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Demand Forecasting, Artificial Neural Network, Price, Promotion, Federal Funds Rate

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ARTIFICIAL NEURAL NETWORK BASED DEMAND FORECASTING INTEGRATED WITH FEDERAL FUNDS RATE

Abstract

Adverse effects of inaccurate demand forecasts; stockouts, overstocks, customer loss have led academia and the business world towards accurate demand forecasting methods. Artificial Neural Network (ANN) is capable of highly accurate forecasts integrated with many variables. The use of Price and Promotion variables have increased the accuracy while the addition of other relevant variables would decrease the occurrences of errors. The use of the Federal Funds Rate as an additional macro-economic variable to ANN forecasting models has been discussed in this research by the means of the accuracy measuring method: Average Relative Mean Absolute Error.

1. INTRODUCTION

Demand forecasting, projection of future demand for a specific product is a principal element for continuous balancing of demand and supply of that product (Hewage, Perera & De Baets, 2021). It is a major concern across all supply chains since most functions depend on demand forecasts and is a critical aspect of managing operations, procurement, production, local distribution, replenishment plans, transportation, sales, finance and marketing (Fildes, Ma & Kolassa, 2019; Parker, 2014; Oliva & Watson, 2009). Stockouts and overstocks are caused due to inaccuracy of demand forecasts which result in long-term customer dissatisfaction, customer loss, high inventory costs and waste of resources (Huang, Fildes, & Soopramanien, 2019; Yang, Goh, Xu, Zhang, & Akcan, 2015). Thus, accurate demand forecasting is crucial to take proactive measures in supply chain risk management (Perera, Thibbotuwawa, Rajasooriyar & Sugathadasa, 2016; Sugathadasa, Wakkumbura, Perera & Thibbotuwawa, 2021).

The foremost difficulty for accurate demand forecasts is the volatility due to unpredictable customer behaviour caused by endogenous and exogenous factors. Among these factors, sales promotions have a large impact on consumer behaviour causing changes in market

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demand and sales trends (Balachandra, Perera & Thibbotuwawa, 2020). In addition, macroeconomic variables linked with consumer behaviour influence the demand forecasts (Tangjitprom, 2012). Hence a single traditional statistical forecasting technique comprises historical sales data which is inadequate to deliver proper forecasts where the impact of related sales data to mitigate the bullwhip effect in the supply chain is proven (Matharage, Hewage & Perera, 2020). With the prerequisite of a method to incorporate many variables with significantly improving data availability, the capability of ANN which is a part of Artificial Intelligence which creates sales forecasts with high accuracy integrated with many variables is to be assessed with the integration of macroeconomic variables based on model's accuracy.

2. LITERATURE REVIEW

Several complex statistical methods and simple practical methods are found to be applied in time series demand predictions where Exponential Smoothing Models, Auto-Regressive Integrated Moving Average (ARIMA) Models, State Space and Structural Models, Nonlinear Models and Long Short Memory Models (LSTM) have been identified as the methods of forecasting. ML algorithms are exercised as an alternative to traditional methods in the recent past. It enables systems capability of automatic learning and improving from experience without being programmed or any human intervention. ML models are trained with a portion around 80% of the available historical data set and exercising the rest, the training dataset to evaluate the expected performance of the models (Harris, Nadler & Bhan, 1984; Ni, Xiao & Lim, 2019). As per literature, ML models are more accurate than the traditional demand forecasting methods especially Neural Networks (NNs) being capable of using non-linear algorithms in statistical predictions (Barker, 2020; Spiliotis, Makridakis, Semenoglou & Assimakopoulos, 2020). Thus, these functional improvements in forecasting models have improved the competitiveness of supply chains (Perera & Sudusinghe, 2017; Ranil, Sugathadasa, Senadheera & Thibbotuwawa, 2021).

