A Dynamic Combination and Selection Approach to Demand Forecasting

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Summary: This research presents a dynamic approach for selection among forecasting models. The context of this work is an automotive battery supplier in Malaysia. Using a nonlinear optimization, individual forecasting techniques were combined by assigning weights to each forecasting method to achieve a set of different combination forecasts. By developing an algorithm that allows switching between different forecasting models in every new period, a robust forecasting method is devised which has proved to perform better in case of volatile demand forecasts like the case of automotive batteries in the present context.

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KEY INSIGHT

- It is more beneficial for a firm to use a combination of multiple forecasts rather than selecting a single best forecast.
- Combined forecasts using optimal weights will give better forecast accuracy than simple average of forecasts

Introduction

Autobat is an automotive battery supplier based in Malaysia. Autobat holds 17% market share of the automotive battery market in Malaysia with sales of about a million units a year. The automotive battery market in Malaysia has an average annual growth of 4% and the company has enjoyed 13% sales growth for the past five years in Malaysia. Autobat supplies automotive batteries to two markets: OEM Market and Replacement Market. 80% of Autobat sales come from the replacement market.

For the replacement market, Autobat sells its batteries to distributors who then sell them to retailers and then to the consumer. Downstream sales patterns from retailers and consumers are not visible to Autobat as distributors and retailers are tight lipped about it. Based on a previous survey done by Autobat, 70% of the purchase decision of the consumers are influenced by their local mechanics. The survey also shows that consumers of automotive batteries typically have their batteries replaced once every two years. Distributors of automotive batteries do not have brand loyalty as end users often do not as well. This has led autobat to push as much inventory as possible towards the market rather predicting and responding to the market demand.

Research Objective

The company intends to implement an analytical approach to better forecast demand in order to ensure the right amount of inventory is maintained. For demand planning, the firm currently relies on the expert judgment of its marketing team to make decisions on the right quantities to order from the manufacturer. Expert judgment is an established method of forecasting, but as it is highlighted in the literature review, judgmental forecasts is known to perform better if it is based on a quantitative forecast model (Mathews and Diamantopolous, 1986). The objective of the thesis is to build a robust quantitative forecasting model to accurately predict demand and thereby help the company better manage its inventory.

Literature Review

Historically, much work has been done to develop new quantitative forecasting methods and improve the old ones. Despite these developments in theory, knowledge of forecasting is only useful if applied to an organizations decision-making and planning process (Spyros Makridakis, 1979). There are many applications of quantitative forecasting methods in business and industry, examples of which are in production planning (Miller, 1993), airline ticket sales (Grubb, 2001), and tourism (Du Preez, 2003). However, there is still a big gap between the extensive work done in theory and application in industry.

Concerning combining quantitative forecasts, Zou (2004), demonstrated how to combine similar quantitative models with weights that were sequentially updated. The study sought to demonstrate the advantage of combining forecasts over selection among forecasts. This work improves on this approach by both combining individual forecasts and then selecting the best among different combination types. Fang (2003) provided some insights into why competing forecasts may be fruitfully combined to produce a forecast superior to individual forecasts. It can be infered from their research that a forecasting technique which combines various methods will outperform the use of any one method in the long run. Hence the following proposition is suggested.

> *Proposition 1: Combination forecasts perform better than individual forecasts*

The topic of combining forecasts from linear and non-linear time series models, with ordinary least squares (OLS) weights as well as weights determined by a time-varying method was addressed by Terui and Herman (2002). Their study showed that combined forecasts performed well especially with time varying coefficients. Thus:

> *Proposition 2: Combination forecasts with periodically varying weights is better than combination forecasts with fixed weights*

Weighted averages are not the only way to combine forecasts. Forecasts can also be combined by a simple average method. From the results of the "M-Competition", which is a forecasting competition organized by Makridakis, Makridakis and Winkler (1983) observed that weighted averages outperform simple averages even though the differences in the MAPE values were not large (MAPE stands for mean absolute percent error and it is the most common measure of forecast accuracy). Hence we expect:

> *Proposition 3: combination forecasts using optimized weights gives better result than simple average method.*

Methodology

46 months of sales data was available for 407 SKUs. The top 25 SKUs contributing to 72% of the total sale volume (in number of units) for Autobat, are selected as the scope of this work.
The steps undertaken in the development of the model are visually represented in figure 1 below.

