Forecasting the spare part demands for mobile phones

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Abstract: The overall efficiency of the supply chain depends not only the improvement of the infrastructure, but also the comprehensive information exchanges and seamless coordination between different units of the entire supply chain. Among these units the forecasting one plays an important role for the effectiveness of a supply chain. In this paper based on the business practice of a supply chain management company, the role of the forecasting unit is discussed and some potential prediction models for the application of this specific application are investigated. Furthermore, the computational experiments are conducted to choose the most suitable prediction model for the practice.

1. Introduction

Nowadays the technologies in internet and data mining arenas encourage the scholars and practitioners to focus on the following aspects for the supply chains management:

- Logistic data mining. According to He [2] and Xu [4], the inefficient daily business data management of the traditional supply chain is unable to achieve the goal of interactive and synchronized management for a supply chain. It requires deep data analysis to extract useful information for the efficient supply chain management.
- Supply chain integration. The isolation of the supply chain units is hard to provide an effective service. Mouritsen [5] pointed out that the "cure all" integration assumption is challenging. The major issue is to make it fit for the business environment, customer requirements, and the available technologies. Huang [6] proposed the transportation and warehousing integration, which is linked by the demands.
- The intelligent decisions. The demand prediction is the key to improve the efficiency and smartness of decisions for the supply chain management. With its help, we can achieve not only the on-time transportations but also lower warehousing costs. Hu [7] presented a two-dimensional preventive policy where replacements of objects were determined based on both calendar and usage times. Besides the common short-term prediction, Mei [8] proposed a method for long-term volatility predictions.

The research of this paper is conducted based on the business practice of a supply chain management company in Shanghai, China. This company manages the distributions of spare parts for the service centers associated with different cellphone manufactures domestically and internationally. The company attempts to streamline their operations by applying information and data science technologies to meet the customers' satisfactions and reduce the operational costs. The company possesses the distribution network as shown in figure 1, where spare parts are delivered from the manufactures to their warehouses within China. These parts are then shipped to foreign service providers/centers, and finally distributed to the specific stores (forward transport) according to the plans/demands.

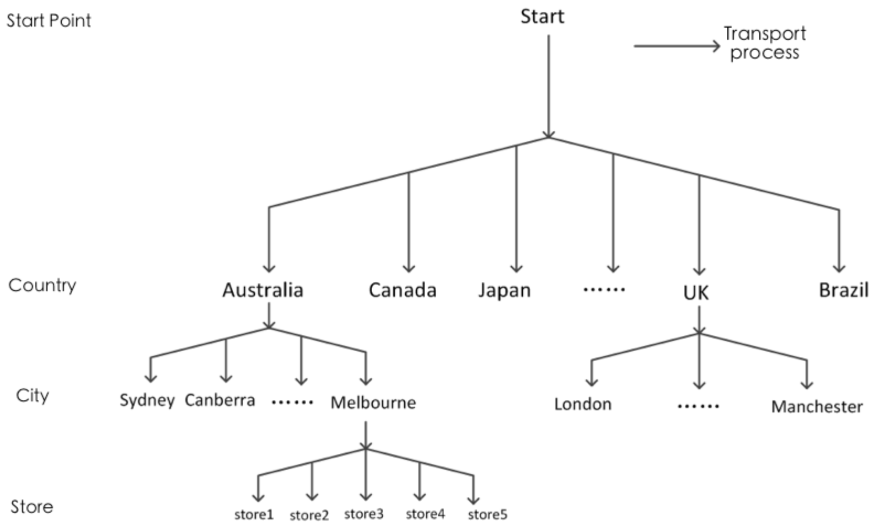

Figure 1 Distribution network

In order to manage the supply chain proficiently, it is crucial to know the needs of spare parts for various cellphones. In this case the plans or decisions for warehousing and transportations can be made accordingly. Hence, how to forecast the spare part demands will be the focus of our paper.

