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DEMAND FORECAST METHOD FOR BUILD-TO-ORDER PRODUCTS USING ESTIMATE INFORMATION AS A LEADING INDICATOR

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A method for forecasting the number of parts shipments is proposed for build-to-order products using pre-sales estimate information as a leading indicator. Since the target number of parts shipments changes irregularly and over a short lifecycle, it is difficult to forecast with conventional methods. The method uses Kalman filter to correct for the noise associated with the leading indicator and to facilitate the practical application. The method was evaluated using 78 different parts of an electronic product. Experimental result revealed that the method is useful for forecasting the target shipping number.

1. INTRODUCTION

Recently, the demand for increased product variety and short delivery time has strengthened as customer needs have become more diverse. For manufacturers therefore, access to inventory has become essential in order to satisfy these demands. Conversely, short product life cycles and the concomitant increase in the obsolescence of parts due to technical improvements act to increase the need for shorter inventory periods. Consequently, reducing the parts inventory while avoiding stockout risk is an important problem for manufacturers trying to secure earnings. To resolve this problem, a variety of improvements to the supply chain have been implemented, including improved demand forecast accuracy, implementing short-term planning cycles, and bringing the stock point closer to the market (Suguro, 2006).

Build-to-order manufacturing has traditionally been limited to products with long delivery dates and with relatively low requirements such as industrial machines. However, in recent years, build-to-order manufacturing is increasingly being applied to products with a short delivery date and with high requirements such as electronics products. Consequently, it has become necessary to forecast requirements accurately to minimize inventories while ensuring short delivery dates. In this study, any product that has short delivery date requirements and which is mass produced according to order specifications on an assembly line using parts held in stock is referred to as a mass customized product. For these products, the number of parts shipments often varies markedly as the number and type of parts that need to be installed vary in response to the customer specifications. In addition, the mass customized products such as electronics products often have short life cycles. Taken together, these factors complicate the process of forecasting part shipments.

Many demand forecast methods have been proposed to date, including time series analysis (Kitagawa, 2005), the method for estimating the required number of parts employing Kalman filter (Ohta, 1974), and the method for estimating the required number of parts using neural networks (Araki, 1996). However, the restrictions associated with these methods are that data changes with some rules and that enough data is necessary to be able to statistically analyze before forecasting, making it difficult therefore to apply these methods when forecasting the number of part shipments, which is the aim of this study.

A method is therefore proposed for forecasting the number of individual parts. The method corrects for the delay associated with order probability and shipping time, which is variable, using estimated order information as a leading indicator with which to solve the aforementioned problem. It also applies to forecasts of the number of electronics product of part shipments and demonstrates the effectiveness of the method.

2. FORECAST PROBLEM: NUMBER OF PARTS SHIPMENTS

2.1. Feature of Forecast Object

The mass customized product targeted in this paper is one with two or more combined parts. The decision to install parts in the product and how many pieces to actually install depend on customer specifications. By stocking each part, it is possible to ship products immediately after assembly without the procurement lead-times of parts, even if assembly was initiated after the order has been finalized. Mass customized products therefore have the advantage of being able to make various products in a short time.

For mass customized products, because prices differ depending on the type of part installed, the estimate becomes an important consideration in the order process. Figure 1 is a schematic drawing of a certain order process. The horizontal axis represents time, and each row refers to the various parties concerned. First, the sales person makes an estimate based on the specifications that the customer presented. The number of parts to be installed in the product at the stage is decided and the order is confirmed through price negotiation. Then, parts being stocked by the factory are installed in the product and the product is shipped to the customer.

Mass customized products are manufactured according to monthly or weekly production plans. In every plan cycle, the number of parts shipments, the number of parts coming in, and inventory figures for each part are calculated, with additional parts ordered so as not to cause stockout. However, in case of mass customized products such as electrics products, losses due to unsalable stock and those that arise due to differences between current low prices and those initially procured from the supplier can occur easily because the life cycle of products is short and parts of those products become obsolete fast. Therefore, forecasting the number of part shipments while ordering the minimum number of parts to avoid stockout is particularly important.

However, the number of part shipments can fluctuate because orders for products equipped with the same part may occur with a relatively narrow period even though the orders themselves are random. In addition, since the parts of products are updated between different generations, the data for of each part only applies to one product generation. Consequently, since the number of forecasted part shipments for parts fluctuate irregularly over the short term, it is difficult to apply forecasting techniques such as time series analysis because the data period is short and there are no periodic changes.