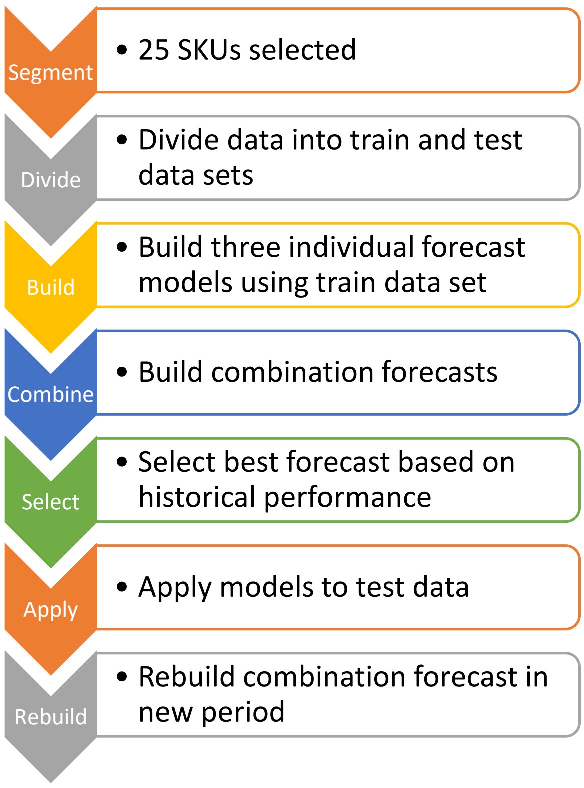

Figure 1 – Model development

Step 1: Pattern detection

The autocorrelation plot was used to detect the seasonality in the given data set. It provided a visual representation of similarity between observations as a function of a timelag between them. Other pattern detection techniques used were, aggregate plot to reduce variability in the data by pooling the demand of several SKUs, the subseries plot and multiple linear regression plots. After applying these techniques, an upward trend and a 12-month seasonality was detected from the data.

Step 2: Dividing the time series

Before applying any forecasting techniques, the data is divided into test data and train data. The train data is the portion of the historical data used to discover potentially predictive relationships, while the test data is used to assess and validate the strength of the predictive relationship. The use of the entire data set for the purpose of building the model was avoided. Setting aside some part of the historical data to test the model allows the forecaster to better judge how the model will perform in the future. From the 46 months of sales data available to us, 36 months' of data was selected for the test set and 10 months' of data for the train set. A wider range was selected for the training than for the test to ensure as much of the demand characteristics as possible is built into the model.

Step 3: Build individual forecasts

Next three different models were selected to serve as the base models, Holt-Winters double exponential smoothing, Holt-Winters triple exponential smoothing and ten month moving average. The three models were selected to cover the three main components of the timeseries, viz: level (moving average), trend (double exponential smoothing) and seasonality (triple exponential smoothing).

Step 4: Build Combination forecasts

The data was again divided into training set and test set. At this point, forecasts data from the three base models have been obtained for 22 months. The 22 months were divided into 12 months training data and 10 months' test data. An optimization model was then developed to deduce weights, using a specific sets of constraints, to combine the forecasts. These weights were then applied to the test data to obtain a combined forecast.

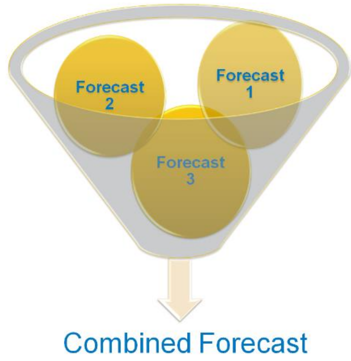

Figure 2 – Combining forecasts

The general expression for the nonlinear optimization model with positive weights summed to 1 is:

Minimize: $$MAPE = \frac{\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i}}{n} \qquad (1)$$

Where: $$\hat{y}_i = \sum_{j=1}^{k} (w_{i,j} \hat{y}_{i,j}) \quad \forall i \qquad (2)$$

Subject to: $$\sum_{j=1}^{k} w_{i,j} = 1 \quad \forall i \qquad (3)$$

$$w_{i,j} \geq 0 \quad \forall i, \forall j \qquad (4)$$

Where:

$\hat{y}_{i,j}$: is the basic forecast *j* in period *i*.

