A Fuzzy Forecasting Model for Women's Casual Sales

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Abstract

In this research, forecasting models were built based on both univariate and multivariate analysis. Models built on multivariate fuzzy logic analysis were better in comparison to those built on other models. The performance of the models was tested by comparing one of the goodness-of-fit statistics, R^2, and also by comparing actual sales with the forecasted sales of different types of garments. Five months sales data (August-December 2001) was used as back cast data in our models and a forecast was made for one month of the year 2002. The performance of the models was tested by comparing one of the goodness-of-fit statistics, R^2, and also by comparing actual sales with the forecasted sales. An R^2 of 0.93 was obtained for multivariate analysis (0.75 for univariate analysis), which is significantly higher than those of 0.90 and 0.75 found for Single Seasonal Exponential Smoothing and Winters' three parameter model, respectively. Yet another model, based on artificial neural network approach, gave an R^2 averaging 0.82 for multivariate analysis and 0.92 for univariate analysis.

Introduction

Sales Forecasting is an integral part of apparel supply chain management and very important in order to sustain profitability. Apparel managers require a sophisticated forecasting tool, which can take both exogenous factors like size, price, color, and climatic data, price changes, marketing strategies and endogenous factors like time into consideration. Although models built on conventional statistical forecasting tools are very popular they model sales only on historic data and tend to be linear in nature (Kincade et. al., 1998). Soft computing tools like fuzzy logic and Artificial Neural Networks (ANN) can efficiently model sales taking into account both exogenous and endogenous factors and allow arbitrary non-linear approximation functions derived (learned) directly from the data (Kuo and Xue, 1999).

In order to reduce their stocks and to limit stock out, textile companies require specific and accurate sale forecasting systems. One of the approaches (Thomassey et. al., 2004) analyses two complementary forecasting models, appropriate to textile market requirements. The first model (AHFCCX) allows to automatically obtain mean-term forecasting by using fuzzy techniques to quantify influence of explanatory variables. The second one (SAMANFIS), based on a neuro-fuzzy method, performs short-term forecasting by readjusting mean-term model forecasts from load real sales. In yet another approach (Ansuj et. al, 1996) the researchers compared the use of time series ARIMA model with interventions, and neural network back propagation model in analyzing the behavior of sales in a medium size enterprise. The forecasts obtained using the back propagation model were reported to be more accurate than those of ARIMA model with interventions.

In our approach a multivariate fuzzy model has been built based on important product variables of color, time and size. This model is being currently further extended to include other variables like climate, economic conditions etc., which would be used in building a comprehensive forecasting software package.

Methodology and Results

Since our present research is based on multivariate analysis, sales data containing multiple independent variables are being used in a multivariable fuzzy logic and ANN models. Two product variables color, and combined time and size, which significantly affect apparel sales, were chosen to model sales. The converted data were grouped based on different class-size combinations, trained, and then sales were forecasted for each grouping using fuzzy logic and ANN modeling.

Fuzzy logic approach Fuzzy logic allows the representation of human decision and evaluation in algorithmic form. It is a mathematical representation of human logic. The use of fuzzy sets defined by membership function constitutes fuzzy logic (Von Altrock, 1995). The basic terms are summarized below.

Fuzzy Set: is a set with graded membership over the interval [0, 1].

Membership function: is the degree to which the variable is considered to belong to the fuzzy set.

A sales fuzzy logic controller is made of:

Fuzzification: Linguistic variables are defined for all input variables (color and size).

Fuzzy Inference: rules are compiled from the database and based on the rules, the value of the output linguistic variable is determined. Fuzzy inference is made of two components:

Aggregation: Evaluation of the IF part of the rules.

Composition: Evaluation of the THEN part of the rules.

Defuzzification: linguistic value(s) of output variable (sales) obtained in the previous stage are converted into a real output value. This can be accomplished by computing typical values and the crisp result is found out by balancing out the results.

Fuzzy logic model was applied to grouped data and sales values were calculated for each size-class combination. Total sales value for the whole period was calculated by summing up the sales values of all the grouped items. The daily sales were calculated from grouped sales using two different methods: fractional contribution method and

Winters' three parameter model. The forecasted daily sales were then compared with actual sales by using goodness-of-fit statistics, R^2.

