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Using Machine Learning and Demand Sensing to Enhance Short-Term Forecasting for CPGs

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ABSTRACT

Consumer packaged goods companies (CPGs) account for some of the biggest industries in the world, providing essential items on a regular basis. Supply chain management at CPGs is complex because several products are supplied through multiple channels and distribution methods. Products follow complex order patterns characterized by promotional events, seasonal influences, natural disasters, and so on. Given this complexity, it is crucial to generate accurate short-term forecasts of order quantities that reflect the realistic demand for products. Such forecasts enable companies to drive an efficient supply chain response to improve customer service.

This paper uses machine learning along with traditional time-series forecasting models to generate enhanced weekly and daily forecasts by using historical-demand signal data and point-of-sale data. The model first creates enhanced weekly forecasts, and then breaks down enhanced weekly forecasts into daily forecasts. For weekly forecasts, a combination of a traditional time-series forecasting model and a neural network is used to create a product-wise forecast. This model combination allows for capturing the complex weekly order patterns and provides an accurate forecast of product demand. Weekly forecasts are divided into daily forecasts using an ensemble of three models: a seasonal model, a trend model, and a neural network model. The paper discusses the methodology behind this approach, along with short-term forecasting results.

INTRODUCTION

Consumer packaged goods companies (CPGs) account for some of the biggest industries in the world and provide items that are used regularly by average consumers including food, beverages and other household products. Since products provided by CPGs have short shelf lives and are intended to be used quickly, companies need to routinely replenish products in store shelves in order to meet consumer needs. Effective supply chain management is critical to ensure the timely replenishment of products by properly managing the movement and storage of raw materials and finished goods from the point-of-origin to the point-of-consumption. A key component of supply chain management is demand forecasting to predict an estimate of the number of products that the consumer needs in the near-term future. Demand forecasting is complex because different products follow different order patterns and CPGs deliver several products through multiple channels and distribution methods. Demand forecasting needs to account for promotional events, seasonal influences, natural disasters, and so on, and adapt the estimate of product demand.

Traditional time-series forecasting techniques like autoregressive integrated moving average (ARIMA) models and exponential smoothing (ESM) models are typically used for demand forecasting at CPGs. These models consume historical demand pattern data and provide an estimate of demand forecast into the future. In addition to the historical demand data, CPGs also have access to other data feeds like point-of-sale information, future firm open orders, promotional events data, and so on that collectively constitute demand signal data. SAS® already provides the engine that drives demand forecasting at several CPGs. These CPGs can leverage the same toolset that is based on SAS to improve short-term forecasting by augmenting traditional time-series forecasting techniques with machine learning techniques and by using additional demand signal data. Key benefits for using demand sensing include: (1) Increase in sales revenue by improving sensing capability to drive an agile supply chain response to meet customer demand needs. (2) Improvement in transportation planning with preferred carriers, reduction in execution costs by reducing redeployment and lowering inventory carrying costs. (3) Improvement of customer service levels and on-shelf availability of products ensuring customers get the products that they want. (4) Improved revenue/profit through improved replenishment efficiencies and fewer stock-outs.

In this paper we present our study conducted with a large food manufacturing CPG company. We have used machine learning and traditional time-series forecasting models to generate enhanced weekly and daily forecasts by using historical-demand signal data and point-of-sale data.

METHODOLOGY

In this section, we will describe the methods that were used to prepare the data, generating enhanced weekly forecasts, and breaking down the weekly forecasts into daily forecasts. For the weekly and daily forecasts, we used the order history data along with future open orders data. In a separate section, we will analyze the impact of using point-of-sale (POS) and customer inventory data on the weekly forecast.

