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PREDICTING DONATIONS USING A FORECASTING-SIMULATION MODEL

Isaac A Nuamah
Lauren Davis
Steven Jiang
Nicole Lane

Department of Industrial and Systems Engineering
North Carolina A&T State University
1601 East Market Street
Greensboro, NC 27411, USA

ABSTRACT

This paper presents a methodology to estimate donations for non-profit hunger relief organizations. These organizations are committed to alleviating hunger around the world and depend mainly on the benevolence of donors to achieve their goals. However, the quantity and frequency of donations they receive varies considerably over time which presents a challenge in their fight to end hunger. We develop a simulation model to determine the expected quantity of food donations received per month in a multi-warehouse distribution network. The simulation model is based on a state-space model for exponential smoothing. A numerical study is performed using data from a non-profit hunger relief organization. The results show that good estimation accuracies can be achieved with this approach. Furthermore, non-profit hunger relief organizations can use the approach discussed in this paper to predict donations for proactive planning.

1 INTRODUCTION

1.1 Background

Proper nutrition is an essential part of living a healthy lifestyle. Whenever the availability of nutritionally adequate and safe foods or the ability to obtain acceptable food by socially conventional means is limited or uncertain for an individual, they are considered food insecure (Haering 2009). Studies have shown that unemployment and poverty can be strong indicators of those at risk of becoming food insecure. Most food insecurity is associated with chronic poverty and temporary unemployment (Barrett 2010). Fortunately, there exists non-profit hunger relief organizations (NPHROs) that are actively fighting to end the war against hunger. One such organization is 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 Americans through a network of associated food banks. The Feeding America organization assists local food banks in acquiring and dispensing 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 (Feeding America 2012).

The quantity and frequency of donations received by food banks vary considerably over time which presents a challenge in their fight to end hunger. The operational efficiency of food banks depend on effectively estimating donations to determine additional food purchases required to satisfy the nutritional needs of the population they serve. Their inability to determine additional food purchases due to inaccurate donation estimation poses a challenge as they strive to balance supply with demand. This research proposes an approach to estimate donation supplies. Our study consists of a food bank distribution network consisting of multiple branch warehouses. Using data provided by a local food bank, we simulate future donation supplies for five branches using the state space model for simple exponential smoothing (SSMFSES) via simulation. The SSMFSES resulted in good estimation accuracies in all five branches.

1.2 Related Literature

There is an extensive amount of literature related to forecasting. Forecasts for donated items has been done for cash (Britto and Oliver 1986) or blood (Drackley et al. 2012, Pereira 2003) donations. There has also been some work related to forecasting sales for fresh food items in the retail sector (Doganis et al. 2006, Chen and Ou 2009). The literature for forecasting food donations is sparse. Neural network models were used to forecast in-kind donations from retail donors for a local food bank (Brock and Davis 2015). Time series models have also been explored in the context of food donations for a NPHRO that has multiple warehouses (Davis et al. 2015). However, in both of these studies, only point forecasts were generated.

There are numerous publications of state space model based forecasting in various sectors. There are publications in inventory management, sports, energy, traffic management, financial and biological sectors.

In the energy sector, Dong et al. (2013) used an exponential smoothing state space (ESSS) model to forecast high-resolution solar irradiance time series. They compared the ESSS model to other time series models. The simulation results showed that the ESSS model has generally better performance than other time series forecasting models.

In inventory management, Yelland (2009) compared the forecast performance of three simple state-space models using demand data obtained from Sun's inventory management records. He compared the accuracy of these probabilistic forecasts using techniques borrowed from the field of meteorology, allowing the assessment of the suitability of the candidate models for this type of application.

In the biological sector, Rueda and Rodríguez (2010) introduced multivariate state space models for estimating and forecasting fertility rates. Their model besides providing very satisfactory short-and medium-term forecasts, provides practitioners with several suitable interpretative tools, and the application here is an interesting example of the usefulness of the state space representation in modelling real multivariate processes.

In the financial sector, Forbes et al. (2013) produced non-parametric maximum likelihood estimates of forecast distributions in a general non-gausssian, non-linear state space setting. They applied their method to produce sequential estimates of the forecast distribution of realized volatility on the S&P500 stock index during the recent financial crisis.