Distinguishing the relative impact of various factors affecting the demand has been challenging in demand forecasting hence researchers have focused on incorporating such variables in forecasting models to improve its accuracy (Huang, Fildes & Soopramanien, 2014). The input variables are selected based on the importance of the variable with its impact relevancy towards the model (Abolghasemi, Eshragh, Hurley & Fahimnia, 2020). Thus, a superior forecasting performance with high accuracy can be achieved through the incorporation of competitive information by choosing the correct variables out of many available variables.

Price and promotion variables, being marketing tools in the form of price discounts affecting the sales level are highly incorporated in forecasting models with proven accuracy increment over baseline model (Guidolin, Guseo & Mortarino, 2019; Huang, Fildes & Soopramanien, 2014; Ma, Fildes & Huang, 2016). Studies have demonstrated the average of Pearson's Correlation between price and demand gained as -0.83 indicating a strong negative relationship which hypothetically explains a high percentage of variation in demand. The impact of promotions on sales forecasting is explicitly addressed by Ali et al. (2009) with time-series autoregressive models.

Moreover, the literature suggests the integration of macroeconomic variables to increase the accuracy levels in demand forecasting approaches. Macroeconomic variables such as unemployment, employment, inflation, Gross Domestic Product, interest rates are indicators of economic performances of markets which can be used to increase the forecast accuracy in the medium and long-time horizons (Sagaert, Aghezzaf, Kourentzes & Desmet, 2018b, 2018a; Sharma, Singh & Singh, 2012). According to Verstraete et al. (2020), the impact of macroeconomic variables could be incorporated with two methods including manually adjusting the statistical forecast and expert forecast where both methods are expensive and biased.

Macroeconomic variables have been used in several studies of tactical sales forecasting using LASSO regression along with ARIMA models and non-linear ML methods attaining significant improvement in accuracy and it was found that traditional forecasting techniques such as regression illustrate poor performance over ML and shrinkage methods (Ludwig, Feuerriegel & Neumann, 2015; Sagaert et al., 2018b, 2018a). Moreover, the application of macroeconomic data for operational purposes is found challenging since data is more often published (Sagaert et al., 2018a). Hence, ML methods capable of incorporating several variables are more focused on sales prediction using various input variables. Among these predictive sales models built on ML, Adebayo (2018) has designed a Multilayer Feed Forward Neural Network (FFNN) along with a backpropagation algorithm comprised of 10 inputs and 10 nodes at the hidden layer to predict the sales of beer products and Carbonneau et al. (2008) has demonstrated the application of a NN model built with three layers feed-forward error back-propagation comprised of 5 inputs and using Hyperbolic tangent function as transfer function (Vhatkar & Dias, 2016).

Furthermore, researchers have evaluated the developed forecasting techniques integrated with multiple variables where Wang et al. (2019) has concluded that SVM is the best forecasting method for perishable products while LSTM is the best for non-perishable products considering evaluation index of overall performance while Shahrabi et al. (2009) has stated that ANN presents more persistent results while SVM performs better than the traditional forecasting techniques based on a comparison of forecasting results. Suzuki (2012) demonstrated ANN especially capable of identifying the most salient variables low weight for redundant and noise variables at training even at the presence of numerous variables as inputs, performs better than traditional and ML forecasting methods. Thus, the architecture of ANN can be exercised with any combination of fine predicting input variables with arbitrary flexibility, and it can be successfully trained.

Nonetheless, Guidolin et al., (2019); Huang et al., (2014); Ma et al., (2016) have assessed the effect of economic variables such as price and promotion focusing on the accuracy improvement of demand forecasts through various forecasting techniques. They concluded that the addition of economic variables adds value to the forecasting method by increasing its accuracy. No major study in the literature has been conducted using ANN models which has a significant impact on accuracy improvements with the addition of macroeconomic variables apart from price and promotion to assess its impact on the accuracy of demand forecasts.

Thus, this study is focused on building up an ANN model integrated with Price, Promotion and Macroeconomic variables to evaluate the accuracy of the model relative to the additional variables.