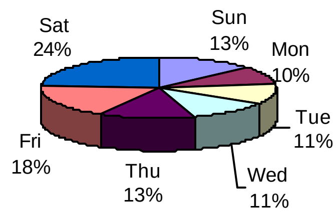

Figure 1. Fraction of Weekly Sales Distributed Among 7 Days

Fractional contribution method

It was observed that the fraction contribution of each weekday towards total week sales was constant (Frank et. al., 2002). Figure 1 depicts the average fractional contribution of a weekday towards total sales of a week, which can be used to forecast the daily sales from the forecasted weekly sales.

The daily sales were calculated as a fraction of total sales.

The R^2 of the model was 0.93 and the correlation coefficient R between actual and forecasted daily sales for October 2002 was 0.96. Figure 2 shows the actual versus forecasted sales values for October-2002 month.

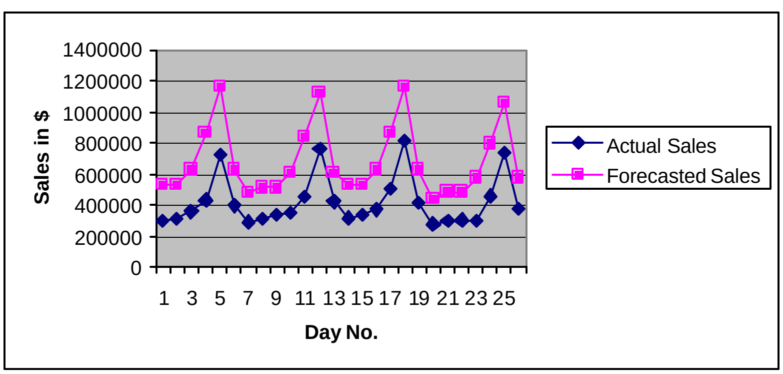

Figure 2. Actual vs. forecasted sales for October 2002 using fuzzy model

Winters' Three Parameter Exponential Smoothing Model

Winters' smoothing model assumes that:

$$Y_{t+m} = (S_t + b_t)\, I_{t-L+m} \qquad (1)$$

where: S_t - smoothed nonseasonal level of the series at end of t; b_t- smoothed trend in period t; m - horizon length of the forecasts of Y_{t+m}; I_{t-L+m} - smoothed seasonal index for period t + m. That is, Y_{t+m} the actual value of a series equals a smoothed level value S_t plus an estimate of trend b_t times a seasonal index I_{t-L+m}. These three components of demand are each exponentially smoothed values available at the end of period t (DeLurigo, 1998). The smoothed values were estimated as follows:

$$S_t = a(Y_t/I_{t-L}) + (1 - a)\,(S_{t-1} + b_{t-1}) \qquad (2)$$

$$b_t = ß(S_t - S_{t-1}) + (1 – ß)b_{t-1} \qquad (3)$$

$$I_t = ?\,(Y_t/S_t) + (1 - ?)\, I_{t-L+m} \qquad (4)$$

$$Y_{t+m} = (S_t + b_t\, m)I_{t-l+m} \qquad (5)$$

where: Y_t - value of actual demand at end of period t; a - smoothing constant used for S_t; S_t- smoothed value at end of t after adjusting for seasonality; ß - smoothing constant used to calculate the trend (bt); b_t - smoothed value of trend through period t; I_{t-L}- smoothed seasonal index L periods ago; L - length of the seasonal cycle (e.g., 5 months); ? - smoothing constant, gamma for calculating the seasonal index in period t; I_t - smoothed seasonal index at end of period t; m - horizon length of the forecasts of Y_{t+m} Equation 2 is required to calculate the overall level of the series. S_t in equation 3 is the trend-adjusted, deseasonalized level at the end of period t. S_t is used in equation 5 to generate forecasts, Y_{t+m}. Equation 3 estimates the trend by smoothing the difference between the smoothed values S_t and S_{t-1}. This estimates the period-to-period change (trend) in the level of Y_t. Equation 4 illustrates the calculation of the smoothed seasonal index, I_t. This seasonal factor is calculated for the next cycle of forecasting and used to forecast values for one or more seasonal cycles ahead. Alpha, beta, and gamma values were chosen using minimum mean squared error (MSE) as the criterion. Applying a forecast model built on five months sales data, a daily forecast of sales ratio was done for October of 2002. Figure 3 shows the actual versus forecasted sales values for October-2002 month. The parameters used were: ? = 0.6, ?= 0.01, ?=1, and R^2 = 0.97, R=0.98.