SUMMARY OF DATA PROVIDED

We were provided with order shipment history from 2012 to 2019 for triplets of Product (Prod), Shipping Location (ShipLoc) and Customer Location (CustLoc) at a daily resolution as shown in Figure 1. Shipping locations corresponded to the CPG distributions centers (DCs) and customer locations were customer DCs. Thus, the order history corresponded to the number of daily Product shipments from ShipLoc to CustLoc. We were also provided future open orders for both datasets at the lowest {Prod – ShipLoc – CustLoc} level. The shipment order history and future open orders were the main inputs in our forecasting pipeline. We were also provided with point-of-sale (POS) data and customer inventory data for one specific CPG customer, that is {Prod – ShipLoc – CustLoc = customer}, for the year of 2019.

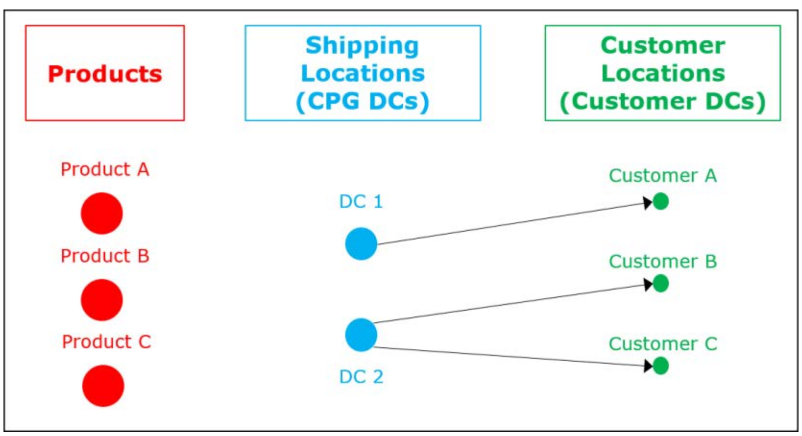


Figure 1. Graphical representation of the provided data. There are three main levels to the data – Product (Prod), Shipping locations (ShipLoc) that are CPG distribution centers (DCs), and Customer locations (CustLoc) that are customer DCs.

In addition to the order history, future open orders and POS data, the CPG also provided us with weekly forecasts estimated using their current forecasting procedures. Two such forecast estimates were provided. One was generated using standard procedures based on SAS (FC-Base) and another was generated by experts who had adjusted FC-Base to further refine the existing forecasts (FC-Base+Expert). Each of these forecast estimates were provided at the {Prod} and {Prod – ShipLoc} levels. The main goal of this project was to generate better forecast estimates compared to FC-Base and FC-Base+Expert at both {Prod} and {Prod – ShipLoc} levels. Note that the forecasts for comparison were only provided at the weekly level. The CPG did not provide daily forecasts for comparison.

DATA PRE-PROCESSING

Prior to modeling using the given data, we performed data validation to ensure data consistency between the different data tables and prepared the data in the correct format to run the models. We analyzed the order history of each {Prod – ShipLoc – CustLoc} triplet and ran our forecasting procedure on products that had at least one year of order history data, and which had order shipments in 2019.

We used the SORT and TIMESERIES procedures to perform weekly and daily aggregation of the order history data for weekly and daily forecasts respectively. For weekly forecasts using machine learning, we used the order history over the last four years. Thus, after running PROC TIMESERIES with weekly aggregation, we used the EXPAND procedure with four lag periods – 52, 104, 156 and 208 to get previous four years of order history data for each {Prod – ShipLoc – CustLoc} triplet.

ROLLING WEEKLY FORECASTS

We generated multiple rolling weekly forecasts for different forecast starting dates. Order history data prior to a given forecast start date was used for training and twelve weeks of data after the start date was used as the holdout data for validation as demonstrated in Figure 2. For each rolling forecast, we compared performance for the current week (Lag 0) and up to twelve weeks into the future (Lag 11).