3. METHODOLOGY

The research aims to evaluate the effect of a macroeconomic variable in an ANN forecasting model. The feedforward error backpropagation method has proven to use with multiple variables which are chosen as the ANN structure. To assess the accuracy difference of the ANN model, Average Real Mean Absolute Error (*AvgRelMAE*) is preferred while Simple Exponential Smoothing is used as the benchmark forecasting model. The variables proposed for the process are Price and Promotion, and Federal Funds Rate (FFR) as a macroeconomic variable for the ANN model.

The basic structure of the feed-forward error backpropagation model consists of an input layer, hidden layer and output layer where the structure is mainly varied with the number of hidden layers and neurons in the model apart from the parameters such as activation function, batch size, loss value, number of epochs and dense layer value. By varying these parameters, the model structure can be modified in a way as to change forecast accuracy. Thus, it is important to define these parameters appropriately to create the best model (Goodfellow, Bengio & Courville, 2016).

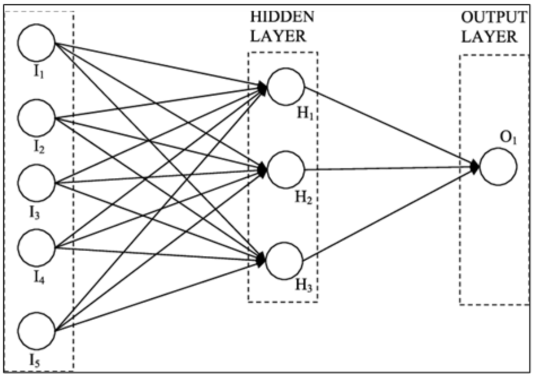

Fig. 1. Basic Structure of a NN (Srivastav, Sudheer & Chaubey, 2007)

The Initial ANN model (Model 1) proposed in the methodology is built only with price and promotion as variables. The second model (Model 2) is built by adding FFR value to the price and promotion variables to assess the accuracy improvement due to the addition of FFR values. The initial structure for both models contain 3 hidden layers. The input layer comprises neurons equal to the number of input variables and the output layer only with one neuron since forecast value is the only output as illustrated in Fig.1 while other parameters are defined accordingly with the data set as described below.

The hyper-parameters: number of neurons in the hidden layers, epochs, batch size and dense layer are defined according to the data with hyperparameter tuning either by manual adjusting by considering combinations defined by the modeller. But the identification of the best parameter values cannot be assured with manual adjustment since the manually evaluated combinations are less. Finding optimal values for the parameters can be automated with programmed functions to calculate the errors for all combinations. The common practice of defining some probable ranges for all the parameters and processing the automatic function within that range is exercised in this study. Thus, a considerable number of combinations is to be tested to find the best hyperparameter values.

In evaluating the results, the accuracy measuring method plays a vital role with the presence of many methods with several drawbacks in each error measuring method. *AvgRelMAE* which uses a benchmark model to compare the selected forecasting method is being suggested as the most suitable method by Davydenko & Fildes, (2016) with practical recommendations. It is chosen to compare the accuracy changes and the calculations will be done based on the following equations.

For each time series i in $1\ldots m$:

$$r_i = \frac{MAE_i^A}{MAE_i^{B\prime}} \tag{1}$$

where: *MAE* – Mean Absolute Error,
γ_i – relative MAE,
A – proposed forecasting model,
B – benchmark forecasting model.

$$r_i\, l_i = n_i \ln r_i \tag{2}$$

$$AvgRelMAE = exp^{\left(\frac{1}{\sum_{i=1}^{m} n_i}\sum_{i=1}^{m} l_i\right)} \tag{3}$$

The *AvgRelMAE* values of Model 1 and Model 2 are compared with the *AvgRelMAE* value of the benchmark model. *AvgRelMAE* of the benchmark model is 1. If the *AvgRelMAE* of any other model is higher than 1, it concludes that the accuracy of the proposed method has been reduced over the benchmark model.