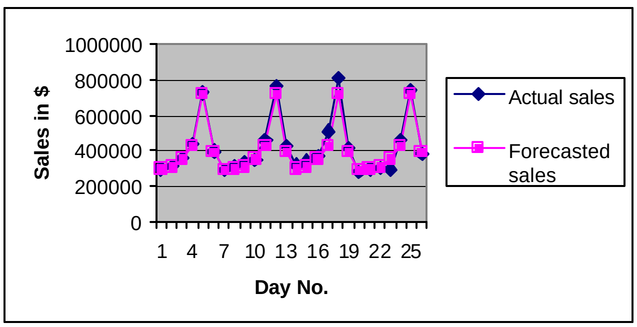

Figure 3. Actual vs. forecasted for fuzzy approach with Winters three parameter model

Neural Network Model In our research, a self generated, feed forward neural network (Sztandera, 1994), was implemented with 10 neurons in the input layer, 30 neurons in the hidden layer and 1 neuron in the output layer. The number of neurons in hidden layer(s), and the number of hidden layers are generated by the algorithm based on the training data (Sztandera, 1994). Grouped sales data over a period of 10 months was used, out of which the first 32 rows were used as training set, next 34 rows were used in test set and the last 234 rows were used in production set.

Fractional contribution method The fractional contribution method described under fuzzy logic section was implemented for NN model. R^2 of the model was 0.82, and the correlation coefficient R between actual and forecasted daily sales for October 2002 was 0.93. Figure 4 shows the actual versus forecasted sales values for October-2002 month.

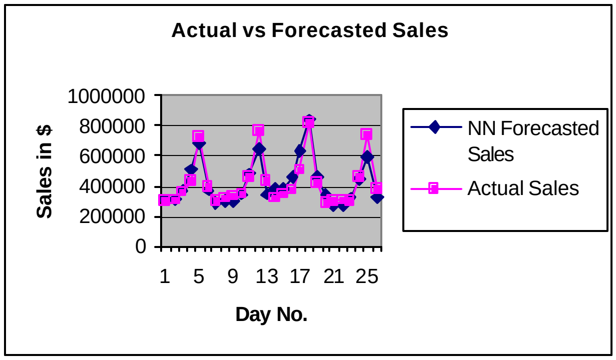

Figure 4. Actual vs. forecasted sales by using ANN

Winters' three parameter model The Winters' three parameter model method described under fuzzy logic section was implemented for NN model. The following parameters were used: ? = 0.6, ?= 0.01, ?=1, and R^2 = 0.44, R=0.67 were obtained. Figure 5 shows the actual versus forecasted sales values for October-2002 month.

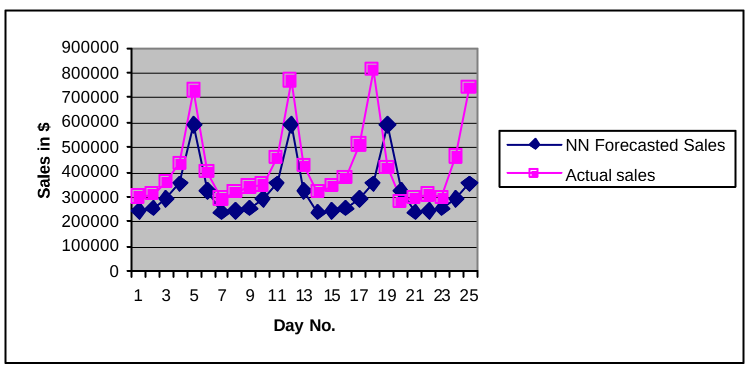

Figure 5. Actual vs. forecasted sales using ANN

Univariate Forecasting Models Forecasting models were built on univariate analysis using both conventional statistical models as well as unconventional soft-computing methods. Among all the models, the ANN model performed the best. However all the models could not forecast with precision because they were built using a single variable time. A plot of actual versus forecasted sales for various models done using univariate analysis are shown in Figures 6, 7 and 8.