In traffic management, Dong, et al. (2014) developed a multivariate state space model for network flow rate and time mean speed predictions using historical time series. They compared their model to the ARIMA models and deduced that the benefit is much more evident in the proposed models for all cases, and the accuracy can be improved by 5.62% on average. They concluded besides accuracy improvement, their proposed models are more robust and the predictions can retain a smoother pattern.

In sports, Glickman and Stern (1998) developed a state-space predictive model for National Football League (NFL) game scores using data from the period 1988-1993. Their model accounts for team strength variability by assuming team strength parameters follow a first-order autoregressive process. Their model outperformed the Las Vegas "betting line" on a small test set consisting of the last 110 games of the 1993 NFL season.

Hyndman et al. (2002) applied random simulation from the underlying state space model to the 1001 series of the M-competition data, (Makridakis et al. 1982) and M3-competition data, (Makridakis &

Hibon, 2000).Their method provides forecast accuracy comparable to the best methods in the competitions and it is particularly good for short forecast horizons with seasonal data.

1.3 Research Contribution

To the best of our knowledge, the application of SSMFSES to predict the quantity of food donations in food banks has not been addressed in the open literature. We present strategies to apply SSMFSES to predict food related donations. Future donation quantities for five different branches were simulated using the SSMFSES. The specific research question we seek to address is as follows. Given the underlying structure of the donations data, how best can donation quantities be estimated?

The remainder of this paper is outlined as follows. Section 2 summarizes our approach to applying the SSMFSES to predict food related donations. The results of the study are summarized in Section 3. Section 4 provides some concluding remarks about the implication of our results on operational efficiency and service delivery.

2 METHODOLOGY

Before describing the simulation model, we first describe the general form of simple exponential smoothing and the state space model.

2.1 Simple Exponential Smoothing

Suppose we have an observed data of time series, y_t, and we wish to forecast the next value of our time series, $\hat{y}_t$, the forecast error will be equal to $y_t - \hat{y}_t$ when an observation y_t becomes available. According to (Brown, 1959), the forecast for the next period is simply the old forecast plus an adjustment for the error that occurred in the last forecast. Equation (1) shows the forecast for the next period.

$$\hat{y}_{t+1} = \hat{y}_t + \alpha(y_t - \hat{y}_t) \tag{1}$$

Where α is a constant between 0 and 1. Another way to represent equation (1) is as shown in equation (1a).

$$\hat{y}_{t+1} = \alpha y_t + (1 - \alpha)\hat{y}_t \tag{1a}$$

It is assumed that the forecast function is “flat” for longer range forecasts that is

$$\hat{y}_{t+h|t} = \hat{y}_{t+1}, \qquad h = 2,3, \ldots \tag{2}$$

Suppose the level of the series, $\ell_t = \hat{y}_{t+1}$, equation (2) can be rewritten as

$$\hat{y}_{t+h|t} = \ell_t\,, \qquad \ell_t = \alpha y_t + (1 - \alpha)\hat{y}_t \tag{3}$$

2.2 State Space Models

All state-space models have three elements namely the forecast function, the observation equation, and one or more state equations (Polasek, 2013). There are two main forms of state space models namely the conventional state space model and innovations state space model. The main difference between the two is that the conventional state space model has multiple sources of error while the innovations state space model has a single source of error. In this paper, we will only discuss innovations state space model.

There are two forms of the innovations state space model namely the linear and non-linear innovations state space model. We will only discuss linear innovations state space model in this paper and equations (4-5) show its general form. Equation (4), the observation equation, describes the relationship between the unobserved states x_{t-1} and the observation y_t. The state vector (x_t) contains unobserved components that describe the series level at time *t* (ℓ_t), the slope at time *t* (b_t) and seasonality of the series at time *t* (s_t). Equation (5), the state equation, describes the evolution of the states over time. $\boldsymbol{F}$, $\boldsymbol{w}$ and $\boldsymbol{g}$ are coefficient matrices. ε_t is the white noise series at time *t.* The use of identical errors in equations (4-5) makes it an innovations state space model.