4. DATA ANALYSIS AND RESULTS

Data was extracted from James M. Kilts Center; University of Chicago Booth School of Business which was selected from the freely available data sources. The set of data has been collected from the company, Dominick's Finer Foods (DFF) inclusive of more than 25 categories and 100 store chains. 5 Data sets were chosen from 5 categories based on the number of weeks available. Tab.1 consists of the details of the selected Universal Product Codes (UPCs).

Tab. 1. Selected UPCs

Category	UPC Number	Name	Weeks	Tag
Frozen Entrees	1380010068	STFRS SWEDISH MTBALL 11 OZ	396	UPC1
Refrigerated Juices	3828154001	HH ORANGE JUICE 64 OZ	396	UPC2
Front-end-candies	4000000102	SNICKERS 1 CT	396	UPC3
Frozen Juices	3828190029	HH ORANGE JUICE CONC 12 OZ	396	UPC4
Cheeses	2100061223	KR PHILA CREAM CHEESE 8 OZ	392	UPC5

The raw data of daily sales of a product in each shop was aggregated to the units sold within a week in all the stores. Due to the promotions and other possible reasons such as inflation, the price of a product has a range in the time horizon. Therefore, the unit price has been calculated by converting the price distribution for the promotions into a standard normal distribution. Also, there were 3 types of promotion, and a promotional index has been introduced to evaluate the power of promotions in a particular week. The ratio, the quantity sold under any promotional type divided by the total units sold in a has been calculated as the promotional index to reflect the power of the promotion across all stores. It reflects the percentage of units sold under any promotion. After calculating the sold quantity, unit price, promotional index, the macroeconomic value is added to the model. Federal Funds Rate (FFR) in the USA has been chosen as the macroeconomic variable and has been merged with the relevant week of the data set. The sample of a data set after refining is as shown in Tab. 2.

Tab. 2. Sample Data View

Quantity	Price	Promotion	FFR
994	0.505254	0	8.25
1030	0.505254	0	8.27
4838	-1.26969	1	8.28
871	0.505254	0	8.27
936	0.505254	0	8.27
836	0.549627	0	8.26

The 0.8 to 0.2 split has been used for the training and testing data sets where 317 data points were used to predict 80 weeks sales. The training data set has been rescaled taking the mean as the centre and standard deviation as the scale (Z score method). The mean of the training data set and standard deviation of the training data is used in the test data for normalization since the test data is only used for validation purposes.

The ANN models have been created using the R software. The basic model for Model 1 and 2 is made with one input layer, one output layer and three hidden layers. Input shape is the number of inputs varying from 3 to 4 inputs whether the model is using the FFR value or not. The models have been created using the R project for statistical computing. Fig. 2 shows a basic plot of a neural net of a model 2 which includes all three inputs. 3 hidden layers have been used in this model.

Rectified linear unit activation function has been used as the activation function for the input layers and hidden layers and MAE has been used as the loss function. The initial model had 50 epochs and the batch size was 4. After creating the initial model, the hyperparameter tuning is done by changing each variable. Below are the hyperparameters which are tuned to find the best accuracy.

1. The number of neurons in the 1st hidden layer.
2. The number of neurons in the 2nd hidden layer.
3. The number of neurons in the 3rd hidden layer.
4. The dropout value of the 1st hidden layer.
5. The dropout value of the 2nd hidden layer.

