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An Improved Analogy-based Demand Forecasting Method for Service Parts

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***Abstract*—For manufacturers, a support service is one of the most important factors to maintain customer satisfaction. In order to ensure that repair services are available for users, manufacturers must hold appropriate service part inventories. However, the technologies used for service parts become obsolete over time and production of the parts terminates. Indeed, a service part production period is usually shorter than the period for which a support service is offered. Thus, manufacturers must procure service parts for the period following the termination of service part production. Currently, service part production periods are becoming shorter and manufacturers must hold large inventories of long-term service parts. Thus, for the purpose of holding appropriate service part inventories, an accurate demand forecasting method for service parts is required. In this paper, we propose a new demand forecasting method that is an improvement of an analogy-based method. The improvement is based on the findings of an investigation of service part demand data. Following this investigation, we added a liner regression term into the original analogy-based method. The proposed method was then evaluated using the data provided by a home electrical appliance manufacturer. The numerical experiment showed that the improved analogy-based method achieved higher forecasting accuracy than the conventional method.**

Keywords—service parts; analogy; liner regression; home electrical appliance; parts holding period

I. INTRODUCTION

For manufacturers, a repair service is one of the most important factors to maintain customer satisfaction. A shortage of service parts delays repair work and results in a decrease of customer loyalty. In the worst cases, customers change to other brands. In this context, repair services for durables such as home electrical appliances that include refrigerators, air conditioners, and microwaves have been provided for a considerable time.

In Japan, each manufacturer decides on a service part holding period and guarantees that repair parts are available during this period. The period is usually from five to ten years depending on the types of product; however, manufacturers hold service parts longer than the guaranteed service part holding periods because they value customer loyalty highly. For example, service parts for built-in, ceiling air conditioners are usually held for 20 years.

The technologies used in service parts become obsolete over time and production of the parts terminates. Usually, a service part production period is shorter than the service part holding period. Thus, manufacturers must procure service parts for holding periods when production of the parts is due to terminate. Currently, electronic parts such as large-scale integrations (LSIs) and integrated circuits (ICs) are used in many components in many products. Control circuit boards, remote controls, and receiver units are examples. The production periods for such electronic parts are as short as one or two years. This means that manufacturers must forecast long-term demand for service parts and procure large numbers of the parts before their production terminates.

Holding long-term inventory is risky. If the inventory exceeds actual demand, a manufacturer must dispose of service parts as industrial waste when the service part holding period expires. The storage charge for service part holding is also a potentially unnecessary expense. However, if the inventory runs short, reproducing a small number of service parts is costly. Sometimes, instead of repairing a product, a manufacturer provides a new product as a replacement because of the shortage of service parts. Thus, an accurate demand forecasting method for service parts is required.

In this paper, we propose a new demand forecasting method for service parts that is an extension of an analogy-based method. We introduce a liner regression term into the demand model and improve forecasting accuracy. In Section 2, we briefly review the demand forecasting of service parts and clarify the problems of conventional methods. The new method is then proposed in Section 3. The result of numerical experiments with the data provided by a home electrical appliance manufacturer is presented in Section 4, and we conclude the paper in Section 5.

II. Demand Forecasting For Service Parts

A. Inventory management of service parts

The trend of demand for a service part is known to have three phases, as shown in Fig. 1. A rising trend is seen in the initial phase. Here, the product for which the service part is used diffuses in the market and the product population increases. Accordingly, the number of product failures increases. The major source of service part demand is initial failure in this phase. Demand then becomes relatively stable in the next phase. Here, the major source of demand is chance failure. The product becomes older over time and is discarded and replaced with a new product. Thus, demand gradually decreases in the final phase. The major source of demand in this phase is wear-out failure.

In many cases, service part production is discontinued in the initial phase. In particular, the production of electronic parts and service parts used for a specific product model tend to be discontinued earlier. Thus, manufacturers must purchase a large number of service parts for future repair work. In order to decide the purchase quantity of such parts, a high accuracy demand forecasting method capable of forecasting total demand from the initial phase to the final phase is required.

In this paper, we use year as the time unit. There are two reasons for this. One is that detailed forecasting is not required because the purpose of forecasting is to decide total demand. The other reason is to remove the effect of seasonality.

B. Time series forecasting methods

Time series forecasting methods such as the Croston model [1] and the bootstrap method [2, 3] are widely used for the demand forecasting of service parts where demand is intermittent. The Croston model separately applies exponential smoothing to the interval between demand occurrences and demand quantity, and forecasts mean and standard deviations of demand. The model is used to decide appropriate inventory levels and ordering points. The bootstrap method, which utilizes re-sampling from historical demand records and estimates demand distribution during production lead times, is used for the same purpose.