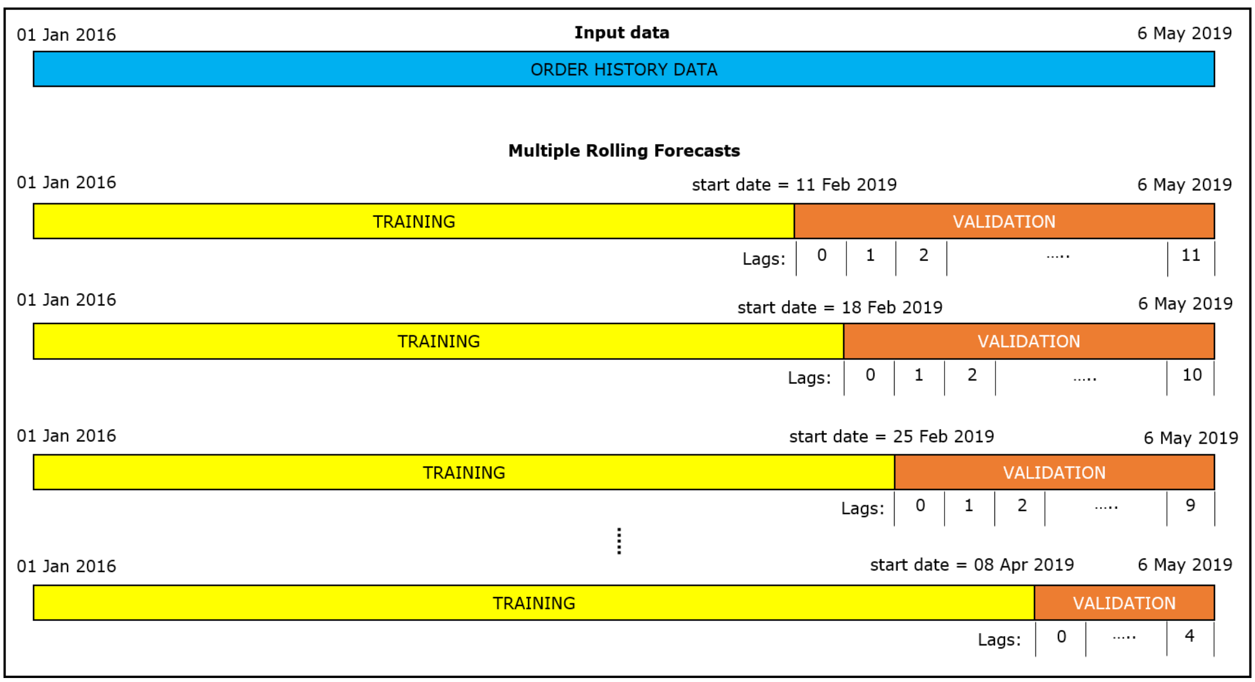


Figure 2. Demonstration of how order history data was split for multiple rolling weekly forecasts. A start date was chosen, and all data prior to that date was used as training data to train the models and the data after the start date was used as the holdout validation data.

For each rolling forecast, we used two methods to generate forecasts:

1. Time-series based forecast
2. Neural Network + Time-Series (NNTS) forecast.

For the time-series based forecast, we used the HPFDIAGNOSE procedure to diagnose the statistical characteristics of each {Prod – ShipLoc – CustLoc} triplet time-series and identify appropriate forecasting models for each time-series. We used the diagnosis results from PROC HPFDIAGNOSE and used the HPFENGINE procedure to generate a time-series forecast estimate and a trend estimate for each {Prod – ShipLoc – CustLoc} triplet.

For the NNTS forecast, we trained a neural network using the HPNEURAL procedure for each Product separately by using the following inputs:

- ShipLoc location
- CustLoc location
- Previous four years of order history
- Forecast estimates
- Trend estimates

Forecast estimates and trend estimates were used from the PROC HPFENGINE results. The neural network had one hidden layer with 10 neurons with 'tanh' activation function. The network was trained for 50 iterations for each Product separately using the training data and scored on the holdout validation data. On the training data, residual quantities were calculated as the difference between the actual order quantities and the predicted order quantities. The HPF procedure was then run on the residual quantities to generate a time-series based forecast of the residuals over the validation period. The final NNTS forecast was generated by simply adding the neural network predictions with the residual forecast estimates. Note that an implementation of the NNTS forecast is already available in SAS® Visual Forecasting.