2. Prediction and its roles

2.1 Forecasting role

According to the business analysis, forecasting the spare part (main boards, batteries, screens, etc.) demands is equivalent to predict the failure rates of spare parts of cellphones. The spare part prediction is usually performed based on the associated cellphone's category (brand, model, etc.). The prediction outcomes confine the strategies for early warning, warehousing, and transportations. The interactions and collaboration between different units in the supply chain are shown in figure 2.

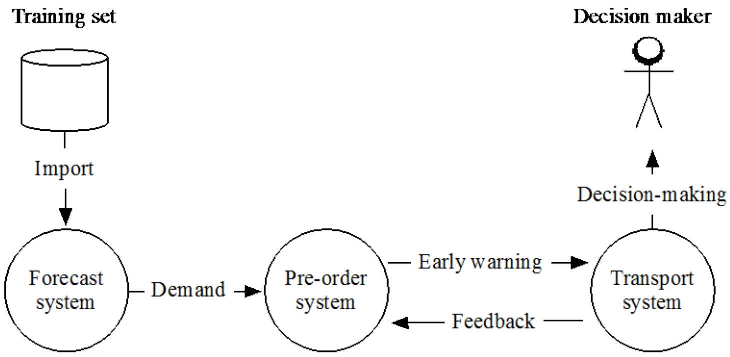

Figure 2. The interactions the supply chain units

The prediction provides the spare part demands to the pre-order unit managing the warehousing and parts ordering. The pre-order function using the predefined rules (it is out of the scope of this paper) decides when and where to acquire (how many) spare parts, and sends the early warning (preparing, ordering, and shipping) message to the proper unit in the supply chain for taking appropriate actions.

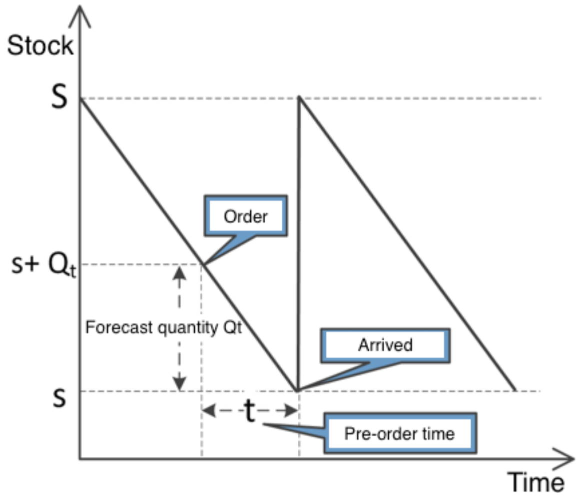

Figure 3. Replenishment strategy

The warehousing strategy won't require continuous spare parts purchasing. In the practice, the replenishment will be defined by the leading time t and the demanding quantity Q_t during t taking the ordering and transportation times into account. Figure 3 illustrates this strategy. It is important to obtain demand Q_t provided by the prediction unit of the supply chain management. The failure rates will be forecasted for spare parts and the demands (i.e., the number of spare parts) can be then derived from the predicted results.

Furthermore, using Q_t and t as the parameters the transportation unit decides the optimal shipping modes based upon tariffs, time constraints, etc.

2.2 Prediction models

A forecasting model in our study is trained by applying partial company's multi-year business data and it will be validated by applying the test data (also a portion of the business dataset). Figure 4 shows the process of building a prediction model.

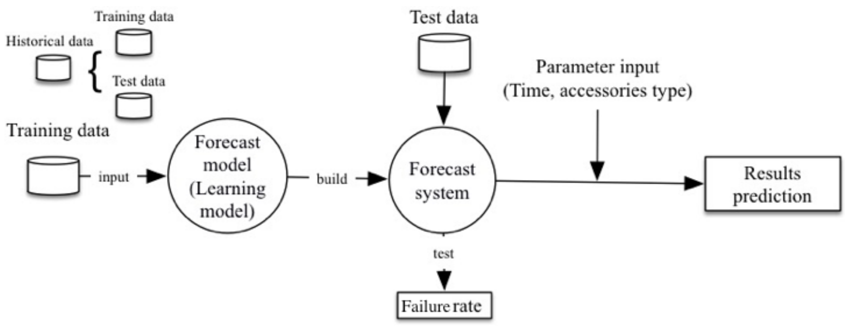

Figure 4 The creation of a forecast model

a. Moving average model

The classic moving average (MA) model is commonly used in the forecasting applications, which is being applied by the company mentioned in the paper as well. This methodology predicts the future by employing the mean value of the selected historical subset, that is:

$$F_{t+1} = \left(x_t + x_{t-1} + \ldots + x_{t-N+1}\right) / N = \frac{1}{N}\sum_{t-N+1}^{t} x_i$$

where x_t is the nearest time series value while F_{t+1} is the dependent variable to be predicted. It is obvious that the result could be varying if different periods of time for the series is selected. For spare part A269i figure 6 depicts the results for various periods of time:

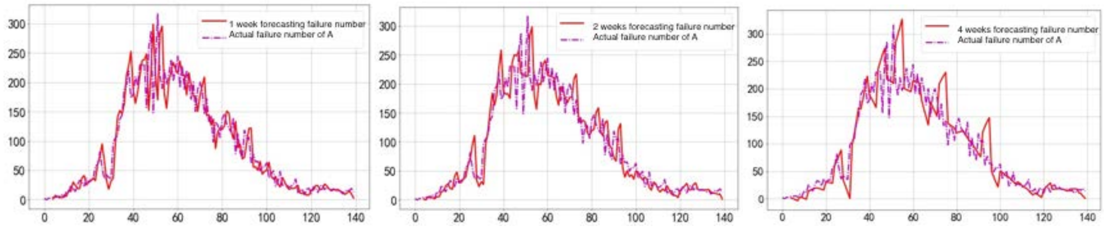

Figure 5 The failure rate predictions with various periods of time

The figure indicates the prediction based on one-week period is closer to the actual failure rate than two-week and four-week periods, at least visually.

Nevertheless, MA depends heavily on` the average of some closest series values and predict near future one. Usually it is unable to provide stable long-term predictions very well, while the lifecycle of a spare part for a cellphone may last several years. This scenario inspires us to study GM (Grey Method) model for our specific need.

b. GM model

GM model can potentially provide the solution for long-term predictions under the uncertainty due to random factors. In GM model, the errors are offset by its accumulation mechanism, and the effect is more significant if the accumulative period is longer. From this aspect, we assume that GM model would be suitable for our long-term prediction purpose.

Assuming the failure rate (*FR*) needs to be predicted, it can be determined by the failure count (*FC*) and the full amount (*TC*) of a spare part used in cellphones as follows:

$$FR = FC / TC$$

At a certain time, if all up-to-date data is concerned the above formula can be revised as:

$$FR^* = FC^* / TC^*$$

where the asterisk (*) represents the accumulated series values. The performance of the accumulation mechanism of GM can be verified by applying the multiple linear regression. The validation steps are:

a. For a given spare part, we collect unaccumulated values *FR*, *FC*, *TC* and accumulated values *FR**, *FC**, *TC** respectively.
b. Build the multiple linear regression for *FR*, *FC*, and *TC*, where *FR* is the dependent variable while *FC* and *TC* are explanatory ones.
c. Use t-test and F-test to assess the coefficients and the regression model given the significance level.
d. Record R-squared to assess the goodness-of-fit for the regression model.
e. Repeat steps b to d for *FR**, *FC**, and *TC**.

Table 1 The multiple linear regression test of A269i before accumulation

		Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.331e-04	4.677e-06	28.45	<2e-16	***
FC	8.661e-06	1.124e-07	77.04	<2e-16	***
TC	-1.117e-09	3.462e-11	-32.28	<2e-16	***
F-statistic: 3000 on 2 and 598 DF, p-value: <2.2e-16					
Multiple R-squared: 0.9094, Adjusted R-squared: 0.9091					

Table 2 The multiple linear regression test of A269i after accumulation

		Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.230e-04	1.972e-06	163.852	<2e-16	***
FC*	-1.748e-09	5.276e-10	-3.313	0.000977	***
TC*	-1.887e-12	6.432e-14	-29.341	<2e-16	***
F-statistic: 7765 on 2 and 598 DF, p-value: <2.2e-16					

Multiple R-squared: 0.9629, Adjusted R-squared: 0.9628

Taking *FR**, *FC** and *TC** as examples (shown in table 2), both the *p*-values of F-test (for regression model) and t-test (for regression coefficients) below the significance level 0.05. It validates the goodness-of-fit of our model. Furthermore, R-squared increases after the accumulation mechanism of GM is applied, and it indicates the improvement in the goodness-of-fit.

