Managing Stock Availability in East Malaysia

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Summary:

The project analyzed current stock availability of the selected base products for East Malaysia and recommended the process improvement exercise needed to improve the product availability. This involved mapping current process and suggesting statistically robust stock policies with lowest stock points at 98% availability or more, without changing the distribution model. Further the resultant model was tested (for the identified base products) to compare and analyze the change over the earlier model.

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Key Insights:

For the Sponsor Company the project will serve to:

- Define the optimum stock policy.
- Quantify the reduction from stock-outs.
- Quantify the new Customer Service Level at the distributor level for each of the inventory models.
- Reduce the forecast errors.
- Work as a tool for testing different scenarios and situations.

Introduction

Product availability is an important component to maintain consumer satisfaction and secure revenue streams for the retailer and the product supplier. A consumer will select one of four actions when faced with an out-of-stock (OOS) situation. Two reactions are to substitute, either a different product in the same brand or another brand entirely. The other two reactions are delaying a purchase or not purchasing at all. Any of these four actions directly affect sales and subsequent profitability; thus it is important to ensure that products are sufficiently available to ease a consumer's search and selection activities during the buying process.

The company-MTX wanted to maximize its sale opportunity and ensure high stock availability whilst minimizing delivery time which had a high variability varying from 3 to 6 weeks. In addition to this, sales demand also showed high variability making it difficult to arrive at an optimum stock policy when the demand as well as lead time is fluctuating. The prominent key questions that the research addressed are as follows:

Key questions:

- If several symptoms of problematic processes are occurring simultaneously, which one to tackle first?
- Is there a better way to define stock policies and influences without changing the distributor model in order to reduce working capital to operate at high order fill rates?
- How does Demand and Demand variability impact the Service Level at the Distributor Level in East Malaysia?
- How does Lead Time and Lead variability impact the Service Level at the Distributor Level in East Malaysia?

Distribution Model

The distribution model for Malaysia is best explained in the diagram below. It explains the Company MTX's Products route to the market.

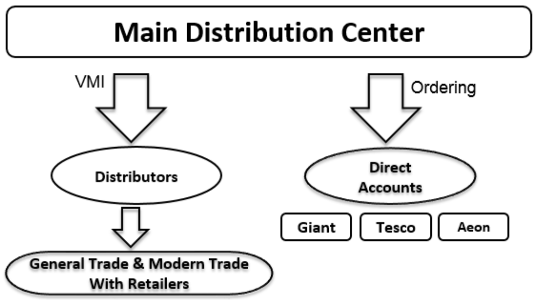

Figure 1: Distribution model for Malaysia.

There were two kinds of Accounts-Distributors and Direct Accounts. The direct accounts consisted of retail giants such as Giant, Aeon, Tesco etc. Here the company replenished the products based on orders placed by the retailers. The order size was high and uncertainty factors in demand and lead time was less impactful compared to the route to customers through distributors.

In case of replenishment through distributors, the company managed its inventory at the distributor end. The company had the visibility of the stock balance. The procurement order was generated based on the proposal frequency and stock balance.

Methodology

Based on scope of the thesis, a process improvement was planned. With the identified problematic symptoms occurring simultaneously there was need for prioritization.

Process Selection Matrix

A process selection matrix helps to decide which process to tackle first. Here each process is rated according to the criteria how easily it might be changed and how problematic it could be for the customers. Then, each problematic process is rated on a scale of 1 to 5, with 5 being the highest and 1 the lowest. The total score suggests the process that is required to be improved first.

Three processes were chosen for improvement:

1) Creating different scenarios of proposal frequency and order up to a point quantity (R).
2) Changing the Replenishment Model.
3) Forecast accuracy

SKU Segmentation

The SKUs were classified into A, B and C ("A" = Fast Moving, "B" Medium Moving, "C" Slow Moving"). This involved arranging all the sell-out data (demand values) in descending order and then finding the cumulative percentage of the total volume contribution. A distribution by value curve was plotted to understand the volume spread of the base products.

Two base products each from Class A and B and one from C were chosen after consultation with the company. The entire modelling was then carried out using the data pertaining to these base products.