Thus, using the above methods, we generated two versions of the forecast. For each forecast, we calculated the mean absolute percentage error (MAPE) for each {Prod – ShipLoc – CustLoc} triplet over the training period and used the forecast with the lower MAPE as the enhanced forecast for a given triplet.

Next, we incorporated the future open orders data to further refine our enhanced forecast. For each rolling forecast over the validation period, we compared our enhanced forecast estimate with the future open orders and replaced the forecast estimate with the open order quantity, if the open order quantity exceeded the forecast estimate.

For analyzing the impact of using point-of-sale (POS) data and customer inventory data, we created two versions of the NNTS forecast. One forecast using inputs to the neural network listed above, and another one with two additional inputs corresponding to POS and customer inventory data.

WEEKLY FORECASTS TO DAILY FORECASTS

We generated daily forecasts by disaggregating or breaking down the enhanced weekly forecasts for each {Prod – ShipLoc – CustLoc} triplet into enhanced daily forecasts. We achieved this by estimating the relative daily order proportions to disaggregate the weekly forecast into daily forecast. We estimated these proportions for each {Week – Prod – ShipLoc – CustLoc} combination and then used the proportions to multiply the weekly forecast estimate and obtain a daily forecast estimate. The weekly disaggregation proportions were estimated using three separate models.

Seasonal model

This model was used to capture the slow-moving seasonal nature of daily order patterns. For each week, we analyzed the daily order patterns over the last three years (2016-2018) and averaged the proportions for each day to estimate the weekly disaggregation proportions for each {Week − Prod − ShipLoc − CustLoc} combination.

Trend model

This model was used to capture the more recent daily order trends. For each week, we analyzed the daily order patterns over the previous thirteen weeks and averaged the proportions for each day to estimate the weekly disaggregation proportions for each {Week − Prod − ShipLoc − CustLoc} combination.

Neural network model

This model was used to estimate daily order quantities based on previous two years of daily order history using a neural network. For training, we used the daily order history from 2016 and 2017 to estimate the daily order quantities of 2018 using a neural network with one hidden layer containing 10 neurons and 'tanh' activation function. After training the neural network for 100 iterations, we used the daily order quantities from 2017 and 2018 to predict daily order quantities of 2019. The estimated daily order quantities of 2019 were normalized to get weekly disaggregation proportions for each {Week − Prod − ShipLoc − CustLoc} combination.

Thus, weekly forecasts were disaggregated into daily forecasts using the three methods described above. For each forecast, we calculated the mean absolute percentage error (MAPE) for each {Prod − ShipLoc − CustLoc} triplet over the training period and used the forecast with the lowest MAPE as the enhanced daily forecast for a given triplet.

RESULTS

We generated enhanced weekly and daily forecasts for 205 products which passed our data validation criteria, that is, order shipments in 2019 and at least one year of order history. The performance of weekly and daily forecasts was evaluated using two metrics:

- Accuracy, which considers the absolute error between the forecasted order quantity (F_i) and the actual order quantity (O_i), and is calculated as,

$$\text{Accuracy} = 100 \times \left[1 - \frac{\sum_{i=1}^{n} |F_i - O_i|}{\sum_{i=1}^{n} F_i}\right]$$

- Bias, which considers the ratio between the actual order quantity (O_i) and the forecasted order quantity (F_i). A negative bias is interpreted as an under-forecast of the actual quantity whereas a positive bias is interpreted as an over-forecast of the actual order quantity.