$$y_t = \boldsymbol{w}x_{t-1} + \varepsilon_t \tag{4}$$

$$x_t = \boldsymbol{F}x_{t-1} + \boldsymbol{g}\varepsilon_t \quad (5)$$

In this paper, we applied the local level model of the linear innovations state space model which has only one single state, ℓ_t and the resulting state space model is defined by the equations (6-7). In the equations below , $\boldsymbol{g} = \alpha, \boldsymbol{F} = [1], \boldsymbol{w} = [1]$.

$$y_t = \ell_{t-1} + \varepsilon_t \quad (6)$$

$$\ell_t = \ell_{t-1} + \alpha\varepsilon_t \quad (7)$$

From the above model, we seek to determine the expected value of future observation conditioned on the value of the state vector x_t. This is formally defined as $E(y_{t+h}|x_t)$ and can be determined by simulating many future sample paths conditional on the last estimate of the state vector. Prediction intervals can also be obtained from the percentiles of the simulated sample path. Point forecasts can be obtained by taking the average of the simulated values in each future time period.

In order to completely specify the model, the initial state values must be specified (ℓ_0), the smoothing constants must be estimated, and the properties of the random error term must be specified. Below are the assumptions of the model:

1. The expected value of each error term is zero.
2. The errors for different time periods are independent of (or at least uncorrelated with) one another and also independent of past states.
3. The variance of the errors is constant.
4. The errors are drawn from a normal distribution.

2.3 Forecasting-simulation Model for monthly donations

Table 1 summarizes the model notation within the context of the donations forecasting problem. The objective is to predict the expected food donations (in lbs.) received per month. We assume that initial model parameters (ℓ_0, α, s) are estimated from prior observations (Q_t) defined in a test data set, consisting of N_T observations. The simulation approach is described first, followed by the initialization procedure.

Table 1: Forecasting-simulation model notation.

Variable	Description
y_t	Observed gross weight of food donations in period *t* determined from the observation equation
ℓ_t	The state at time *t* (level of the series)
ε_t	The error term in period *t*
α	The smoothing constant
$\tilde{\mu}_t$	Simulated mean gross weight in period *t*
UL_t	Upper limit of the 95th percentile prediction interval in period *t*
LL_t	Lower limit of the 95th percentile prediction interval in period *t*
R	The number of replications
Q_t	The actual donation quantity received in period *t*
B_t	The smoothed estimate for level in period *t*
$\hat{Q}_t$	The forecast of the donation quantity in period *t*
s	Standard deviation of the forecast error
N_T	The total number of periods in the test data set
N_V	The total number of periods in the validation data set

2.3.1 Simulation Approach

The Monte-Carlo simulation approach is outlined in the steps in Table 2. The initial model parameters are determined from an optimization procedure described in section (2.3.2). Future monthly donations are determined for each period in the validation data set (line 13). For each period, the error terms are generated according to a normal distribution (line 7). The error terms are used to determine the simulated donation values (observation y_t) and state values according to the corresponding equations (lines 8-9). For each period, the observation and state equations are simulated for a total of R iterations. The 95th percentile prediction interval for the R observations (y_t) for each period is computed according to the corresponding equations (lines 9-10). The mean value for the R observations (y_t) for each period is then recorded (line 13). The simulation model is implemented in Matlab.

Table 2: Simulation procedure.

Steps
1: GetInitialValues ($\alpha^*, s^*, \hat{Q}_{N_T}$)
2: $\alpha \leftarrow \alpha^*$
3: $\ell_0(i) \leftarrow \hat{Q}_{N_T}$ $for\ i = 1..R$
4: $s \leftarrow s^*$
5: **For** $t = 1$ **to** N_V
6: **For** $i = 1$ **to** R
7: $\varepsilon_t(i) \leftarrow normrnd(0, s)$
8: $y_t(i) \leftarrow \ell_{t-1}(i) + \varepsilon_t(i)$
9: $\ell_t(i) \leftarrow \ell_{t-1}(i) + \alpha\varepsilon_t(i)$
10: **End For** $\boldsymbol{i}$
11: $LL_t \leftarrow prctile(\boldsymbol{y}_t, 2.5)$
12: $UL_t \leftarrow prctile(\boldsymbol{y}_t, 97.5)$
13: $\tilde{\mu}_t \leftarrow \sum_{i=1}^{R} y_t(i)/R$
14: **End For** t