Creating different scenarios of proposal frequency and order up to a point quantity(R)

The methodology involved analyzing current stock availability of affected products at 17 stock locations in Sarawak, Brunei, and Sabah for respective LTPs (Long term Partners). A model was then developed to calculate the number of stock-outs for different scenarios of proposal frequency and order up to a point quantity(R).

To build the model for the project, a number of key inputs were acquired from the information system for the modelling purpose. The period of study was 24 months (year-2012, 2013). The type of data used are listed as follows:

1) Sell-in data- Orders that are keyed in the by the company, but not yet implemented.
2) Pipeline inventory –These are the stock en route.
3) Daily Stock Balance- Stocks physically available in the warehouse (on-hand)
4) Sell-out data- Stock already booked/sold.

The lead time data was not available. The average lead time was assumed for each of the LTPs based on the inputs from company-MTX.

Calculations:

The available stock (economic stock) Se was calculated as:

$$Se = S_{in} + S_{er} + S_{ioh} - S_{out} \quad (1)$$

Where:

S_{in}=Sell-in data- Orders that are keyed in the by the company, but not yet implemented.

S_{er}=Pipeline inventory –These are the stock en route.

S_{ioh}= Daily Stock Balance- Stocks physically available in the warehouse (on-hand).

S_{out}=Sell-out data- Stock already booked/sold.

The parameter S (also called the maximum stock level) was defined as follows:

$$S = D * (LT + T) + SS \quad (2)$$

Where:

D - Mean demand in a unit of time used (e.g. day, week)

T – Mean review interval (time between two successive proposals).

LT - Replenishment cycle time (time between the review and delivery of goods).

The safety stock SS was expressed as:

$$SS = \omega * \sigma \quad (3)$$

Where:

ω - Safety factor, which depends on the applied service level and the type of the demand frequency occurrence distribution,

σ–Total standard deviation incorporating the standard deviation of demand in the time equal to the sum of review interval and inventory replenishment time and standard deviation of the replenishment lead time.

Where: $\sigma = \text{sqrt}(\sigma^2_D * (LT+T) + \sigma^2_{LT} * D^2)$ (4)

σ_D = Standard deviation of demand in a unit of time used (the same as for D)

σ_{LT} = Standard deviation of replenishment lead time.

Here the type of distribution of demand D is assumed to be normal distribution, typical for fast moving goods.

Forecast Accuracy

To study the seasonality and trend, Sell out (demand data) was charted. It included the individual and combined graphs (Q vs T) with demand distribution spread month wise, week wise and Day wise to see the pattern by the use of Bar Chart.

Further, to this an appropriate underlying model (moving average, exponentials smoothing using level, trend and seasonal data) was selected to study the demand pattern over time and forecast the future demand. Finally the forecast accuracy was estimated and validated using tracking signal.

Two methods were explored-simple moving average and exponential smoothing with level, trend and seasonality component. Two year company demand data was available; the first year data points was used to forecast the second year demand data.

Simple moving Average

It is nothing but the average of the last M data points.

Calculations:

Underlying Model:

$$x_t = a + e_t$$

Where: $e_t \sim \text{iid}\ (\mu=0, \sigma^2 = V[e])$

Forecasting Model:

$$\hat{x}_{t,\, t+1} = \left(\sum_{i=t+1-M}^{t} x_i\right)/M$$

Exponential Smoothing with level, trend and seasonality component.

This model was based on Holt Winter's Method with level, trend and seasonality component as shown below:

Calculations:

Underlying Model:

$$x_t = (a + bt) * F_t + e_t$$

Where: $e_t \sim \text{iid}\ (\mu=0, \sigma^2 = V[e])$

Forecasting Model:

$$\hat{x}_{t,\, t+T} = (\hat{a}_t + T\,\hat{b}_t)\,\hat{F}_{t+T-P}$$

Where:

$$\hat{a}_t = \alpha\,(x_t/\hat{F}_{t-P}) + (1-\alpha)\,(\hat{a}_{t-1} + \hat{b}_{t-1})$$

$$\hat{b}_t = \beta\,(\hat{a}_t + \hat{a}_{t-1}) + (1-\beta)\,\hat{b}_{t-1}$$

$$\hat{F}_t = \Upsilon\,(x_t/\hat{a}_t) + (1-\Upsilon)\,\hat{F}_{t-P}$$

Where:

α -is a smoothing constant

β- accounts for seasonal variation

ϒ- accounts for trends

The values of (α) alpha, (β) beta and (ϒ) gamma were adopted such that the Mean of Square of Errors (MSE) was minimized. The steps followed were as follows:

I. Create the forecasting model with alpha, beta and gamma as decision variables.
II. Define Mean of Square of Errors (MSE) as the objective function.
III. Minimize the objective function using non-linear optimization technique.
IV. Use the corresponding values of alpha, beta and gamma as the model parameters

Changing the Replenishment Model.

