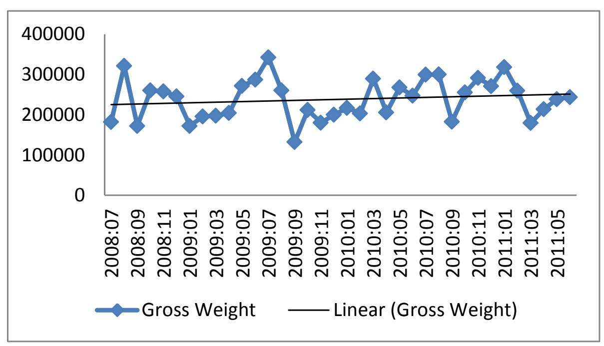
(b) Raleigh



(c) Greenville



(d) Wilmington



(e) Sandhills

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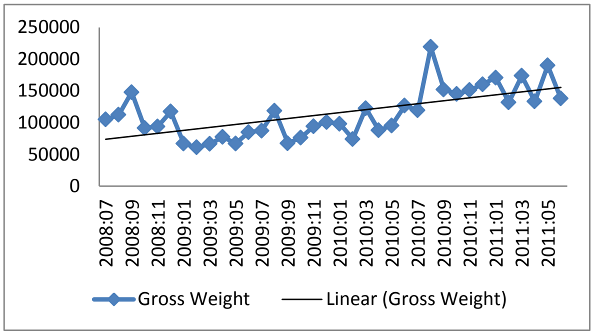
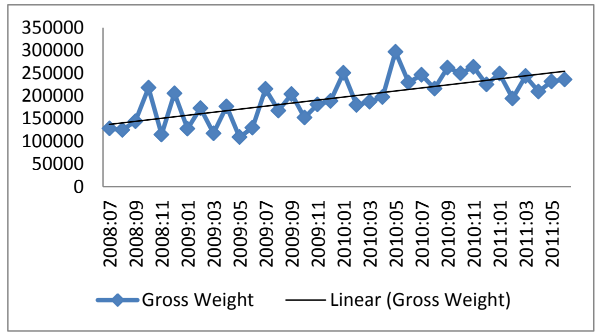
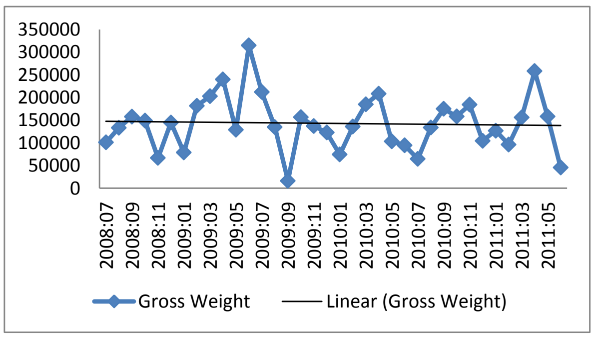
Figure 18. Time Series Plots - Branch vs Donor Type