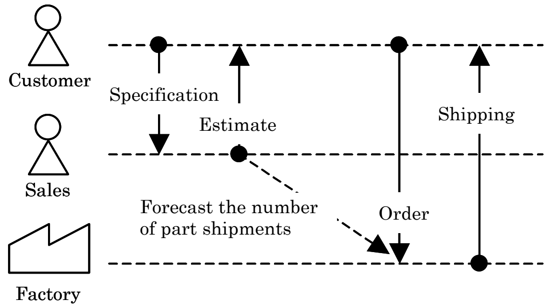

Figure 1. Ordering process

2.2. Forecast model

Based on the order process shown in Figure 1, the number of part shipments can be accurately determined when the order is fixed, when it is too late to control procurement. Conversely, while the number of parts included in the estimate is not final at the time of shipping, it is known early enough to control procurement. Therefore, estimate information is used as a leading indicator in this research. The total number of parts included in the estimate, compiled during the plan cycle, is defined as a leading indicator of the number of shipments. All of the electronic data in the estimate is compiled in the plan cycle and collected, and the number of each part is totaled. This leading indicator is referred to as the estimated number in this paper. In addition, the number of forecasted part shipments for an object is totaled using a procedure similar to that employed for the leading indicator. All of the electronic data related to the shipment slip is produced in the plan cycle and collected, and the number of each part is totaled. The number of part shipments required for this forecast will henceforth be referred to as the number of shipments.

Comparisons of the waveforms for estimate and shipment number, revealed that the shape of both numbers is similar to each other and that the number of estimates precedes the number of shipments for one or two terms, and indicates that the number of estimates is a useful indicator for forecasting. However, the height of the peak position and the amount of shift between those two waveforms differ depending with respect to time, indicating the existence of noise in the ordering process. For example, the made estimate being not received an order, a similar estimate made repeatedly, and the time required from the time at which an estimate made to the shipment varies by a single order correspond. Therefore, to use estimate information as a leading indicator, correcting this noise factor becomes a problem.

Figure 2 shows the approach employed by this study regarding the above-mentioned problem. The number of estimates is assumed to be an input into the system and the number of shipments to be an output, as shown at the left of Figure 2. The parameter that converts the input into the output is assumed for the state to be preserved at the subsequent period though changes for the long term. At this time, if the above-mentioned noise factor can be corrected using the I/O relationship, and if the parameter of the order production system can be presumed, then the output wave type can be predicted for any arbitrary input wave. The assumptions made using the above-mentioned parameter and predictions derived using the parameter are described further in Chapter 3.

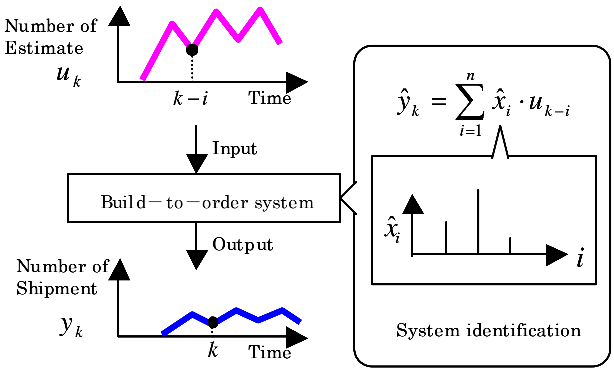

Figure 2. Basic concept of the proposed method

3. METHOD OF PREDICTION IN WHICH ESTIMATE INFORMATION IS SEQUENTIALLY CORRECTED

3.1. Predictive Model of Using Estimate Information as the Leading Indicator

In this chapter, the order production system presented Figure 2 is formulated according to the idea described in the preceding chapter. When considering the lifespan of an order, from the time an estimate is made to when it is shipped, there are rare instances in which the shipping of an order occurs immediately after the estimate has been made, or, conversely, when the estimate is made a long time before the shipment. This means that the lump of the shipment exists at a point that passes the time that is after making the estimate, which can be defined as an order probability. Then, shapes of the overlapping waves from the estimates shown in Figure 2 are assumed to correspond to the number of shipments in each period. This means that the number of shipments is an impulse response to the number of estimates, and that the number of shipments can be described as a convolution of the number of estimates and the order probability as

$$y_k = \sum_{i=1}^{n} x_i u_{k-i} + \upsilon_k \tag{1}$$

Here, y_k is the number of shipments at plan cycle k, u_k is number of estimates, and the coefficients x_i are the order probabilities of converting the number of estimates into the number of shipments. The order probability is a function of delay i, and the degree is assumed to be n. υ_k is the tabulation error for the number of shipments, obtained by subtracting the number of shipments unrelated to estimates. Here, if order probability x_i is obtained, the number of shipments at plan cycle k is predictable by the input of the number of estimates before cycle k of the plan to expression (1). However, the subscript that refers to the kind of part in this expression is omitted (it is similar in the following expressions). Here, at $k-i<0$, it is $u_{k-i}=0$.