Both continuous and periodic review systems are described in the paper Alternative Inventory Control Policies (Elion, Elmaleh, 1968). The recommended inventory policies for classes of A, B and C is shown in the table below:

Classification	Continuous Review	Periodic Review
A	(s,S)	(R,s,S)
B,C	(s,Q)	(R,S)

Table1: Recommended inventory policies

R,s,S is a combination of s,S and S,T policy. Generally, the calculation of 's' is same as in equation (2), and S=s+Q. This will require calculation of economic order quantity, which is not the objective of study.

The system was evaluated by creating different scenarios of proposal frequency and order up to a point quantity(R) in the earlier section. Therefore analysis pivoted upon "Changing Replenishment Policy" was covered comprehensively, given the scope and objective of this thesis.

Assumptions

I. A year consists of 52 weeks.
II. Demand of the individual SKUs are not correlated.
III. The port capacity in East Malaysia was assumed to be unlimited.
IV. The Main Distribution Center in West Malaysia caters has unlimited supply of all the SKUs under study.
V. The storage capacity at the LTPs end are unlimited.
VI. The lead time variability affected by port to port distance, not by the SKUs.
VII. The Lead time and Demand are independent random variables and requires measurements of each.
VIII. The type of distribution of demand D is assumed normal distribution, typical for fast moving goods.

Analysis and Results

The section deals with the results obtained as a result of the analysis performed within the scope of the project. The results are constrained by the assumptions as discussed earlier and accuracy of the available data.

Results of ABC Classification:

The first 54 products, which is around 5.5% of the Base Products by Number contribute to 80% of the Base Product by Volume. These are classified as A type Products.

The next 123 products, which is around 12.6% of the Base Products by Number contribute to next 15% of the Base Product by Volume. These are classified as B type Products.

The left over 802 products, which is around 81.9% of the Base Products by Number contribute to only 5% of the Base Product by Volume. These are classified as C type Products.

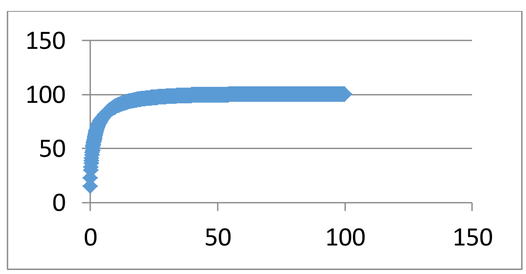

Figure 2: Cumulative % of Base Product by Volume

After A-B-C segmentation based on the sell-out data, the following base products was selected for analysis:

Class A

A1-Product 1(MY002512)

A2-Product 2(MY000214)

Class B

B1-Product 1(MY003962)

B2-Product 2(MY003316)

Class C

C1-Product 1(MY004001)

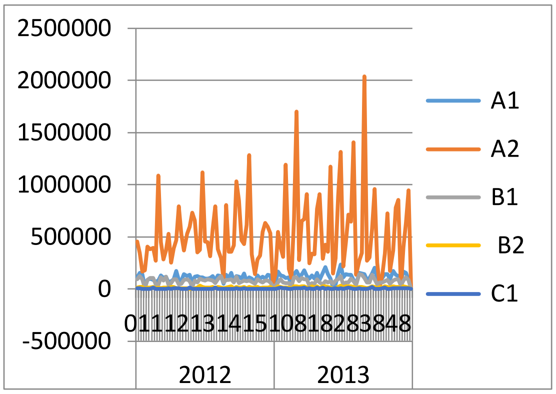

Figure 3: Demand Profile for Base Products

The lead time data for different locations are the respective average time to that location. To predict the SKU lead time for the entire East Malaysia, the mean lead time along with its standard deviation was considered.