6. The dropout value of the 3rd hidden layer.
7. The number of batches.
8. The number of epochs.

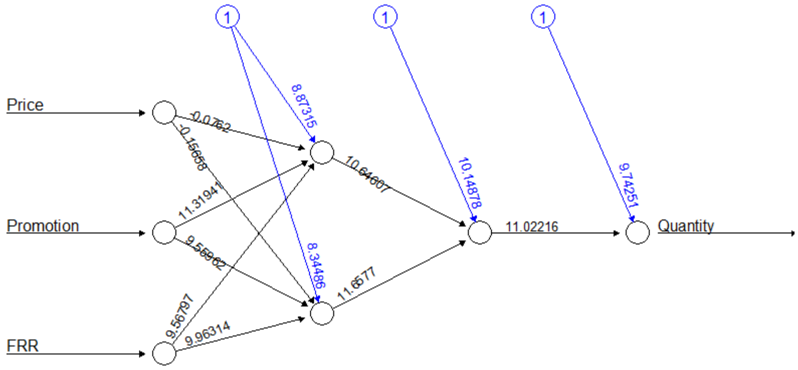

Fig. 2. Neural net plot of basic Model 2 structure

The hyperparameters were selected based on the common practice of testing in each parameter in relevant ranges. To get a value of a one parameter, it was selected as a variable while others were taken as non-variables where the variable was tested for a range comparing the error. Consequently, the values for each parameter were chosen based on the same method. The hyperparameters of the UPC 1 is shown in the table.

Tab. 3. Hyperparameters of UPC1 Models

Parameter	1st	2nd	3rd	4th	5th	6th	7th	8th
UPC1 Model 1	50	60	70	0.3	0.2	0.1	2	40
UPC1 Model 2	80	40	70	0.3	0.2	0.1	2	40

After calculating optimal hyperparameter values, the forecasted results and the error has been calculated separately. Since there are 5 data sets, 10 ANN models were created for both Model 1 and 2. The final results are focused on two accuracy comparisons that need to be assessed using the error measuring method, as mentioned below:

1. Benchmark model (SES) vs Model 1 (Price & promotion).
2. Benchmark model (SES) vs Model 2 (Price & promotion & FFR).

Figure 3 below is a plot of the forecast values of Model 1, Model 2 and simple exponential smoothing with the actual value. Based on the plot, it can be clearly seen that Model 2 has over forecasted than the Model 1 where Model 1 is the closest to the actual value for UPC1. Since there are 5 UPCs considered, as explained in the methodology, *AvgRelMAE* has been used to mathematically compare the models.

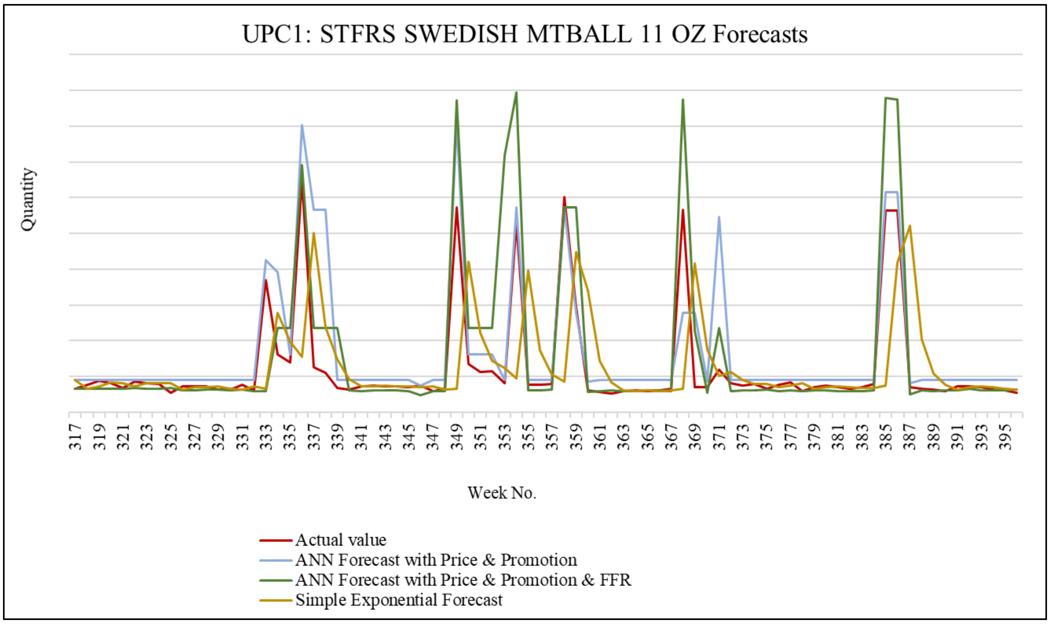

Fig. 3. Plot of forecasts for UPC1

Since there are 5 UPCs; i = 1,2,3,4,5 for all i; n_i = 80. The r_i and l_i have been calculated for all i using Equation 1, Equation 2 and Equation 3 as shown in a previous paragraph. The results of the comparisons are presented in Tab.4.