3.2. Noise Correction Method Using the Kalman Filter

To accurately estimate the order probability x_i of expression (1), correcting the noise that the order probability in Figure 2 possesses, is problematic. The noise associated with this order probability is considered to have a normal distribution because it is led from a lot of mutually irrelevant orders, and which is why it is corrected with Kalman filter (Katayama, 2000). To apply the Kalman filter, expression (1) is described by the following state equations (2) and observation equations (3):

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \boldsymbol{\omega}_k \tag{2}$$

$$y_k = \boldsymbol{H}_k \boldsymbol{x}_k + \upsilon_k \tag{3}$$

where, $\boldsymbol{x}_k$ is order probability vector, $\boldsymbol{\omega}_k$ is the order probability noise, and $\boldsymbol{H}_k$ is the number of estimates.

$$\boldsymbol{x}_k = \left[x_1(k), \cdots\cdots, x_n(k)\right]^T \tag{4}$$

$$\boldsymbol{\omega}_k = \left[\omega_1(k), \cdots\cdots, \omega_n(k)\right]^T \tag{5}$$

$$\boldsymbol{H}_k = \left[u_{k-1}, \cdots\cdots, u_{k-n}\right] \tag{6}$$

Here, the normal distribution type noise $\boldsymbol{\omega}_k$ of the mean value vector $\boldsymbol{0}_n$ and the covariance matrix $\sigma_\omega{}^2 \boldsymbol{I}_{n\times n}$ ($\boldsymbol{I}_{n\times n}$ is a unit matrix of $\boldsymbol{0}_n$) and υ_k of the mean value 0 and variance $\sigma_\upsilon{}^2$. The next expression is obtained by applying Kalman filter to expression (2) and (3).

$$\hat{\boldsymbol{x}}_{k|k-1} = \hat{\boldsymbol{x}}_{k-1|k-1}$$

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k \left(y_k - \boldsymbol{H}_k \hat{\boldsymbol{x}}_{k|k-1}\right) \tag{7}$$

$$\boldsymbol{K}_k = \hat{\boldsymbol{P}}_{k|k-1} \boldsymbol{H}_k^T \left(1 + \boldsymbol{H}_k \hat{\boldsymbol{P}}_{k|k-1} \boldsymbol{H}_k^T\right)^{-1} \tag{8}$$

$$\hat{\boldsymbol{P}}_{k|k-1} = \hat{\boldsymbol{P}}_{k-1|k-1} + \frac{\sigma_\omega^2}{\sigma_\upsilon^2} \boldsymbol{I}_{n\times n}$$

$$\hat{\boldsymbol{P}}_{k|k} = \hat{\boldsymbol{P}}_{k|k-1} - \boldsymbol{K}_k \boldsymbol{H}_k \hat{\boldsymbol{P}}_{k|k-1} \tag{9}$$

Here, Kalman gain $\boldsymbol{K}_k$ and $\hat{\boldsymbol{P}}_{k|k}$ exhibited covariance matrix of the assumed error margin, and was assumed to be $\hat{\boldsymbol{P}}_{-1|-1} = \varepsilon_0 / \sigma_\upsilon^2 \boldsymbol{I}_{n\times n}, \varepsilon_0 > 0$. The order probability vector $\hat{\boldsymbol{x}}_{k|k-1}$ can be derived by sequential calculation of (7), (8), and (9). Then shipments of k periods y_k can be predicted from the number of estimates until the $k-1$ period.

$$\hat{y}_k = \boldsymbol{H}_k \hat{\boldsymbol{x}}_{k|k-1} = \sum_{i=1}^{n} \hat{x}_i u_{k-i} \tag{10}$$

4. EVALUATION

The proposed method was evaluated using real data for electronic components. A subset of equipments consisting of 78 different parts obtained by numerous shipments was selected. The evaluation period was taken as 32 terms, which exceeded the product life cycle of this product. In the evaluation, the short-term forecast was used to forecast the number of shipments based on the number of estimates and shipments until a previous period of time. For comparison, the exponential smoothing method (Goodrich, 1992) was performed under the same conditions. The exponential smoothing method is suitable for short-term forecasts as it tracks short-term changes relatively well than other known forecast method. The first-order method is adopted, and a coefficient is selected to minimize a past prediction error by the least squares method.