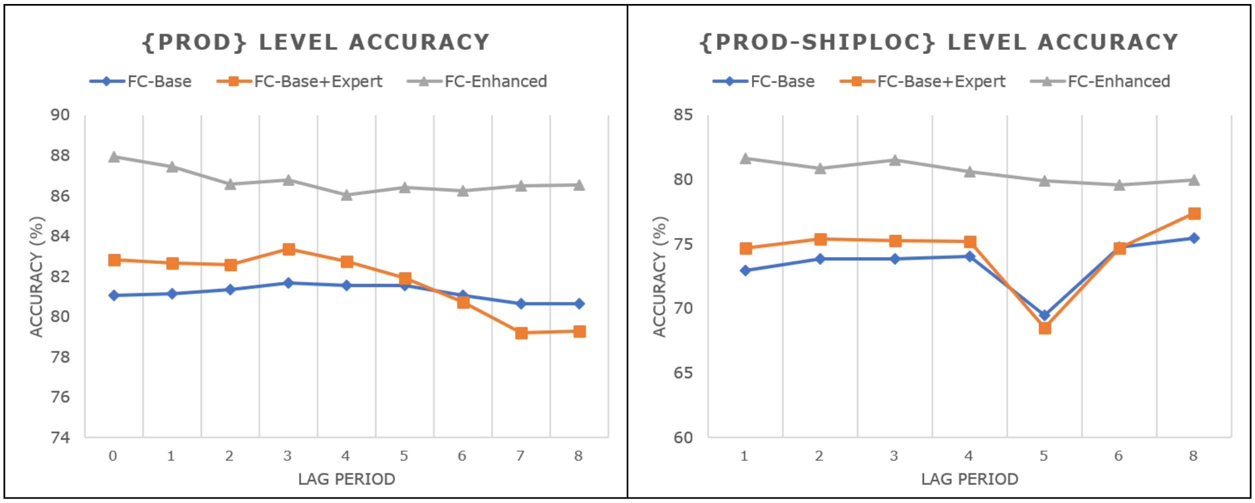
$$\text{Bias} = 100 \times \left[1 - \frac{\sum_{i=1}^{n} O_i}{\sum_{i=1}^{n} F_i}\right]$$

For weekly forecasts, we evaluated the above measures for our enhanced forecast (FC-Enhanced) and the two forecasts provided by the CPG viz. FC-Base and FC-Base+Expert at both {Prod} and {Prod − ShipLoc} levels.

Weekly forecasts

We demonstrate a significant improvement in forecasting accuracy using FC-Enhanced compared to both FC-Base and FC-Base+Expert as shown in Figure 3 and summarized in

Table 1. At the {Prod} level we observe that FC-Base+Expert is better than FC-Base for lags 0-5, however FC-Enhanced is better than both the forecast across all eight lags. At the {Prod – ShipLoc} level, we observe a dip in accuracy for both FC-Base and FC-Base+Expert forecast, however we do not observe such a dip in accuracy using FC-Enhanced forecast. Note that lags 0 and 7 are missing in {Prod – ShipLoc} level, because forecasts for these lags were not available in the data provided by the CPG.



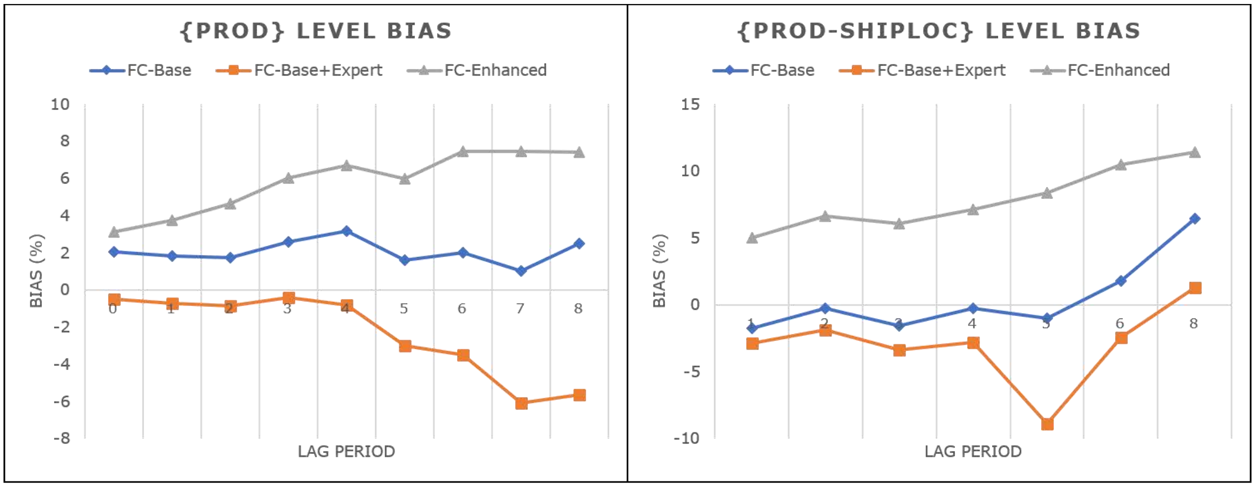
(a) (b)