These methods work well for the purpose of inventory control when service part production is continued in the stable phase. However, they are not capable of forecasting total demand, which includes the final phase.

C. Renewal theory approach

Renewal theory [4] is based on service part failure time distribution and is able to forecast total demand. A basic forecasting model is proposed in [5] and [6]. In the model, $D(t)$, the expected demand for a service part at time t, is given as follows:

$$D(t) = a \cdot \sum_{j=1}^{t} S(j) \cdot \exp(-b \cdot (t-j)) \tag{1}$$

where a, b, *and* $S(t)$ are the failure rate of a service part, the repair rate of a failed part, and the number of products in which the service part is used shipped at time t respectively. Repair rate is the probability that the product for which the service part is used is repaired instead of being replaced with a new product. The basic model assumes that a service part failure occurs at a constant rate in the product life cycle and that the failure interval time follows exponential distribution.

Failure occurrence can be illustrated by a so-called bathtub curve. Some extended methods have been developed making use of Weibull distribution, which represents the failure time shaping the bathtub curve [7, 8].

In order to use a renewal theory approach, failure rate and repair rate must be known. Usually, failure rate is decided after endurance experiments and repair rate is estimated based on consumer research. However, endurance experiments and consumer research are costly.

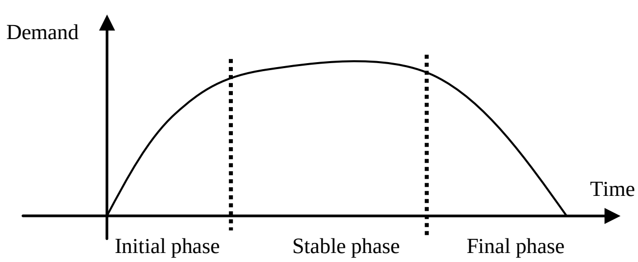

Fig. 1. The trend of demand for a service part

D. Analogy-based method

Practitioners know that the pattern of demand for a service part is similar to the patterns of comparable service parts. Based on this, many practitioners have used an analogy-based approach. This assumes that service parts can be placed in several groups and that the demand for the service parts in a group follows the same probability distribution. This approach does not require the probability distribution of failure time intervals. The demand for a service part is modeled as follows:

$$X_{py} = \alpha_{G(y-y_p)} + \varepsilon_{G(y-y_p)} \qquad (2)$$

where p denotes a service part with modeled demand; G is a group of service parts to which service part p belongs; X_{py} is the normalized demand quantity for service part p at year y; and y_p is the year when service part p begins to ship. Demand quantities are normalized as the quantity of service parts for each product shipped so far in which the service part is used.

Further, α_{Gt} is the mean demand of a service part in group G at year t and ε_{Gt} is the probability variable representing the variation of demand. For these variables, t is counted as the number of years that have elapsed since the year in which the service part was shipped for the first time. $\alpha_{Gt} = 0$ and $\varepsilon_{Gt} = 0 \; if \; t < 0$.

α_{Gt} and ε_{Gt} are estimated from the past demand records of the service parts in group G. x_{py} denotes the demand record of service part p at time y. Thus, α_{Gt} is:

$$\alpha_{Gt} = \frac{1}{|G|}\sum_{p\in G} x_{p(t+y_p)} \qquad (3)$$

Assuming ε_{Gt} follows normal distribution, ε_{Gt} ~N(0, σ_{Gt}), the standard deviation is estimated as:

$$\sigma_{Gt} = \sqrt{\frac{1}{|G|-1}\sum_{p\in G}\left(x_{p(t+y_p)} - \alpha_{Gt}\right)^2} \qquad (4)$$

Instead of assuming normal distribution, empirical distribution constructed from past demand records can be used. In order to make groups of similar service parts, empirical rules are widely employed, although there are several methods such as statistical clustering, because service parts are usually categorized by the attributes defined in their specifications. For instance, motors are classified into DC or AC, by power ranges, and by interior purpose or exterior purpose.

In addition, it is known that forecasting accuracy improves by applying some transformation to demand quantity such as a logarithm:

$$f\left(X_{py}\right) = \alpha_{G\left(y-y_p\right)} + \varepsilon_{G\left(y-y_p\right)} \qquad (5)$$

$f(x) = \log_{10} x$ is an example of transformation.