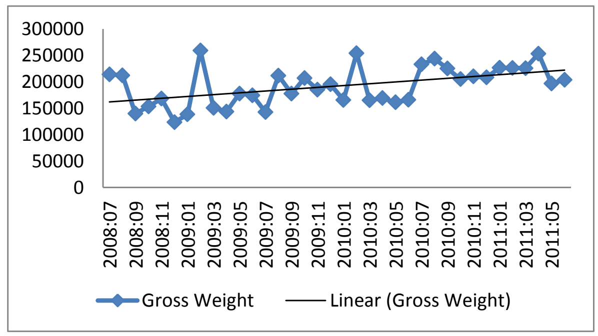
a. Sandhills vs RET/WHLSLE



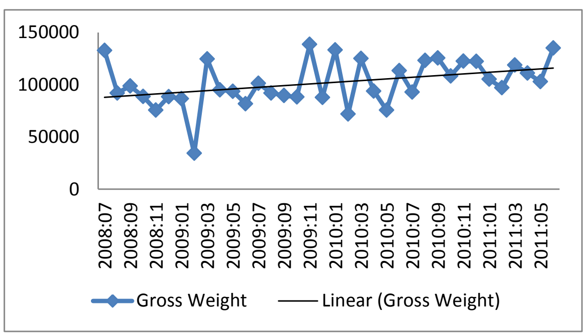
b. Wilmington vs RET/WHLSLE



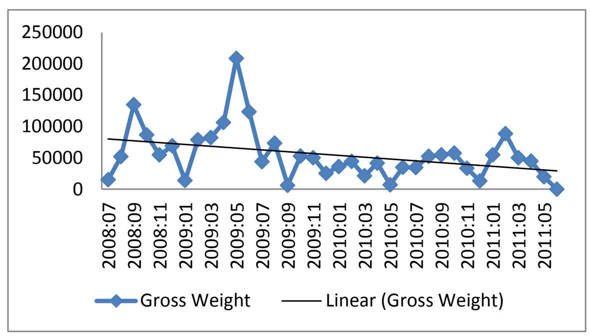
c. Greenville vs MFGD



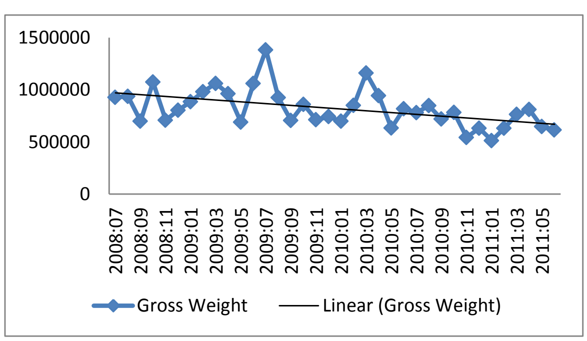
d. Greenville vs RET/WHLSLE



e. Durham vs RET/WHLSLE



f. Durham vs MFGD



g. Raleigh vs MFGD

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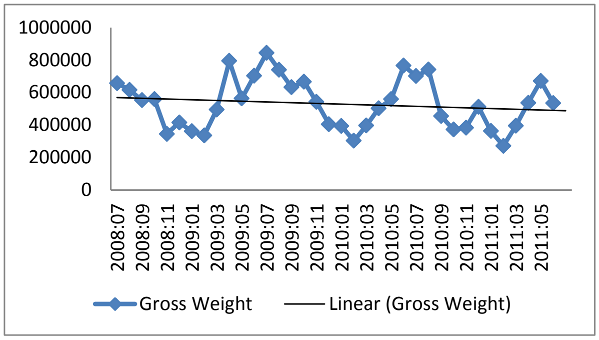
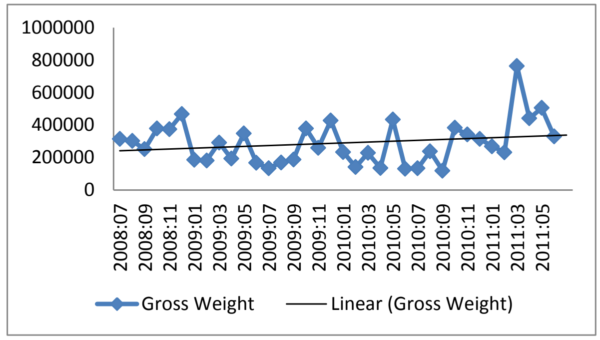
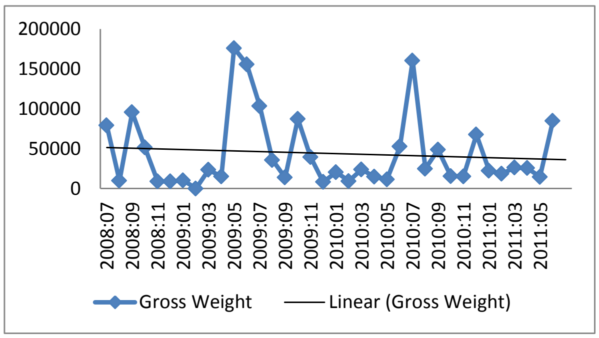
Figure 19. Branch vs Food Type