2.3.2 Model Initialization

To improve the forecast accuracy, we determine value of α using the optimization model below:

$$Minimize \sum_{t=2}^{N_T} [\hat{Q}_t - Q_t)]^2 \tag{8}$$

$Subject\ to$:

$$B_0 = \frac{1}{12}\sum_{t=1}^{12} Q_t \tag{9}$$

$$B_t = \alpha Q_t + (1-\alpha)B_{t-1} \quad \forall t = 1 \dots N_T - 1 \tag{10}$$

$$\hat{Q}_t = B_{t-1} \quad \forall t = 2 \dots N_T \tag{11}$$

$$\alpha \le 1 \tag{12}$$

$$\alpha > 0.1 \tag{13}$$

$$\hat{Q}_t \ge 0 \qquad \forall t = 2 \dots N_T \tag{14}$$

$$B_t \geq 0 \qquad \forall t = 1 \dots N_T - 1 \tag{15}$$

The objective function minimizes the sum of the squared forecast error according to equation (8). Constraint (9) determines the initial smoothed estimate for level. Constraints (10) determine the smoothed estimate for the level in each period. Constraints (11) determine the forecast in period t. Equations (12-15) define the bounds on the decision variables. This model is applied to the data in test data set to determine the optimal smoothing constant α^*. Once the optimal smoothing constant is known, the standard deviation is determined according to equation (16).

$$s = \sqrt{\frac{\sum_{t=1}^{N_T}[\,\hat{Q}_t - Q_t)]^2}{N_T - 1}} \tag{16}$$

The initial state ℓ_0 is assumed to be the final smoothed estimate for the level ($B_{N_T-1} = \hat{Q}_{N_T}$).

2.3.3 Model Validation

Two performance measures are used to investigate the performance of the forecast-simulation model: the mean absolute percentage error and the coefficient of variation. The mean absolute percentage error (MAPE) for both the point estimate and interval estimate (17a-17c), provide a measure of forecast accuracy.

$$MAPE = \left(\frac{1}{N_V}\sum_{t=1}^{N_V}\frac{Q_{t-}\tilde{\mu}_t|}{Q_t}\right) \times 100 \tag{17a}$$

$$MAPE = \left(\frac{1}{N_V}\sum_{t=1}^{N_V}\frac{|Q_t - UL_t|}{Q_t}\right) \times 100 \tag{17b}$$

$$MAPE = \left(\frac{1}{N_V}\sum_{t=1}^{N_V}\frac{|Q_t - LL_t|}{Q_t}\right) \times 100 \tag{17c}$$

The coefficient of variation (CV) is a measure of dispersion and is computed according to equation (18), where $\bar{Q}$ is the sample mean.

$$CV = \bar{Q}^{-1}\left(\frac{\sqrt{\sum_{t=1}^{N_V}(Q_V - \bar{Q})^2}}{N_V - 1}\right) \tag{18}$$

3 RESULTS AND DISCUSSIONS

3.1 Data

Four fiscal years of data (48 records from July 2008 to June 2012) was obtained from The Food Bank of Central and Eastern North Carolina (FBCENC). A fiscal year runs from July until June of the subsequent year. The quantity (in pounds) of food received per transaction is captured in the gross weight field which represents the dependent variable in the forecasting models. Historical data is summarized by month and year. The data is analyzed and aggregated based on the branch where the donations were received. Each data set is partitioned into two sets. The first 36 records represent the test data set (July, 2008-June, 2011) and the next 12 records represent the validation data set (July, 2011-June, 2012). The test data set is used to estimate the forecasting model parameters as well as the simulation model. The validation data set is used to estimate the accuracy of the model for a future time series. Figures (1-5) are the time series plots demonstrating the trend analysis for the data series for all 5 branches. There was neither increasing or decreasing trend in all 5 branches. Moreover, the augmented dickey-fuller (ADF) test was used to test for stationarity of the series in all 5 branches using the hypothesis test below:

1. H_0: The series is not stationary
   H_1: The series is stationary
2. Significance level: 0.05
3. H_0 is rejected when the absolute value of the test statistic is greater than the absolute value of the critical value as noted in (Sjö 2008).
   The test statistics are show in Table 3. The single mean ADF was used for all 5 branches since all their series exhibited a constant and no trend as shown in Figure (1-5).
4. At a 0.05 significance level, all the series for all branches were stationary since their absolute test statistics were greater than the absolute critical value (2.93).