III. Improvement of an Analogy-based Forecasting Method by Introducing a Liner Regression Term

A. Introduction of liner regression term

An analogy-based approach is easy to apply in practice because only the past demand records of similar service parts are required and many manufacturers own such records. Thus, costly but inaccurate consumer research to decide repair rates, as used in the renewal theory approach, is unnecessary. In addition, an analogy-based approach is easy to understand and explain to concerned divisions such as procurement, warehousing, and support services. However, forecasting accuracy is not high enough for some service part groups.

In order to improve accuracy, we propose an extended analogy-based forecasting method. Investigating the demand data of service parts, we found that in many cases, the demand in a certain year correlates to the demand in the prior year. Fig 2 presents the demand for a control circuit board of air conditioners. The x-axis shows the demand quantity in the third year after the product launch and the y-axis shows the quantity in the fourth year. Each dot corresponds to a service part. The quantity is normalized by a method explained later in this paper and an applied common logarithm. Obviously, the demands in the third year and in the fourth year correlate. Based on this observation, we suggest that the demand for a certain year is influenced by the demand in the years before. Thus, we introduce a liner regression term into the original analogy-based method as follows:

$$X_{py} = \sum_{j=1}^{k}\beta_{Gj(y-y_p)}X_{p(y-j)} + \alpha_{G(y-y_p)} + \varepsilon_{G(y-y_p)} \qquad (6)$$

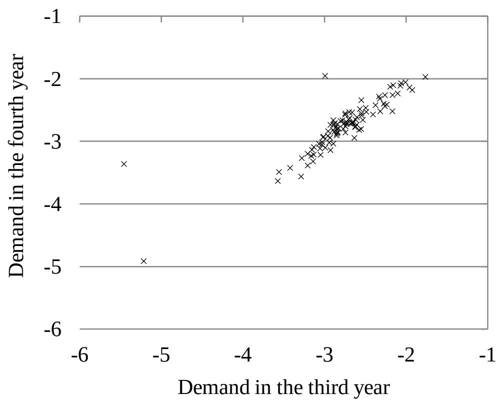

Fig. 2. The demand in the third year and fourth year for service parts

k is the order of the model and defines the number of years for which the influence of demand in the past is taken into consideration. When $k = 0$, (6) is identical to (2). Some transformation can be applied to X_{py}, as is the case with the original model. Thus:

(7)

B. *Parameter estimation*

The parameters of the analogy-based model are estimated with the past demand records. P and R are the sets of service parts and products respectively. $R_p \subseteq R$ is the set of products in which service part $p \in P$ is used. d_{py}, x_{py}, and s_{ry} denote the demand for service part p at year y, the normalized demand for service part p at year y, and the shipped quantity of product r at year y respectively.

First, normalized demand quantities are calculated. Normalized demand quantity is the quantity of the service parts for each product shipped so far. Thus, w_{py}, the quantity of the products in which service part p is used and shipped so far by year y, is calculated as follows:

(8)

Then, normalized demand quantity is as follows:

(9)

Second, the parameters α_{Gt} and β_{Gt} are estimated in order to minimize square error as follows:

Minimize $\sum$ (10)

where e_p is the latest year for which the demand record of service part p is available.

C. *Differences from autoregression*

The analogy-based liner regression model looks similar to an autoregressive (AR) model [9], which is a well-known time series stochastic model. However, there are differences.

1. The AR model is capable of modeling the time series in only one of the three previously described phases, the initial, stable, and final phases, while the analogy-based model encompasses all three.
2. The AR model works well with a stationary time series such that $E[X_t] = E[X_s]$ for $t \neq s$, while the analogy-based model does not require stationarity. As shown in Fig. 1, the demand for service parts does not have stationarity.

3. The parameters of the AR model are estimated from one time series because the model is "autoregressive," while those of the analogy-based model are estimated from a group of time series; namely, past demand records of a number of service parts belonging to a group.
4. The parameters of the AR model are time-independent as shown in equation (11), while they are time-dependent in the analogy-based model shown in (6).

(11)

IV. NUMERICAL EXPERIMENTS

The analogy-based liner regression model was evaluated with the data of a home electrical appliance manufacturer. All appropriate ethical considerations were followed with regard to the manufacturer's involvement in the study. The manufacturer itself used the original analogy-based model; thus, the improvement achieved by the proposed method was evaluated. The data consisted of the demand records of 639 service parts. The service parts were placed in 35 groups by the manufacturer. Such service parts are used in refrigerator doors, the interior mechanisms and outdoor mechanisms of air conditioners, and remote control units.