Figure 3. Comparison of forecast accuracy using three forecasts at (a) {Prod} level and (b) {Prod-ShipLoc} level. Significant accuracy improvement across all lags at both levels of the forecast are seen using FC-Enhanced.

Forecast level	FC-Base	FC-Base+Expert	FC-Enhanced
{Prod}	81.18 ± 0.36 %	81.70 ± 1.48 %	86.71 ± 0.57 %
{Prod – ShipLoc}	73.49 ± 1.80 %	74.46 ± 2.56 %	80.58 ± 0.74 %

Table 1. Summary of weekly forecasting accuracy at {Prod} and {Prod – ShipLoc} levels from Figure 3 summarized using mean ± standard deviation.

In terms of forecast bias, we observe that both FC-Base and FC-Enhanced have a consistent positive bias across all lags at the {Prod} level. FC-Base+Expert has a consistent negative bias across all lags at both forecasting levels as shown in Figure 4 and summarized in Table 2. A positive bias indicates that there is a systematic over-forecast of order quantities compared to actual order quantities, whereas negative bias indicates an under-forecast. A non-zero bias can lead to an over- or under-supply of shipments from ShipLoc DCs to CustTo DCs. The consistent positive bias using FC-Enhanced, can be attributed to the use of a neural network in the NNTS procedure. We found that the neural network tended to produce positive non-zero outputs for zero valued inputs.



(a) (b)

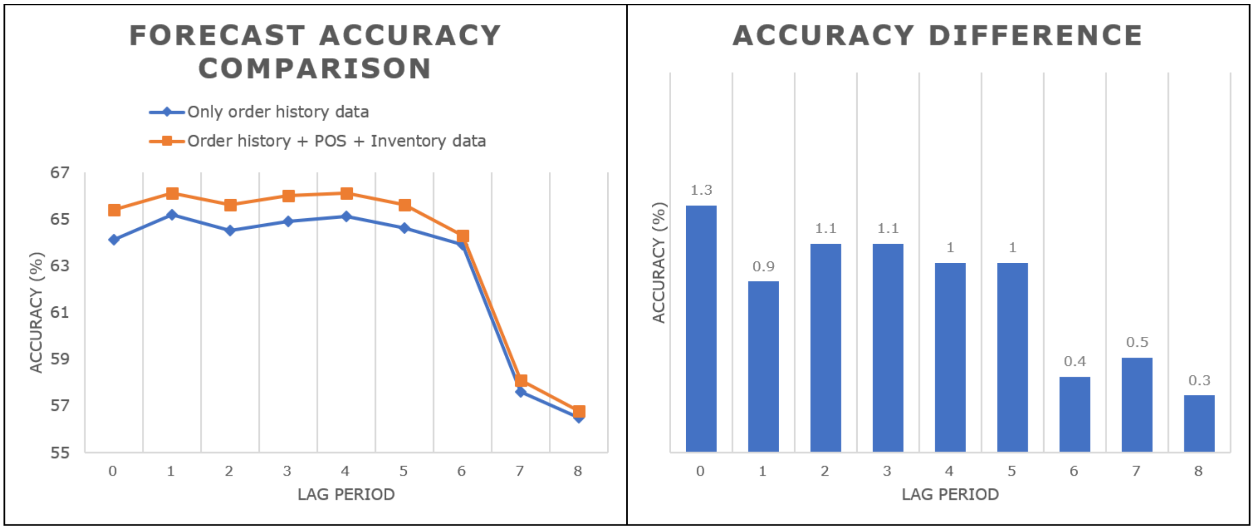
Figure 4. Comparison of forecast bias using three forecasts at (a) {Prod} level and, (b) {Prod-ShipLoc} level. FC-Enhanced is more positively biased compared to FC-Base and FC-Base+Expert.