Tab. 4. Final *AvgRelMAE* Values

	Simple Exponential Forecast	ANN Forecast with Price & Promotion	ANN Forecast with Price & Promotion & FFR
AvgRelMAE	1.00	0.68	–
	1.00	–	0.71
	–	1.00	1.05

According to Davydenko & Fildes (2016), the values are compared against 1, which is the *AvgRelMAE* of the benchmark model. If *AvgRelMAE* is lower than 1, the accuracy is improved. According to Tab.4, it is evident that the ANN model with price & promotion has a higher forecast accuracy over simple exponential smoothing. Although the second model has a lesser value than 1, it is still higher than the initial model with only price and promotion. Therefore, the *AvgRelMAE* can be interpreted that adding the Federal Funds Rate to the initial model with Price and Promotion has not increased the forecast accuracy, rather it has decreased the forecast accuracy.

5. CONCLUSIONS

The possible variables which could impact the accuracy were identified and the performance of ANN models was confirmed through a comprehensive literature study, thus, the ANN-based models with selected multiple variables were developed. A feed-forward back-propagation type ANN model has been identified as the best ANN method for regression type models. The models were built using data extracted from the James M. Kilts Center, University of Chicago Booth School of Business, which was collected from Dominick's Finer Foods, in California, USA. The data consisted of weekly sales of many UPCs of various FMCG product categories, economic information on price and the promotion and some other information. The price and promotional data were filtered and used as two variables of the model. In addition to this, the FFR, which is a macroeconomic indicator of interest rate, has also been used as a variable in creating the models. Thus, price, promotion and FFR were used as multiple variables in building the ANN models. 5 data sets of 5 different UPCs were used in this research which was filtered and selected based on the availability of the data and sales volume. Two models were developed for one data set including an ANN model with price and promotional data and another ANN model with price, promotion and FFR data as variables. It resulted in 10 ANN. The structure of the ANN model was obtained through hyperparameter tuning. The number of neurons in hidden layers, epochs, batch size, dense were defined using hyperparameter tuning for each model. The combination of these parameters which resulted in the least error was taken to measure the accuracy in the following step.

This study covers five simple exponential smoothing models that were created using historical data using Microsoft Excel to be used as baseline models. As the initial accuracy measuring method, MAE was taken for all the models. Assessing the accuracy was done using the Average Relative Mean Absolute Error (*AvgRelMAE*). This method combines all the UPC error rates and gives an overall accuracy comparison of one method over another method. The comparison of the benchmark model, simple exponential smoothing and ANN model with price and promotion concludes that ANN model forecasts are much accurate. Also, it is concluded that the accuracy of the ANN model with price promotion and FFR value is higher than the simple exponential smoothing. Although there is an accuracy improvement of the ANN model with Price, Promotion and FFR value over the benchmark model, the study finds that the accuracy has decreased when adding FFR value to the ANN model.

This study has mainly focused on the interest rate as a macroeconomic variable and can be different variables such as GDP, unemployment rate and many other macroeconomic variables which could be considered as variables in this method of modelling. Also, there are many machine learning methods other than the Feedforward Neural Network model to incorporate any number of variables. In addition to that, assessing the accuracy improvement by the power of the sales force, advertising power and other economic variables integrated with ML models could be researched in further studies. The models were only developed for some products which can be further improved to assess the possibility of creating demand forecasts for the products in other domains using a similar methodology.

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