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ORIGINAL ARTICLE

Demand forecasting for production planning in remanufacturing

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Abstract Remanufacturing is effective for energy and material savings; however, production planning and control in remanufacturing are more complex than those in traditional manufacturing. Developing a reliable forecasting method is critical for facilitating effective production planning and control. This study examined the effectiveness of demand forecasting in remanufacturing by time series analysis. Most existing methods of demand forecasting in remanufacturing assume that the time distributions of new product sales are known and that the time distributions of the demands of remanufactured products are determined by adding the product lifespan to the time distribution of new product sales. In addition, most previous studies focused on relatively long-term demand trends without considering the seasonality of demands. In this study, we examined the Holt–Winters model and the autoregressive integrated moving average (ARIMA) model, both representative time series analysis methods. These methods do not require information regarding the time distributions of new product sales and can handle the seasonality of demands. To examine the effectiveness of these methods, the time series data of the sales of 160 types of remanufactured alternators and starters manufactured by an independent auto parts remanufacturer over a period of 12 years was used. The results of demand forecasting for 2 months yielded average errors of 26.7 % for alternators and 18.4 % for starters, which represent an average improvement of 6.5 points compared to the method involving referencing the demands of the same month of previous year. The implications of the results and future steps are also discussed.

Keywords Remanufacturing · Production planning · Demand forecasting · Time series analysis · Auto parts · Seasonality

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1 Introduction

The industrial process of remanufacturing restores end-of-life products to their original working condition. Because remanufacturing retains the geometrical shape of the product, it preserves the materials and the value add embedded in the original product. In many cases, the ratio of total energy required for fresh production compared to that required for remanufacturing is approximately 6:1 [1]. In consideration of these features, generally, remanufacturing is considered the most environment friendly end-of-life treatment for discarded products [2]. Remanufactured products include auto parts, heavy-duty equipment, aerospace, machinery, information technology products, medical devices, photocopiers, etc. Lund identified 75 separate product types that are routinely remanufactured [3]. Moreover, remanufacturing now holds an important position in economic activity. In the USA, as of 2011, sales of remanufactured products were estimated to be worth $43.0 billion annually, and the remanufacturing industry supported 180,000 full-time jobs [4]. In terms of economic impact, remanufacturing can be compared to large industries such as household consumer durable goods, steel mill products, computers and peripherals, and pharmaceuticals [5, 6].

There are many driving forces for employing product remanufacturing in product recovery, as are barriers against remanufacturing. Lund, for example, proposed seven criteria that should be evaluated for establishing the suitability of products for remanufacturing [3]. In terms of remanufacturing requirements, Guide indicated the following seven characteristics that complicate production planning and control in remanufacturing [7]. (1) uncertainty in terms of the timing and quantity of returned products, (2) need to balance returns with demands, (3) disassembly of returned products, (4) uncertainty in materials recovered from returned items, (5) requirement for a reverse logistics network, (6) complication of material matching restrictions, and (7) problems of stochastic routings for materials for remanufacturing operations and highly variable processing times. The current study investigates the first and second items listed above. Uncertainty in the timing and quantity of returned products is considered to be the major difference between a traditional production–distribution network and a product recovery network [7–10]. In addition, to maximize profit, a remanufacturer must be able to balance the return of cores against customer demand for remanufactured products. If not, the remanufacturer faces the risk of building up excessive amounts of inventory when returns exceed demand or low levels of customer service when demands exceed supply [7]. To deal with these difficulties, forecasting product returns and demand is one of the most crucial issues. Forecasting is effective for used product acquisition management, capacity planning [11], and inventory management [12], which in turn are required for various operational planning activities in remanufacturing [11].

This paper examines demand forecasting for remanufactured products. Figure 1 illustrates the time distributions of new product sales and demand for remanufactured products in the case of auto parts. The new product sales shown in the figure are of products supplied for use in new automobiles. Over time, all new products reach their end-of-life. The proportions of products that reach end-of-life generate demand for spare parts. If the end-of-life of an auto part