Hence the SES model is deployed for the model initialization and the local level model of the linear innovations state space model for the simulation part of the model.

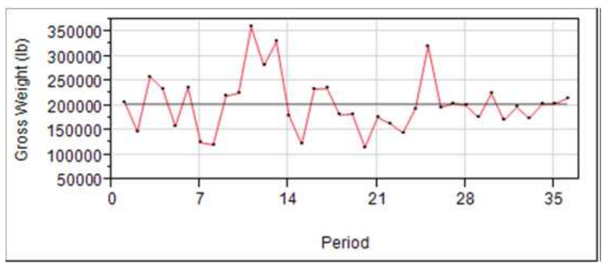

Figure 1: Durham time series plot.

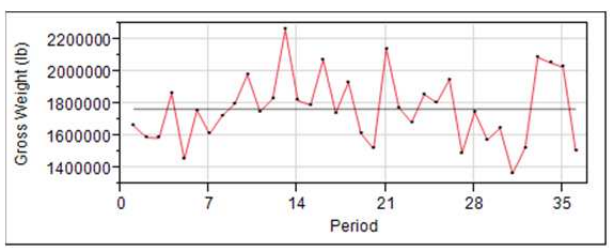

Figure 2: Raleigh time series plot.

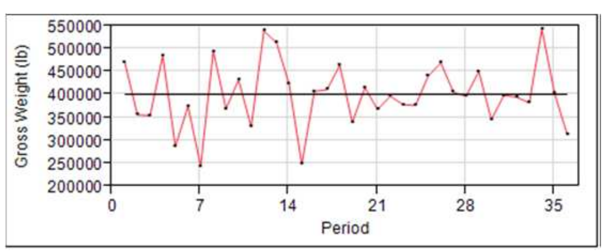

Figure 3: Greenville time series plot.

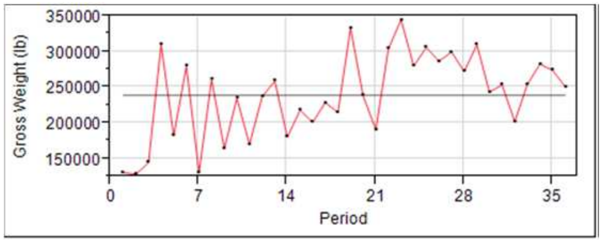

Figure 4: Wilmington time series plot.

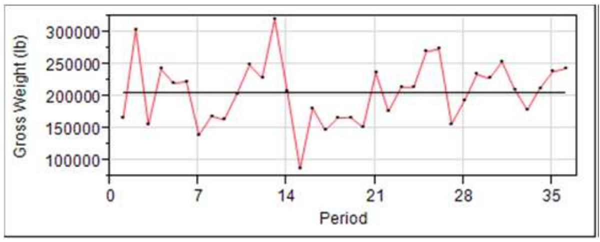

Figure 5: Sandhills time series plot.

Table 3: Test statistics for stationarity test.

	Branch				
	Durham	**Raleigh**	**Greenville**	**Wilmington**	**Sandhills**
Mean	203889.39	1769374.60	401422.89	239236.36	206751.68
Standard Deviation	55659.34	209341.42	70048.59	58198.95	48065.22
N	36.00	36.00	36.00	36.00	36.00
Zero Mean ADF	-0.95	-0.55	-1.01	-0.65	-0.70
Single Mean ADF	-4.50	-5.13	-6.89	-4.97	-5.17
Trend ADF	-4.46	-5.03	-6.92	-6.23	-5.14

3.2 Forecasting-simulation Model

3.2.1 Model Initialization Results

The optimization model described in section (2.3.2) was applied to the first 36 periods (test data set) from July 2008 to June 2011 for 5 branches separately. Figure 6 shows the optimized alpha values, the standard deviations and smoothed estimate for level for periods 36 for each branch. With the exception of the Wilmington branch with an alpha value of 0.2, the alpha values for the rest of the branches was 0.1. The Raleigh branch donation data had the most variability and the highest predicted quantity. This was expected since the Raleigh branch is the main branch and receives the most donations from various sources.