Process Selection Matrix

In order to determine the most critical processes, the team members involved in the thesis project were asked for their point of view. The rated processes are shown in the table below:

Process	Cost Saving Potential	Source of Customer Complaints	Opportunity for Improvement	Easy to change	Source of Staff frustration	Total
Setting a new Model.	5	5	4	2	3	17
Evaluating forecast accuracy	4	4	2	2	4	16
Evaluating inventory policies	3	3	3	2	2	13

Table 2: Process Selection Matrix

Creating different scenarios of proposal frequency and order up to a point quantity(R).

The observations of the model based on (R,S)- Order-Up-To-Level System pivoted upon different values of proposal period for the desired service level of 0.98, 0.99 and 0.995 for the base products are described below:

1. The policy presently in use was replenishment based on stock level, which was erroneous because it did not take into consideration the net available stocks based on pipeline, unimplemented order and products sold out. There will always be stock-out whenever the sum of pipeline inventory and unimplemented stock exceed the demand.
2. The 54 days of up to a level value was unnecessarily high based on average lead time data assumed and given conditions.
3. The proposal frequency was not fixed, leading to uncertainty in lead time and calculation error.
4. The sell-in did not replicate the desired procurement order (difference between the original up to a level(R) of 54 days and available stock).
5. The sell-in was not done in sufficient amount leading to stock-outs.
6. The order up to a level ranges from 29 to 46 days based on different values of review period and service levels chosen. This means that with 54 days of order up to a level, the achievable service level was more than 0.995.Theoretically the current model is more than sufficient, if only the lead time is managed and schedule of activities are accomplished on time.
7. With increase in proposal frequency, the requirement of order up to a level(R) drops to the lowest level, but not very significantly between 1day changes in review periods. The reason could be attributed to low $d\sigma/dT$. The change in order up to a level(R) with incremental service level changes of 0.5 is a function of $d\omega/d(CSL)$. The value of $d\omega/d(CSL)$ causes only a small change in safety stock. There will be definitely enhanced product availability and decreased stock-outs with the existing R of 54 days and declining values of review period. The chart below shows that dS/dT is different for different CSL values. The slope looks constant because of marginal impact from safety stock, which contains the nonlinear terms in the R calculation. For example see below: Order up to a level for different values of review period-A1.

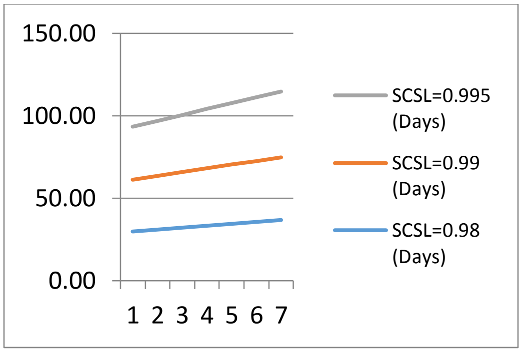

Figure 4: Order up to a level for different values of review period-A1

Procurement order based on 7 day demand and economic stock

There is at least one day of Stock-out /week (current). The number of days of stock-outs range from 1 day to 6 days in a week.

The study is conducted to find out the % of Days of Stock-outs considering weekly Demand for a Procurement order based on the difference between 7 day demand and economic stock. The results are shown below:

Base Products	% of Days of Stock-outs considering weekly Demand (Projected*)
A1	75
A2	40
B1	55
B2	60
C1	3

Table 3: % of Days of Stock-outs considering weekly Demand (Projected*)

There is marked improvement in the % of Days of Stock-outs considering weekly Demand for all the products from A1 to C1.The average improvement is more than 40%.This shows that just by changing the procurement order based on stock balance to procurement order based on economic stock, the availability could be improved.

It is worth mentioning that the C category item shows marked improvement because it is slow moving and therefore availability is affected the most.

Forecasting Accuracy- Moving Average Method

The 5 days moving average method was applied with inputs from the shortlisted base products. The mean average percentage error decreased from A1 to C1.The reason could be attributed to higher span of data points from the mean in the faster moving products.

To check the validity of the underlying forecasting model, tracking signal was computed, which except for C1 lied between the acceptable limits of +6. This means that the 5 days moving average method could be employed for the base products A1, A2, B1 and B2. The closer the tracking signal from 0, more is the validity.