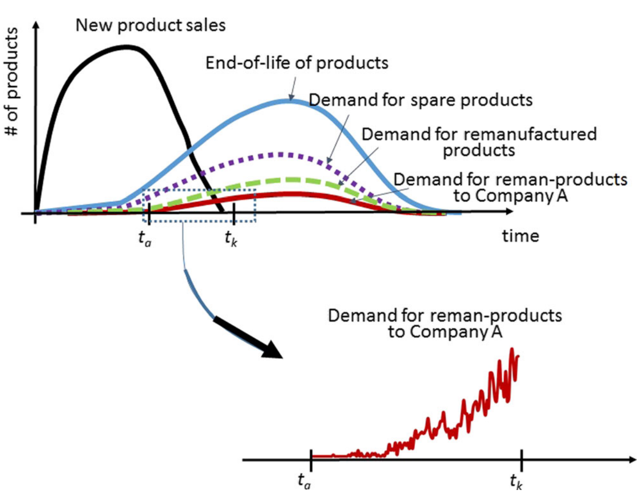


Fig. 1 Time distributions of new product sales, end-of-life of products, demand for spare parts, and demand for remanufactured products

occurs earlier than that of the automobile, there will be demand for a spare part to replace it. A proportion of this demand for spare parts is fulfilled by remanufactured products. Other parts that reach the end-of-life stage are replaced with new products or reused products or are repaired. In the case of multiple remanufacturing companies, a proportion of the demand for remanufactured products manifests as the demand for remanufactured products from company A, which is the subject company of this study. An enlarged image of the section of the plot of demand for company A's remanufactured products from t_0 to t_k is shown at the bottom of Fig. 1. The objective of this study is to forecast the demand for remanufactured products made by company A.

Previous studies on demand forecasting in remanufacturing have several features. First, most studies are based on the assumption that the time distributions of new product sales are known and that the time distributions of product end-of-life and product return are calculated by adding the product use period to the time distribution of new product sales. Second, previous studies tend to attempt forecasting a relatively long-term trend of demands. Third, in relation to the second point, few studies have dealt with the seasonality of demand. The first feature is largely a consequence of the assumption that the original equipment manufacturer (OEM) is the executor of remanufacturing operations. The second and third features are attributed to the facts that some studies have focused on long-term product life cycle planning as their goal and that the products that they targeted may not have had demand seasonality. Therefore, an approach different from conventional methods is required. For example, in auto parts remanufacturing, independent remanufacturers (IRs) usually do not have accurate information regarding the time distribution of new product sales. In addition, both short- and long-term demand forecasting are necessary for production planning, and there is demand seasonality in some types of auto part products.

On the basis of the above-described background, demand forecasting via time series analysis is investigated in this study. In time series analysis, trends are extracted from past historical transitions, and forecasts are performed by extension. Thus, the timing of new product sales or product use period is not used. Also, time series analysis allows the handling of seasonal fluctuations and is useful in short-term forecasting, especially when demand transition is stable. Thus far, few studies have investigated the precision and features of time series analysis demand forecasting using actual data of remanufactured products. To examine the effectiveness of the proposed method, the times series data of the sales of an actual IR of auto parts for 160 types of remanufactured alternators and starters over a period of 12 years were employed.

The remainder of this paper is organized as follows. In Sect. 2, previous studies on forecasting product return and demand are outlined. Section 3 provides an overview of auto parts remanufacturing, the data used in this study, problem setting in this study, and formulation of the time series analysis method employed. Section 4 presents the results, and the conclusions are presented in Sect. 5.

2 Literature review

Production planning and control in remanufacturing are more complex than those in traditional manufacturing [7]. To handle the added complexity, forecasting the timing of product returns and demands is crucial. Previous methods of forecasting product end-of-life, product returns, and demand can be categorized into three types described as follows.

The first type comprises physical-based methods, where the remaining useful life (RUL) of individual products is forecast based on the physical condition of the product. This method is related to reliability engineering. For example, physical-based methods are often used in RUL prediction of dies and molds [13]. The service life of dies and molds is limited by several factors such as dimensional error due to macro-wear, overstress due to stress concentration, and fracture due to fatigue [14]. Physical-based methods quantitatively feature the failure mode behavior using physical models of components and damage mechanics-based damage propagation models [13]. In addition to dies and molds, physical-based methods are applied to industrial machines for product maintenance. In the preventive maintenance of machines, product failures are predicted based on the information obtained by monitoring product condition. Such machines include machine tools [15], aircraft engines, power turbines, and medical equipment. Physical-based models tend to outperform other models when the precise physical model of the product can be developed and when all data necessary for model quantification are available [16]. However, it is not always realistically possible to completely understand the failure mechanisms under the range of relevant operating conditions. Because the data necessary for model quantification are not available in auto parts cases, physical-based methods are not applicable in auto parts remanufacturing.