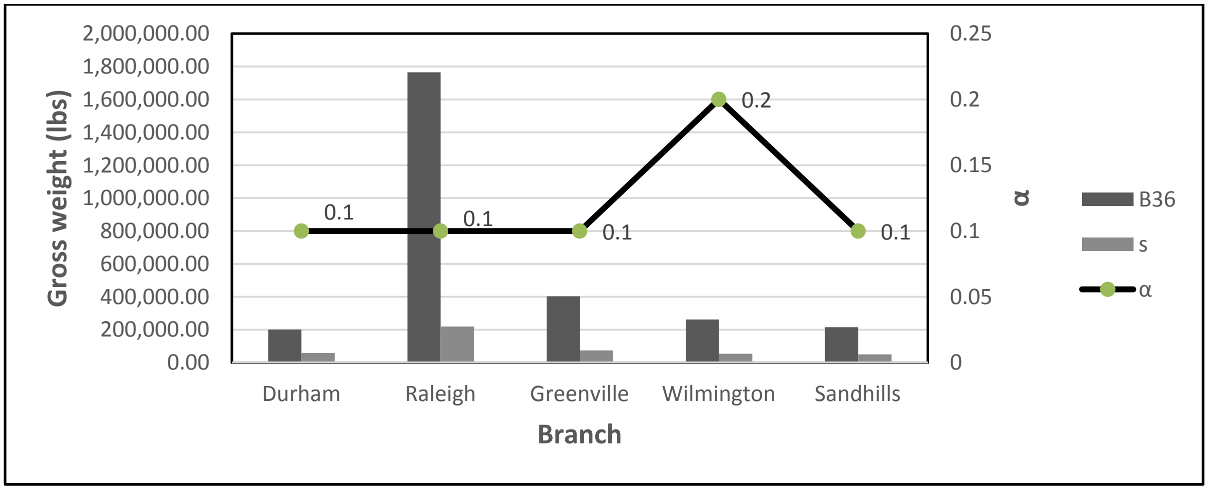

Figure 6: A graph of simulation model parameters.

3.2.1 Model Validation Results

The estimates in the optimization model (B_{35}, α) and the estimate for the standard deviation (s) were used in the simulation model to simulate donations estimates for the next 12 periods (validation data set) from July, 2011 to June, 2012 for 5 branches separately. The simulation was run for R =10,000 iterations for each branch. Their corresponding $\tilde{\mu}_t$ and 95th percentile prediction interval for each of the 12 periods were computed. The validation MAPE (point estimate and interval estimate) and validation CV were also computed for all branches.

Figure 7 shows the validation MAPE (point estimate) as well as the CV for the forecasting-simulation model for each branch. Greenville had the highest estimation accuracy (12.40%) and Sandhills had the lowest estimation accuracy (29.98%). Figure 2 validated our forecasting-simulation model as it demonstrated an increasing trend as MAPE increases with increasing CV. That is the estimation accuracy decreases with increasing dispersion in the data. However, the Raleigh branch did not follow that pattern and it was expected due to its high standard deviation as shown in Figure 6. Moreover, the Shapiro-Wilk test was conducted for the error terms from period 37 through 48 for all branches and the results are as shown in Table 4. The error terms for all branches were normal.

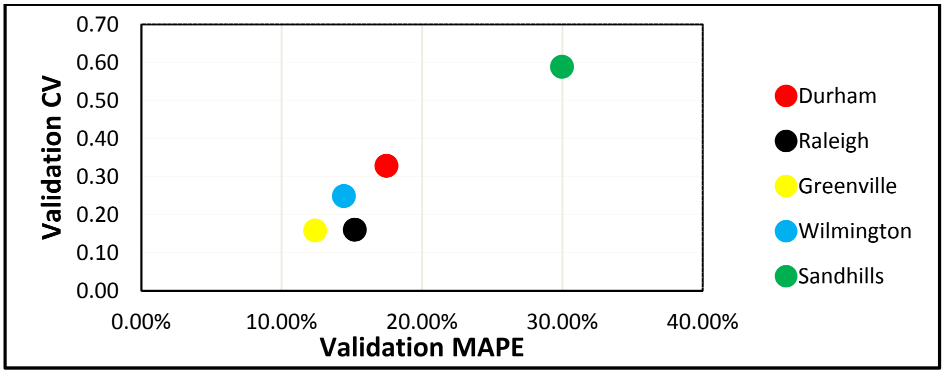

Figure 7: A graph of Validation MAPE vs CV for forecasting-simulation model.