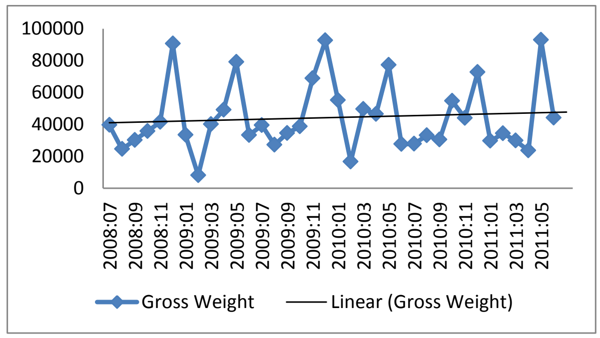
a. Raleigh vs Produce



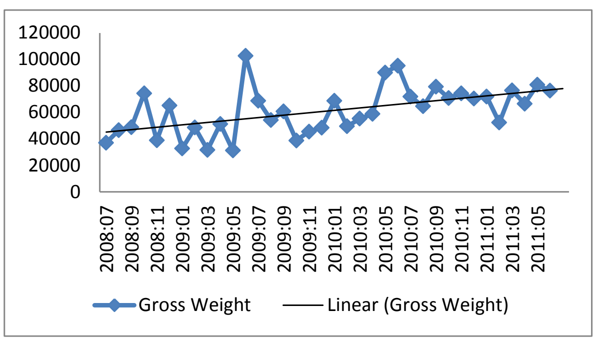
b. Raleigh vs MixFood



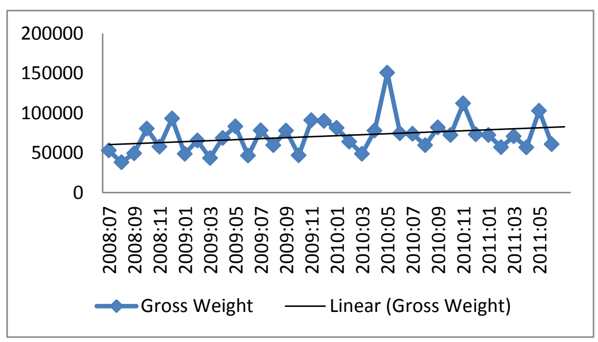
c. Durham vs Produce



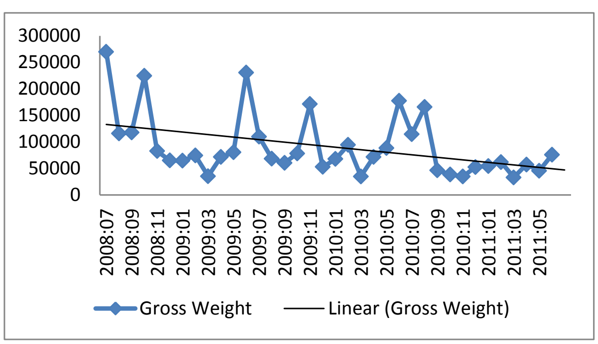
d. Durham vs MixFood



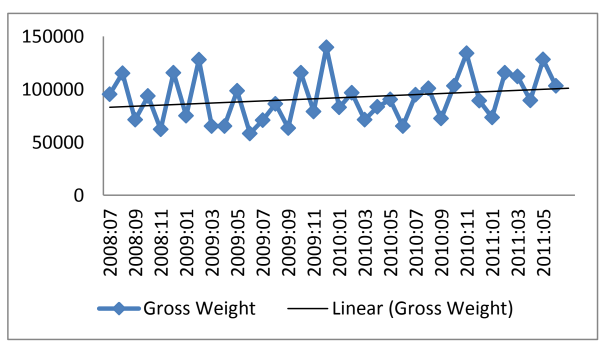
e. Wilmington vs Produce



f. Wilmington vs MixFood



g. Greenville vs Produce



h. Greenville vs MixFood

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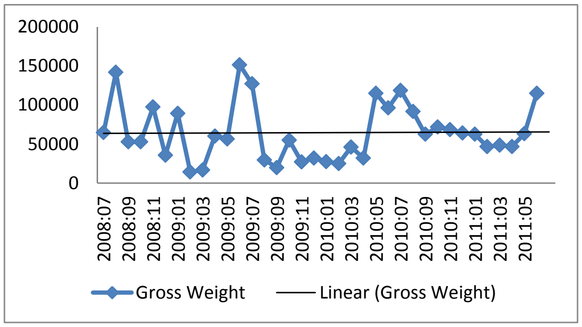
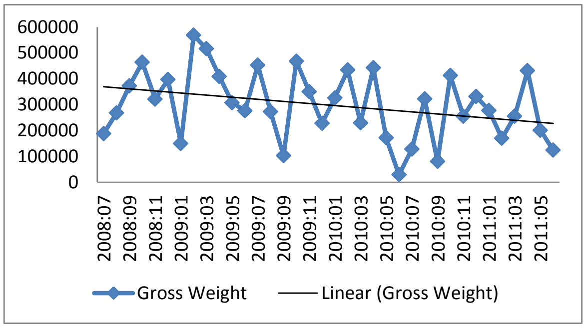
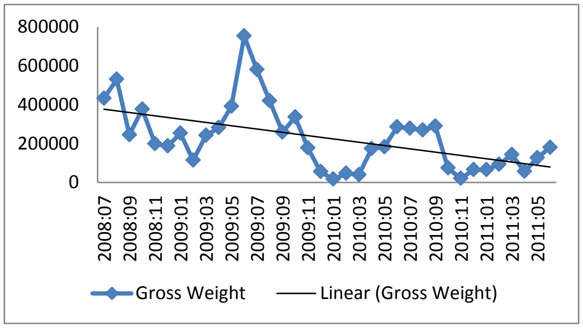