The parameters of the model were estimated from the data, and the demand for the service parts for six years was forecast. We used absolute percentage error (APE) as an accuracy measure. A lower APE means better forecasting accuracy. APE is calculated as follows:

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In the experiment, we set the order of the model to one; namely, k = 1. A common logarithm was applied to the demand quantities as the transformation function.

The results of the numerical experiments are presented in Table I. Except for the service parts used in refrigerator doors, the APE of the proposed method is highly improved compared with the original method. P-values show there are significant differences. The forecasting accuracy of the refrigerator door parts with the proposed method is inferior to the original method; however, the p-value shows that there is no significant difference.

According to repair service experts, the main cause of refrigerator door breakage is not wear-out failure but accidents during transportation. Thus, breakage happens randomly and there is no correlation among the years. We suggest that this is the reason why no improvement is seen in the forecasting for refrigerator door parts.

V. CONCLUSION

Manufacturers must procure large numbers of service parts before service part production terminates. The aim is to ensure that service parts are available during at least the guaranteed part holding periods. Thus, an accurate demand forecasting method for service parts is required.

In this paper, we proposed a new demand forecasting method that is an extension of an analogy-based method. Investigating the demand data of service parts, we found that the demand in a year tends to correlate with the demand in the prior year in many cases. From the finding, we believe that the demand for a certain year is influenced by the demand for the years before. Thus, we added a liner regression term into the original analogy-based method.

TABLE I. FORECASTING ACCURACY OF PROPOSED METHOD

Category of service parts	**Number of kinds of service part in the category**	**APE**		**P-value**
		Analogy-based liner regression model (proposed method)	***Original analogy-based model (conventional method)***	
Interior mechanisms of air conditioners	163	76.36%	122.80%	0.0163
Outdoor mechanisms of air conditioners	228	44.68%	116.19%	0.0152
Remote controls	41	49.90%	148.25%	0.0065
Refrigerator doors	207	77.06%	69.46%	0.3079

The proposed method was evaluated using the data provided by a home electrical appliance manufacturer. The data consisted of the demand records for 639 service parts used in refrigerator doors, the interior mechanisms and outdoor mechanisms of air conditioners, and remote control units. The numerical experiment showed that the method achieved higher forecasting accuracy than the conventional method except for refrigerator door parts. However, it also showed that the proposed method and the conventional method have the same level of forecasting accuracy if they are applied to the refrigerator doors.

REFERENCES

[1] L. Shenstone and R. J. Hyndman, "Stochastic models underlying Croston's method for intermittent demand forecasting," Journal of Forecasting, vol. 24, pp. 389–402, 2005.

[2] T. R. Willemain, C.N. Smart, and H. F. Schwarz, "A new approach to forecasting intermittent demand for service parts inventories," International Journal of Forecasting, vol. 20, pp. 357–387, 2004.

[3] Z. S. Hua, B. Zhang, J. Yang, and D. S. Tan, "A new approach of forecasting intermittent demand for spare parts inventories in the process industries," Journal of the Operational Research Society, vol. 58, pp. 52–61, 2007.

[4] D. R. Cox, Renewal Theory, Methuen, London, 1962.

[5] R. M. Soland, "A renewal theoretic approach to the estimation of future demand for replacement parts," Operations Research, vol. 16, pp. 36–51, 1968.

[6] E. Ritchie and P. Wilcox, "Renewal theory forecasting for stock control," European Journal of Operational Research, vol. 1, pp. 90–93, 1977.

[7] J. S. Hong, H. Y. Koo, C. S. Lee, and J. Ahn, "Forecasting service parts demand for a discontinued product," IIE Transactions, vol. 40, pp. 640–649, 2008.

[8] S. Munakata, M. Tezuka, S. Iizuka, and S. Urabe, "Demand forecasting model of service parts with different failure rate," Proceeding of TENCON 2010—2010 IEEE Region 10 Conference, pp. 1427–1431, November 2010.

[9] R. L. Goodrich, Applied Statistical Forecasting, Business Forecast Systems, Inc., 1992.

BIOGRAPHY

Masaru Tezuka is the Manager of the Research and Development Department at Hitachi Solutions East Japan, Ltd. He received a BE and ME in bio-physical engineering from Osaka University, Japan and a PhD in systems and information engineering from Hokkaido University, Japan. He is a certified Systems Analyst and a certified Application Systems Design Engineer of Japan's Information Technology Engineers. He served in Malaysia as an operations research expert of the Japan International Cooperation Agency in 1998. His research interests include nonlinear optimization, evolutionary computation, computational intelligence, computational statistics, risk analysis, and their industrial application. He is a member of the Information Processing Society of Japan.

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