Forecast level	FC-Base	FC-Base+Expert	FC-Enhanced
{Prod}	2.06 ± 0.59 %	-2.39 ± 2.14 %	5.83 ± 1.54 %
{Prod − ShipLoc}	0.47 ± 2.67 %	-3.01 ± 2.79 %	7.87 ± 2.17 %

Table 2. Summary of weekly forecasting bias at {Prod} and {Prod − ShipLoc} levels from Figure 4 summarized using mean ± standard deviation.

In Figure 5 we demonstrate comparison of forecast accuracy with including point-of-sale and customer inventory data along with order history data. Both forecasts in the figure were generated using the NNTS method. The CPG only had limited point-of-sale (POS) and inventory data for the year of 2019. Recall that the order history data provided was available from 2012-2019. Thus, in order to generate comparable forecasts, we used limited order history data over the same time period that the POS and inventory data was available.

We observe an incremental improvement in weekly forecast accuracy with using the additional POS and inventory data. For lags 0-5, we see around 1-2 % accuracy improvement by including the POS and inventory data, however the improvement is less than 1 % for lags 6-8. Further there is a sharp dip in accuracy for lags 7-8 for both the forecasts. We believe that this incremental improvement in forecast accuracy with using POS and inventory data is due to the limited data availability.



(a) (b)

Figure 5. Comparison of weekly forecast accuracy with using only order history data and with using order history, point-of-sale (POS) and customer inventory data. (a) is a plot of accuracy of individual forecasts and, (b) highlights the lift in accuracy by including the POS and customer inventory data. Note that the forecasts are at the {Prod − ShipLoc − CustLoc = customer} level.

Daily forecasts

Next, we present enhanced daily forecast results which were generated by disaggregating the enhanced weekly forecasts into daily forecasts using three separate models. Daily forecast accuracy and bias over 30 lags, that is 30 days into the future, are shown in Figure 6 and summarized in Table 3. Note that the CPG did not provide any daily forecasts for comparison, hence we have presented only FC-Enhanced results. Comparing Tables 1 and 3, we observe that compared to weekly forecasts, there is a dip in daily forecast accuracy at both {Prod} and {Prod − ShipLoc} levels. This is to be expected since we are breaking down weekly forecasts into daily forecasts. At both {Prod} and {Prod − ShipLoc} levels, we notice a cyclical pattern in the daily forecast accuracy which repeats every seven days. For majority of the lags, the {Prod} level forecast is more accurate than the {Prod − ShipLoc} level forecast, but we observe some exceptions, for example at lags 5, 12, 19, 26. In terms of forecast bias, on average, the {Prod} level forecast has a positive bias, whereas the {Prod − ShipLoc} level forecast has a negative bias.