$w_{i,j}$: is the optimum weight for forecast *j* in period i

$\hat{y}_i$: is the combined forecast for period *i*.

n : is the number of periods in the training data

k : is the number of individual forecasts used in the combination model

$MAPE$: the average of the absolute errors between forecast and actual for *n* periods

Equation (1) is the objective function which is to minimize the MAPE for n periods.

Equation (2) is the combination forecast in period I for k number of individual forecasts.

Equation (3) is the first constraint which is to sum all the weights in a single period to one.

Equation (4) is the second constraint which states that all weights must be positive numbers.

Combination Forecast	Basic Forecasts Holt's	 Holt-Winters	 3-Month Moving Average	Criteria
Combination 1 (C1)	✓	✓	✓	No constraint (Constraint 1)
Combination 2 (C2)	✓	✓	✓	positive weights (Constraint 2)
Combination 3 (C3)	✓	✓	✓	positive weights summed to 1 (Constraint 3)
Combination 4 (C4)	✓		✓	No constraint (Constraint 1)
Combination 5 (C5)	✓		✓	positive weights (Constraint 2)
Combination 6 (C5)	✓		✓	positive weights summed to 1 (Constraint 3)
Combination 7 (C7)		✓	✓	No constraint (Constraint 1)
Combination 8 (C8)		✓	✓	positive weights (Constraint 2)
Combination 9 (C9)		✓	✓	positive weights summed to 1 (Constraint 3)
Combination 10 (C10)	✓	✓		No constraint (Constraint 1)
Combination 11 (C11)	✓	✓		positive weights (Constraint 2)
Combination 12 (C12)	✓	✓		positive weights summed to 1 (Constraint 3)
Combination 13 (C13)	✓	✓	✓	Simple Average
Combination 14 (C14)	✓		✓	Simple Average
Combination 15 C15)		✓	✓	Simple Average
Combination 16 (C16)	✓	✓		Simple Average
Combination 17 (C17)	✓	✓	✓	Fixed positive weights summed to 1

Table 1 - Combination Forecasts

Step 5: Select best forecast.

For every new period (n=n+1), 20 (3 individual and 17 combinations) different forecasts were evaluated over the most recent 12 months, and based on that, a forecast is selected to be used in period n+1. To evaluate the performance of each forecast, the MAPE for 12 months' immediately preceeding the current month is calculated. This constant evaluation ensures the model is dynamic and responsive to any changes in the demand characteristics.

Step 6: Rebuild combination forecasts in new period

Now that optimum weights have been obtained, the next question will be: for how long into the future will the same weights continue to be used? With every new period, more actual data is available to train the model, thereby it makes sense to retrain the model every new period. By running the optimization model every new period, a new set of weights is obtained once new actual data is received.

Results

By comparing the different forecasts developed with the forecasts used previously by the company, it is observed that a 29% improvement in forecast accuracy could be achieved by the implementation of this combination-selection approach. After testing 26 SKUs, the company forecast method gave better accuracy for only one of the SKUs and the new forecasts performed better 25 out of 26 SKUs. This however assumes perfect foresight in knowing which forecast to select in the coming periods. More testing is required to prove the benefits of the method.

Conclusion

"The best collective decisions are the product of disagreement and contest not consensus or compromise"

- James Surowiecki, The Wisdom of Crowds

This research has evaluated the superiority of combining forecasts over individual forecasts. A *combination and selection* approach rather than combination only or selection only has been developed and recommended. At the beginning of this research, three statements regarding combining forecasts were proposed. By testing 20 different forecasts on 1196 data points, 520 MAPEs were generated for comparison. The subsequent analysis of the results proved to be consistent with all three propositions.

Limitations and future work

In this work, three and two individual forecast models were combined and both types of combinations were compared to see what effect the number of individual forecasts have on the accuracy of the combination forecasts. Many more individual forecasts could be used. The expectation is that with more base models, we can conclusively know the effect of more or less individual forecasts in making a combination model. We can also find a “sweet spot” of the number of base models that proves just right.

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