In the second type of methods, the time distributions of product end-of-life and product returns are calculated by adding the product use period to the time distribution of new product sales. This approach has been used widely in existing studies on remanufacturing. Pioneering works on forecasting product return for remanufacturing include those of Kelle and Silver [17] and Goh and Varaprasad [18]. These researchers developed forecasting models for the returns of reusable containers that are used typically to sell or store liquids. Although in strict terms, the return of reusable containers is different from product returns in remanufacturing [7], their works are precursory attempts at product return forecasting. Several researchers have presented case studies to build forecasting models for remanufacturing specific products. Toktay et al. [8] used return data of single-use Kodak cameras to develop a discrete-time distributed-lag model with dynamic information updates to estimate product returns. Marx-Gomez et al. [19] investigated forecasting models applicable to photocopier remanufacturing. They developed a fuzzy reasoning scheme and a neuro-fuzzy model to predict the quantity and timing of photocopier returns to the OEM. Umeda et al. [20] presented a model that describes the balance between product returns and demands for single-use cameras, photocopiers, and automated teller machines based on empirical data. As mentioned previously, conventional forecasting studies in the remanufacturing domain typically assume that the time distributions of new product sales are known and have focused on long-term demand trends without addressing the seasonality of product end-of-life. The assumption that the time distribution of new product sales is known is reasonable when the OEM is the remanufacturer. The condition under which the OEM remanufactures is applicable to photocopiers, single-use cameras, and various other capital goods. However, IRs may not possess accurate information regarding the time distribution of new product sales. The present study investigates demand forecasting by time series analysis, where such information is not required and seasonality of demand is addressed.

The third category is demand forecasting by time series analysis, which has been applied in some fields such as maintenance repair parts [12, 21], tourism [22, 23], food products [24, 25], and electricity [26, 27]. One of the targets is maintenance repair parts. The demands for maintenance repair parts, such as those of aircrafts, are intermittent [12, 21]. Such intermittent demands tend to be random in terms of time and quantity and have a large proportion of time when the demand is zero. Gohbbar and Friend [12] investigated time series analysis methods that are effective for such intermittent demands. The forecasting accuracies achieved using time series analysis often depend on the features of the demand transition data under investigation. Thus, it is important to clarify the features of demand transitions. This study investigates the features of demand transitions of remanufactured auto parts. Moreover, previous studies reported accuracies of time series analysis forecasting in the targeted fields. For example, for tourism, Chu [23] applied autoregressive moving average (ARMA)-based models to forecast the number of visitors to countries and showed that the forecast numbers had an average error of less than 10 % (in terms of mean absolute percentage error (MAPE)). In food product sales forecasting, Eminente et al. [25] applied exponential smoothing to forecast a company's fish product sales, which are highly seasonal, and achieved an average forecasting error of 57 % (MAPE). The abovementioned results provide benchmarks for demand forecasting in the respective fields. Because few studies have applied time series analysis to demand forecasting in auto parts remanufacturing, this study is expected to provide a benchmark for studies targeting that domain. Some researchers have proposed methods that incorporate regression analysis into time series analysis [27, 28]. When there are specific factors that explicitly influence demands, the incorporation of those factors through regression analysis can be effective. Mirasgedis et al. [27], for example, presented a model that forecasts electricity demand by incorporating the influence of weather. Although this study does not examine such incorporation, the possibility is discussed in Sect. 5.

3 Data and method

3.1 Background: auto parts remanufacturing

This study investigated the effectiveness of demand forecasting by time series analysis in remanufacturing. To that end, the time series data of the sales of an IR of alternators and starters were employed.

The auto parts remanufacturing industry is reportedly the world's largest remanufacturing sector, accounting for an estimated two thirds of remanufacturing activity worldwide [4]. While the target of auto parts remanufacturing is wide, alternators and starters are the representative subjects. With 300 entities, alternator and starter remanufacturers constitute the largest group among Automotive Parts Remanufacturers Association (APRA)-associated companies in the USA [29]. Remanufactured auto parts cost on average 20–50 % less than new parts [4]. Remanufacturing is effective for resource and energy saving; in the case of alternators, the material used for remanufacturing is about one fifth compared to that used in manufacturing a new product, while the energy consumption is about one seventh [29]. Auto parts remanufacturers include automobile OEMs, auto parts OEMs, and IRs [4]. Seasonality is an important factor in product demand for products that fail because of the influence of temperature and humidity.

3.2 Data source

The time series data of an IR's alternator and starter sales were used to verify the effectiveness of demand forecasting by time series analysis. The authors used the data obtained from Shin-Etsu Denso Co., Ltd., the largest Japan-based alternator and starter IR [30]. The company has been remanufacturing since the 1960s, but until the late 1990s, when sales in the domestic market began expanding, almost all remanufactured products were exported to the USA and European countries. The company sold about 160,000 alternators and 170,000 starters in 2013, of which about 63,000 alternators and 82,000 starters were sold domestically. The company remanufactures over 7000 types of alternators and starters. Data collected over a 12-year period reflecting the company's sales of 160 types of remanufactured products, including 80 types of alternators and starters each, were used in the present study.