Though the model is able to predict the future values, the forecast accuracy is quite low compared to the existing forecast accuracy. Thus this method is discarded for demand planning purpose.

The results obtained are tabled as follows:

Base Products	MAPE(5 Days Moving Average forecast)	MAD	Tracking Signal
A1	1222.91	12874.99	minus 4.5 to plus 3.7
A2	1011.99	73928.17	minus 8.8 to plus 4.2
B1	452.47	9265.27	minus 4.4 to plus 2.5
B2	157.65	1888.78	minus 4.8 to plus 3.1
C1	152.86	805.94	minus 11.7 to plus 4.3

Table 4: Results-5 Days Moving Average

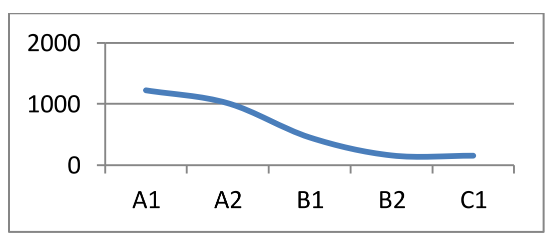

Figure 5: MAPE-5 Days Moving Average

Product A2		
Objective function	MSE(MIN)	2.08972E+11
Deviation	MEAN ABS ERROR	341863.82
Percentage Error	MAPE	60.35
Coefficients	alpha	0
	beta	0.015
	gamma	0.710
Validity of Forecasting Method	Tracking Signal Range	minus 3.4 to plus 3.2

Forecasting Accuracy-Exponential Smoothing:

The exponential smoothing considering the level, seasonality and trend was run with inputs from the shortlisted base products using previous 24 weeks of data. The following observations were made:

1. The initialization procedure based on Centered 4 Point moving Average was effective in handling underlying trend during the historical period. Further the values of a_0 and b_0 is found to be useful in reducing the weight geometrically as the data is traced back in time.
2. This forecast accuracy was not very good, but validity of the forecasting model is well within limit. of ± 6. The poor forecast accuracy could be attributed to some the spikes that happen across the period, which contribute to the chunk of the error contribution in the whole.

Product A1		
Objective function	MSE(MIN)	2387067282
Deviation	MEAN ABS ERROR	35061.49
Percentage Error	MAPE	60.34
Coefficients	alpha	0
	beta	0.015
	gamma	0.174
Validity of Forecasting Method	Tracking Signal Range	minus 3.3 to plus 3.4

3. The underlying model for all the base products so obtained have a high level of seasonality except C1 base products
4. The base product B1 was seen to be most accurate and captures all the three aspects, namely level, trend and seasonality. The results could be summarized in the tables below:

Table 5: Results-Exponential Smoothing-A1

Product B1		
Objective function	MSE(MIN)	1067985067
Deviation	MEAN ABS ERROR	25752.53
Percentage Error	MAPE	37.145
Coefficients	alpha	0.038
	beta	0.082
	gamma	0.529
Validity of Forecasting Method	Tracking Signal Range	minus 3.2 to plus 2.4

Table 6: Results-Exponential Smoothing-A2

Product B2		
Objective function	MSE(MIN)	66394562.4
Deviation	MEAN ABS ERROR	6459.10
Percentage Error	MAPE	63.062
Coefficients	alpha	0
	beta	0
	gamma	0.182
Validity of Forecasting Method	Tracking Signal Range	minus 2.7 to plus 3.2

Table 7: Results-Exponential Smoothing-B1

Table 8: Results-Exponential Smoothing-B2

Table 9: Results-Exponential Smoothing

Product C1		
Objective function	MSE(MIN)	23196464.17
Deviation	MEAN ABS ERROR	3910.34
Percentage Error	MAPE	79.50
Coefficients	alpha	0.123
	beta	0.029
	gamma	0.055
Validity of Forecasting Method	Tracking Signal Range	minus 3.2 to plus 2.2

Recommendations

Based on the analysis and results, which involved generating the Process Selection Matrix; creating different scenarios of proposal frequency and order up to a point quantity(R); developing forecasting models and checking their validity and accuracy; and studying the replenishment model, the following recommendations are made:

1) **Map the Product Flow to identify the bottlenecks**.
   There is a high level of uncertainty in lead time. This leads to high level of stocks for the intended service level. Starting from the Main Distribution Center in West Malaysia to Distributors in East Malaysia map the product flow and understand the reasons for delay. Run a process selection Matrix to see which process improvement effort will lead to maximum impact in minimizing delays. As an example a consolidator could be used to ship to port. This will automatically reduce delays due to full truck-load requirements. It will also reduce the delay due to availability of containers. Even at the port, the irregular shipping schedule could be solved if there is possibility of sharing the chartering with some companies having similar requirements.
2) **Customize Distribution Channel and reorder policy according to product segmentation**.
   Based on the base product segmentation, the distribution channel and method should be customized. First, use ABC segmentation to define the class of items and then apply different replenishment models to cater to each class of items. Class A products (80% of volume) belong to 6% of the total number of base products. Also, use the demand data captured at a base product level to define model parameters. This will help achieve intended customer levels with optimum level of inventory on hand.

Classification	Periodic Review
A	(R,s,S)
B,C	(R,S)

3) **Quantify the uncertainties between different nodes and assess the risks.**
   Define the lead time between nodes and map the process to locate the part that creates the maximum ripple in the entire system in term of stock-outs. Work on the possible solutions to mitigate the negative effects. Locate the nodes with the highest risk potential and take the rectification action. This will add to company's competitive advantage in the longer run.

4) **Change the forecasting model.**
   The forecasting accuracy is very poor. The present model is unable to capture the level, trend and seasonality. Start forecasting at the base product level. Improve the accuracy of feed data and use optimization to minimize the standard error to achieve the closest fit.
5) **Redefine KPIs**
   Presently on time delivery is not one of the KPI for the 3rd party logistic providers. This is very important to be included to improve performance. Also the updating of sell-out data/pipeline data/available stock data do not follow standardized procedures. So there is high possibility of error. Accuracy of Data entry should also be one of the KPIs for monitoring Distributor performance.
6) **Monitor the Lead Time**
   The mean lead time and its variability are high. Understandably, higher lead time is not difficult to manage. More often than not it is the poor knowledge of the variability, which creates mismatch of demand with supply. In this particular case lead time has not been monitored for deliveries from Main Distribution Center to Distributors in East Malaysia. The average value that has been considered for calculation is not good enough to define individual stock levels for individual base products. There will be some base products that will require higher stocks and some lower based on demand and lead time variability plus the segment to which that particular stock belongs.

7) **Increase the proposal frequency and update data promptly**
   Increasing the proposal frequency will definitely improve availability but it should be optimized with inventory holding costs ordering costs for the intended customer service level. As observed in the data, the keying in does not happen regularly creating another level of uncertainty within the system. This random fashion in which key-in is performed is to done away with. It should follow the defined proposal frequency.

Future Work

In future work towards system wide optimization could be initiated taking cue from the present work. It will require high visibility and risk mitigation across the chain. It could be accomplished by utilizing newer technologies that enable system wide information view in real time. The future scope of work then would encompass studying of things located upstream-before Main Distribution Center and downstream-beyond Long term Partners/Distributors. It would be interesting to study the savings incurred as a result of such technology implementations. Building on the present research the impact due to segmentation based on ABC Analysis at the Distributor Level could be conducted. The feasibility study on product consolidation at distributor level could also be an area of future work. Finally, Scenario planning could be used as a tool to understand the inherent risks and develop resilient system models.

Conclusion

This present thesis project was used to understand supply constraints in servicing EM (East Malaysia) and find a way to model different approaches to reduce stock-outs through a statistically determined inventory policy and better forecasting model.

The replenishment based on ABC Classification seems to work well in reducing S (Order up to a level) and has the potential to achieve Customer Service Level more than 0.995 with the current S (Order up to a level) value.

The forecasting model so developed was tested positive for validity by studying the tracking signal. Barring C class items, MAPE value for the tested base products was found to be lesser compared to overall values of Class A, B and C items obtained by the company MPX.

In spite of the improved MAPE, the value is still on a higher side. This can be attributed to some of the random very high and very low demands that happen during the cycle. The company should investigate reasons for such a behavior and if possible try to smoothen it.

The inventory management system so developed takes in feed from the average values of lead time. In reality, there is high variability in lead-time. The success of the model will depend on the accuracy of assumptions made with respect to lead time and lead time variability.

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