To assess the general applicability of the proposed accumulation mechanism, we performed the validation process for different spare parts and the results are presented in table3. Obviously, for all testing cases R-squared is improved significantly when GM is applied that confirms the accumulation mechanism embedded in GM model is helpful for long-term predictions in which noise and uncertainty need to be addressed.

Table 3 The comparisons of with and without accumulation mechanism

Spare part	Before accumulation Multiple R-squared	Before accumulation Adjusted R-squared	After accumulation Multiple R-squared	After accumulation Adjusted R-squared
A269i	0.9094	0.9091	0.9629	0.9628
A369i	0.5622	0.5607	0.6378	0.6366
A536	0.9550	0.9548	0.9793	0.9797

3. Computational experiments

After the prediction models are studied in the previous section, we need to conduct more experiments for comparisons and providing the guideline for selecting the most suitable prediction model to be built in our use case.

Different prediction models possess their own characteristics and may behavior quite differently upon individual datasets. Based on our studies, we find out though at the beginning GM could not predict well due to lacking the accumulated data, the accuracy of GM model improves gradually as the time moves on. The accumulation mechanism embedded in GM supports better predictions and withstanding random errors over a long-time period. While MA is more suitable for the short-term predictions, GM model is selected as the core predicting model in our supply chain management.

To further validate the rational of selecting GM as the core prediction model in our applications, we conduct the computational experiments using various periods of time based upon the same spare part (A269i) data. The results obtained by MA and GM models are using different periods of time (one-, two-, or four-week) are shown in figure 6. It is obvious that GM provides more accurate predictions.

For long-term predictions such as our applications, in addition to the accuracy the robustness/stability of a forecasting model is crucial as well. The computational experiment is conducted to analyze the robustness of a forecasting model. A series of (absolute) differences (will be called predicted error (PE) in the following discussion) between the predicted and real failure numbers are obtained. The standard deviation of a PE series is then computed and the proportion to the mid-value of real failure numbers is yielded, where the predicted failure number for a spare part is the product of predicted failure rate times the full amount. The detail outcomes using the two-week period of time is presented in table 4.

Figure 6 The comparison of the predictions between GM and MA models

The standard deviation of PE for MA 41.89 while the corresponding value for GM is 0.51. Again, it demonstrates that the accumulation mechanism can effectively mitigate the impact of noise and random errors during the whole lifecycle of a cellphone. GM model provides not only more accurate but also stable or robust predictions. It is therefore a suitable choice for our applications.

Table 4. The prediction results obtained by MA and GM models

Models	standard deviation of PE (SDPE)	SDPE to mid-value of actual failure number
MA model	41.89	16.09%
GM model	0.51	0.19%
Statistics for actual failure number per day: Average 165.60, Max 520.57, Mid-value 260.29		

4. Conclusions

According to the real business background, we discuss the importance of the forecasting unit in the entire supply chain management. The accurate and robust prediction forms the great framework for making reasonable decisions for warehousing and transportation operations as whole.

After MA and GM are investigated in detail, GM mode is selected to be the core prediction model in the forecasting unit of the supply chain management though at the beginning of a cellphone lifecycle an additional forecasting model is needed to provide more accurate predictions. GM is able to capture relatively well the patterns of spare part failures and suitable for long-term predictions. The computational experiments demonstrate its capability of producing relatively accurate and stable predictions for the underlying applications.

When the model is deployed in the practice, we will move to the stage where the forecasting, warehousing, and transportation units are integrated and synchronized. As the result, the supply chain is expected to be running more effectively.

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