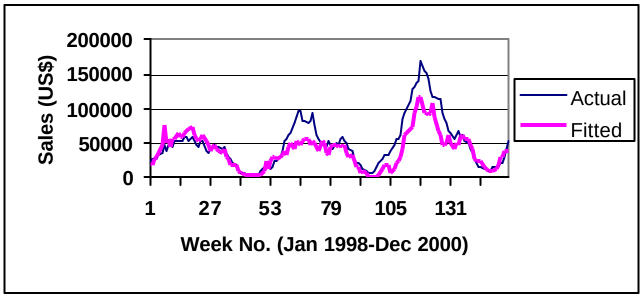

Figure 6. Actual vs. forecasted sales for SES model (R^2=0.90)

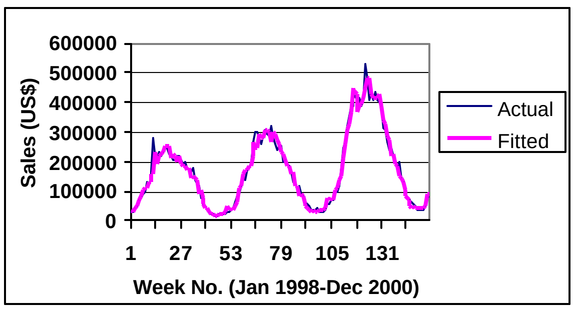

Figure 7. Actual vs. forecasted sales for Winters' three parameter model (R^2=0.75)

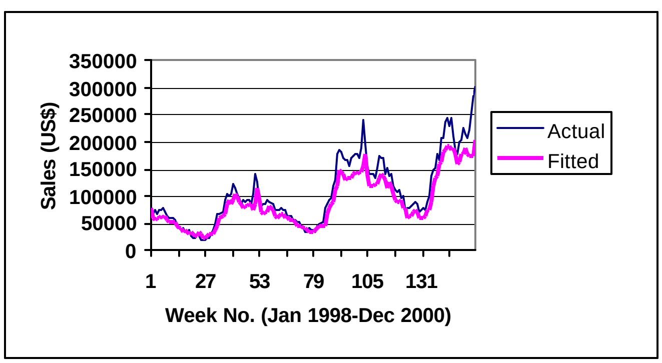

Figure 8. Actual vs. forecasted sales for ANN model (R^2=0.92)

Summary

Multivariable fuzzy logic model can be an effective sales forecasting tool as demonstrated by our results. A correlation of 0.93 was obtained, better than that obtained by using the NN model, which showed a correlation of 0.82 (for the fractional contribution method). The values for the three parameter model were: 0.97 and 0.44, respectively. The poor correlation in the case of the NN model can be attributed to the noise in the sales data. The fuzzy model performed best because of its ability to identify nonlinear relationships in the input data. However, the correlation was better for short-term forecasts and not as good for longer time periods. However the multivariate fuzzy logic model performed better in comparison to those based on univariate analysis, which goes on to prove that multivariate analysis is better compared to that of univariate analysis. A much more comprehensive model can be built by taking into account other factors like climate, % price change, marketing strategies etc.

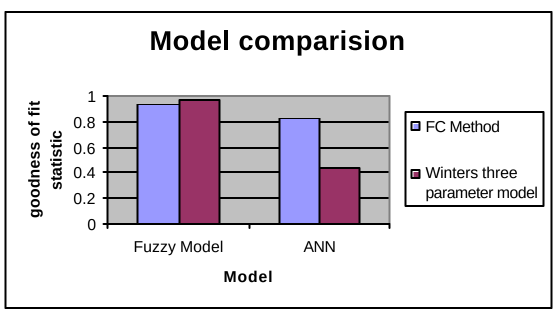

Figure 9. Goodness of fit statistic for models based on multivariate analysis

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