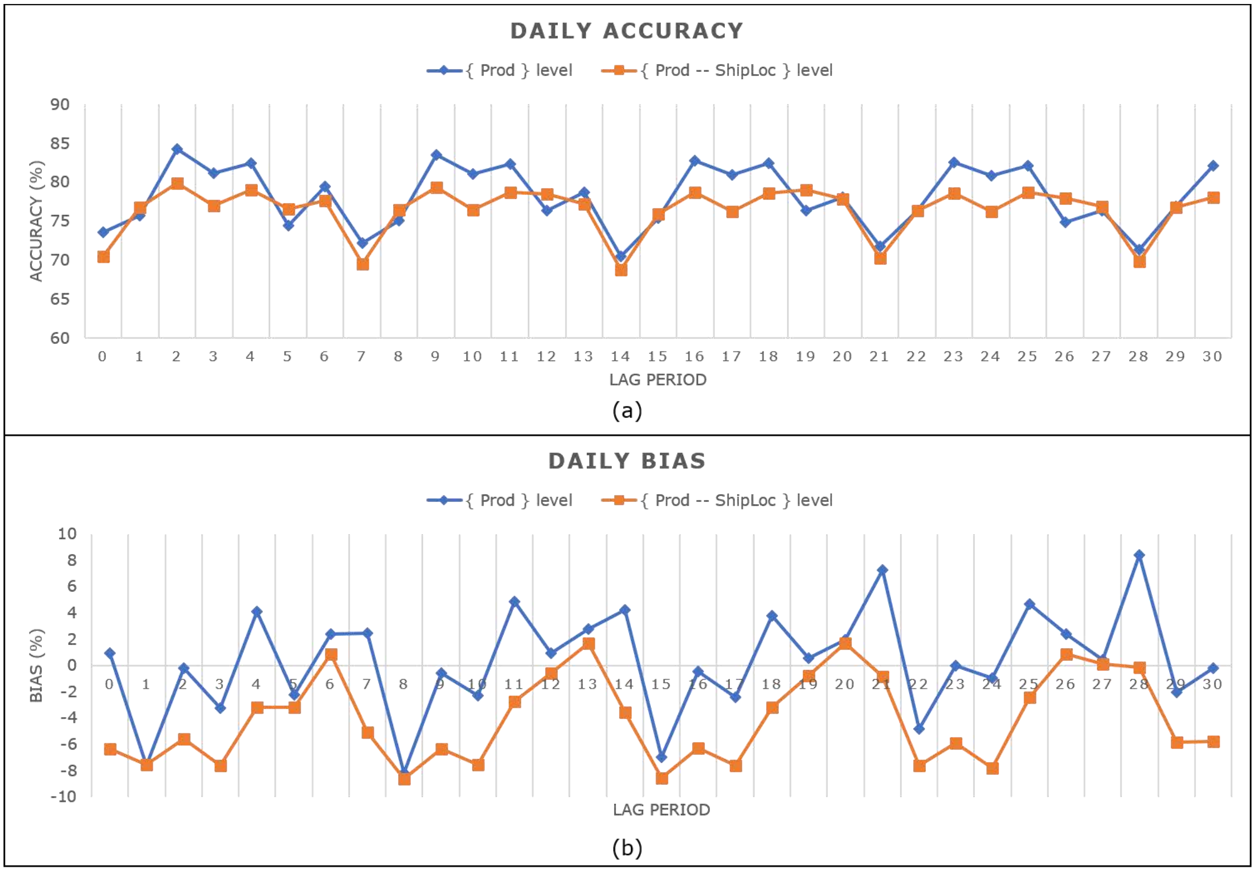


Figure 6. Daily forecasting accuracy at (a) {Prod} level, and (b) {Prod-ShipLoc} level.

Forecast level	FC-Enhanced Accuracy	FC-Enhanced Bias
{Prod}	78.13 ± 3.97 %	0.30 ± 3.91 %
{Prod − ShipLoc}	76.39 ± 3.09 %	-4.06 ± 3.28 %

Table 3. Summary of enhanced daily forecast accuracy and bias at {Prod} and {Prod − ShipLoc} levels from Figure 6 summarized using mean ± standard deviation.

CONCLUSION

We have demonstrated the use of machine learning to generate enhanced weekly and daily forecast of product demand. Our weekly forecasting methodology uses a combination of traditional time-series models and machine learning methods and can automatically choose the best model for each {Prod − ShipLoc − CustLoc} combination. We have demonstrated the efficacy of our techniques by improving short-term forecasts for a large CPG company. At the weekly level, we demonstrated a significant improvement in forecasting accuracy over existing forecasting procedures across multiple lag periods. We also demonstrated that how a point-of-sale data and customer inventory data can be used in addition to order history data to improve forecasting accuracy. We believe that our methods provide a flexible, transparent and scalable solution for effective supply chain management at large CPGs.

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