The evaluation condition can be described as follows: The degree of the order probability was assumed to be three, because most products were shipped within three periods after it had been estimated. While it is preferable to set an initial value for the order probability of each part, but initial values are not be understand beforehand. Therefore, once all common values for the different parts were assumed and then an individual order probability for each kind of part is estimated by an initial forecast calculation. That is, the period from term 1 to term 5 was taken as the settling period and the period from term 6 to term 32 was taken as the evaluation period for the prediction error (Table 1).

In Table 1, the 78 parts are classified by their average rate of change. Here, the average rate of change is an index that shows the degree of change in the shipment number pattern, which can be calculated using the following expression:

$$R = \frac{1}{m-1}\sum_{k=1}^{m-1}\frac{|\, y_{k+1} - y_k \,|}{y_k} \tag{11}$$

The performance was evaluated using the mean and the maximum MAPEs (mean absolute percent error (Mentzer, 1995)) for each range, which were calculated for the proposed method and the exponential smoothing method, which were then compared. In general, demand forecasting is useful when the error is less than 20% error; less than 30% is within the permissible range for practical use (Munekata, 2005).

To remain within a range that could account for 64% of the parts whose average rate of change is ≤0.4, the MAPE for the proposed method is ≤30%, while that of the exponential smoothing method is 35.8%, which exceeds the 30% that is permissible for practical use. In addition, the MAPE of the proposed method is 32.0% while that of the exponential smoothing method is 60.2% paying attention to the maximum value of the error. The proposed method exceeds 30% in the range for the change rate to exceed 0.4 but it is more excellent than the exponential smoothing method in each condition.

Table 1. Evaluation results

Average rate of change	Number of parts types	Average of mean absolute percent error (%)		Maximum of mean absolute percent error (%)	
		Proposed method	Exponential smoothing method	Proposed method	Exponential smoothing method
～0.2	7	21.8	20.4	25.1	30.3
～0.3	27	23.2	26.0	26.9	56.8
～0.4	16	28.2	35.8	32.0	60.2
～0.5	19	34.3	40.2	40.1	63.8
～0.6	9	41.5	45.9	48.0	63.3

Figure 3 shows the example of the forecast result. The horizontal axis represents the plan cycle and the Y-axis shows the number of parts. The predicted results for the proposed method and the exponential smoothing method are displayed overlapping with the number of shipments. The prediction error increases for the period where there is a large rate change because the result of the exponential smoothing method follows the change in the number of shipments after a delay of almost one term (MAPE is 23.6%). On the other hand, the result of proposed method synchronizes with the change in the number of shipments after four terms of settling period. Compared with the exponential smoothing method, the prediction error of the proposed method is improved as a result (MAPE is 20.0%).

The above-mentioned result shows that the proposed method is effective for use as a predictive technique using in this paper.

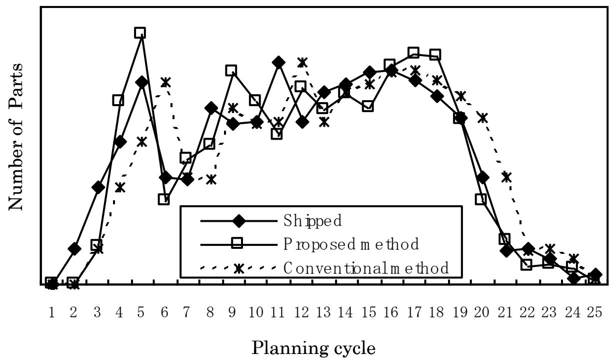

Figure 3. Example of forecasted result

5. SUMMARY

A demand forecasting method for predicting the number of parts, which change irregularly in the short term, that need to be ordered for a mass production product. The proposed method employs peculiar estimate information as a leading indicator for ordering product, sequentially corrects the noise that the order probability possesses by Kalman filter to assume the prediction error to be minimum, and accurately forecasts the number of part shipments.

The method was applied to the problem of forecasting 78 different parts for an electronic product as an actual example. The experimental results demonstrate that the method can be used to predict shipments up to change rate of 0.4 for an associated error margin of 28.2%, which is permissible for practical use.

6. REFERENCES

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