Table 4: Shapiro-Wilk test for the random errors.

H_0: The series is normal.
H_1: The series is not normal
Significance level: 0.05

Branch	**P-value**	**Conclusion**
Durham	0.36	Normal
Raleigh	0.95	Normal
Greenville	0.78	Normal
Wilmington	0.29	Normal
Sandhills	0.79	Normal

Figure 8 shows the validation MAPE (interval estimate) results for all 5 branches. It is interesting to know that Raleigh had the best estimation accuracy and the upper limit estimation accuracy (13.67) was better than that of the point estimate (15.22%).

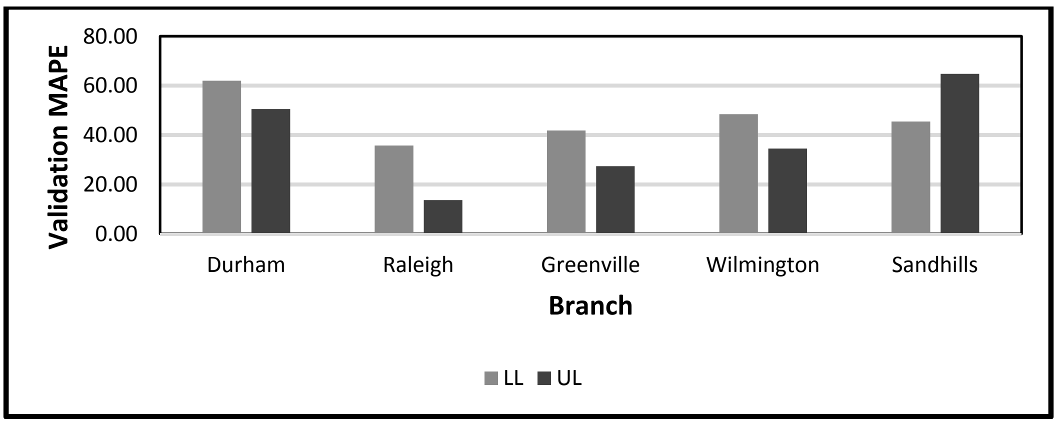

Figure 8: Validation MAPE of the 95th percentile prediction.

4 CONCLUSION AND RECOMMENDATION

The data used in this study was provided by the FBCENC. Although the FBCENC receives food from various sources, a majority of them are from donations. Over 79% of the food received by 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. 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 at varying frequencies over the year and in uncertain quantities. This increases the difficulty in choosing a forecasting technique and evaluating the behavior of the donations.

In this paper, a forecasting-simulation model was used to predict donations for the five FBCENC branches which generated good forecasting accuracies. The advantage of this approach is that point estimates as well as interval estimates can be computed which aids the decision maker in making insightful decisions. NPHROs can used the forecasting-simulation model to estimate future donations which will enable them to be proactive in planning for distribution and future purchases in order to meet their demand.

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AUTHOR BIOGRAPHIES

ISAAC A. NUAMAH is a Ph.D. student in the Industrial & Systems Engineering Department at North Carolina Agricultural & Technical State University. His e-mail address is ianuamah@aggies.ncat.edu.

DR. LAUREN DAVIS, Ph.D. is an associate professor in the Department of Industrial & Systems Engineering at North Carolina Agricultural and Technical State University. Her research interest is in the management of for-profit and not-for profit/humanitarian supply chains with specific focus on performance in environments constrained or uncertain supply, uncertain demand, and disruptions in operations caused by extreme events. She is an active member of IIE and INFORMS.

DR. STEVEN JIANG is an Associate Professor in the Industrial & Systems Engineering Department at North Carolina Agricultural & Technical State University. He received his Ph.D. in Industrial Engineering from Clemson University in 2001. His research interest is in visual analytics and human system integration.

NICOLE LANE is a Ph.D. student in the Industrial & Systems Engineering Department at North Carolina Agricultural & Technical State University. His e-mail address is nicole.t.lane@gmail.com.