i. Sandhills vs Produce

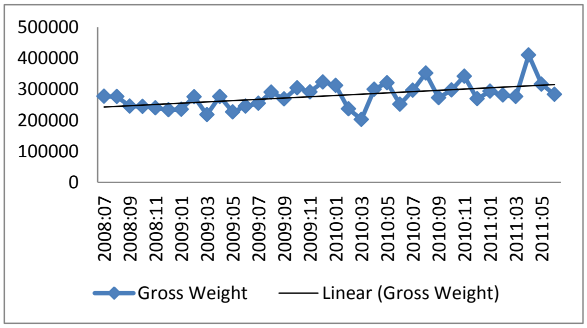
Figure 20. Donor Type vs Food Type



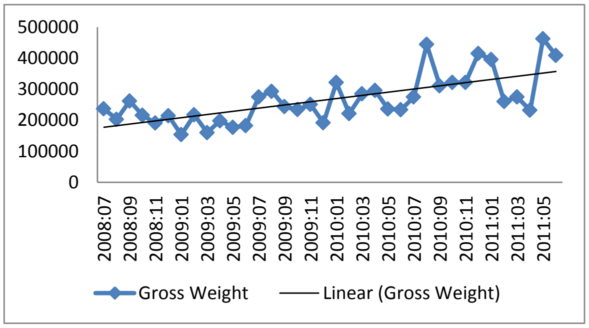
(a) MFGD vs Beverages



(b) MFGD vs Produce



(c) RETWHLSE vs MixFood



(d) RETWHLSE vs Produce

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Appendix D

Table 42 *Results of Behavioral Analysis*

	Trend		**Seasonality**		**Neither**
	Positive	*Negative*	*Quarterly*	*Annually*	
Beverages					x
MixFood					x
Produce				x	
MFGD		x			
RET/WHLSLE	x				
TEFAP					x
Dry					x
Produce				x	
Frozen					x
Raleigh					x
Durham					x
Sandhills					x
Wilmington					x
Greenville					x
Durham vs MixFood			x		
Durham vs Produce					x
Greenville vs MixFood					x
Greenville vs Produce					x
Raleigh vs. MixFood					x
Raleigh vs. Produce				x	
Sandhills vs Produce					x
Wilmington vs MixFood					x
Wilmington vs Produce					x
Durham vs MFGD					x
Durham vs RET/WHLSLE					x
Greenville vs MFGD					x
Greenville vs RET/WHLSLE					x
Raleigh vs MFGD		x			
Sandhills vs RET/WHLSLE	x				
Wilmington vs RET/WHLSLE	x				
MFGD vs Beverages					x
MFGD vs Produce					x
RET/WHLSLE vs MixFood					x
RET/WHLSLE vs Produce					x

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Appendix E

Table 43 *Forecasting Model Selection*

	Mov. Avg.	**Exp. Smooth.**	**Holt's**	**Winter's**	**ARIMA**
Aggregate Total	x	x	x	x	x
Beverages	x	x			
MixFood	x	x			
Produce	x	x		x	
MFGD	x	x	x		
RET/WHLSLE	x	x	x		
TEFAP	x	x			
Dry	x	x			
Produce	x	x		x	
Frozen	x	x			
Raleigh	x	x			
Durham	x	x			
Sandhills	x	x			
Wilmington	x	x			
Greenville	x	x			
Durham vs MixFood	x	x		x	
Durham vs Produce	x	x			
Greenville vs MixFood	x	x			
Greenville vs Produce	x	x			
Raleigh vs. MixFood	x	x			
Raleigh vs. Produce	x	x		x	
Sandhills vs Produce	x	x			
Wilmington vs MixFood	x	x			
Wilmington vs Produce	x	x			
Durham vs MFGD	x	x			
Durham vs RET/WHLSLE	x	x			
Greenville vs MFGD	x	x			
Greenville vs RET/WHLSLE	x	x			
Raleigh vs MFGD	x	x			
Sandhills vs RET/WHLSLE	x	x	x		
Wilmington vs RET/WHLSLE	x	x	x		
MFGD vs Beverages	x	x			
MFGD vs Produce	x	x			
RET/WHLSLE vs MixFood	x	x			
RET/WHLSLE vs Produce	x	x			

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