The domestic and overseas demands at the subject company differ. For overseas products, in most cases, the customer companies place orders several months in advance, and the company remanufactures the products in response and delivers them. In contrast, domestic customers place orders with the company in response to replacement demands from end users. If the required product is out of stock, remanufacturing is performed upon receipt of the order, and the product is shipped within 1 day of receiving the order. Such 1-day remanufacturing activity accounts for approximately 10 % of total domestic sales. In auto parts remanufacturing, in general, a remanufacturer supplies a remanufactured product and, in return, receives a used product from the end user [31]. In the case of Shin-Etsu Denso Co., Ltd., the used product is taken back from the customer when the remanufactured product is supplied. If there is no core stock upon receiving the order, a request is placed with other companies to supply the remanufactured product or a new product may be delivered. As of 2013, the company's response was "can be delivered" for over 99 % of the received orders. Therefore, the time series data of the sales of this company were used in this research, and the sales data can be considered as the time series of demand.

3.3 Production planning case

In auto parts remanufacturing, the production planning is often done such that a remanufacturer can maintain inventory to fulfill the demand for 1.5–2 months. Accordingly, the demand for periods over 1.5–2 months in the future is considered. Many companies conduct demand forecasting by observing the change in the number of orders over previous years. If the forecast is higher than the actual demand, the cost of inventory becomes large, and if the forecast is smaller than the actual demand, the excess requirement must be produced at a quicker pace than normal, which leads to an increase in the cost of remanufacturing. If the precision of demand forecasting can be increased, the production and inventory costs can be reduced.

IRs, in most cases, do not use the time distribution information of new product sales for demand forecasting. For IRs, at least in Japan, it is difficult to accurately grasp the time distribution of new product sales for each type of alternator and starter or the number and period when the new products are supplied via new automobiles. Information regarding the number of sales and the type of alternator and starter used in each type of automobile is available. However, correspondence between the automobile type and alternator/starter type is many-to-many. In other words, an alternator/starter type may be used in several types of automobiles, and multiple types of alternator/starter may be used in a single automobile type according to the engine size and model. Therefore, it is difficult to estimate the time distribution of new product sales of alternators and starters from the sales number of various types of automobiles.

3.4 Forecasting methods

The exponential smoothing model and autoregressive integrated moving average (ARIMA) model are used for time series analysis in this study. The exponential smoothing model predicts by extracting the level component, growth component, and seasonal component from the observed time series data and then extending these components to the desired future period. It was first formulated by Holt [32] and Winters [33]. In component extractions, as the observations become older, the model assigns exponentially decreasing weights. If only the level component is extracted, it is called single exponential smoothing. When the level component and growth component are extracted, it is called double exponential smoothing, and if the seasonal component is also extracted, the extraction is called triple exponential smoothing. These extraction modes are also known as the Holt–Winters models. The Holt–Winters model used in this study is the triple exponential smoothing model, with the assumption that seasonality is additive. The formulation of the Holt–Winters model based on the description of Hyundman and Khandakar [34] is as follows:

$$\text{Level}: l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{1}$$

$$\text{Growth}: b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$

$$\text{Seasonal}: s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)\, s_{t-m} \tag{3}$$

$$\text{Forecast}: \widehat{y}_{t+h|t} = l_t + b_t h + s_{t-m+h_m^+} \tag{4}$$

where $(y_1, y_2, \cdots, y_n))$ is the observed time series, m is the length of seasonality (in this article, m=12 (months)), l_t represents the level of the series, b_t denotes growth, s_t is the seasonal component, $\hat{y}_{t+h|t}$ is the forecast for h periods ahead of t based on all data up to time t, and h_m^+=[$(h-1)$ mod m]+1.

To forecast using this method, values of the initial states l_0, b_0, and $s_{m-1}, \cdots, s_0$, as well as those of the smoothing parameters α, β, and γ, are required. In this study, a statistical tool R was used to calculate the forecasts. The *HoltWinters()* function in the *forecast* package of R calculates and optimizes the values of the smoothing parameters and the initial state variables.

The ARIMA model is another most commonly used time series analysis forecasting method. The model was proposed by Box and Jenkins [35] and is a generalization of an autoregressive moving average (ARMA) model. It is generally referred to as the ARIMA (p,d,q) model where p, d and q are the orders of the autoregressive, integrated, and moving average parts of the model, respectively. The seasonal ARIMA (p,d,q) model is given as follows:

$$\Phi(B^m)\phi(B)(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\varepsilon_t \tag{5}$$

where m is the length of seasonality (in this article m=12 (months)), d and D are the non-seasonal and seasonal differencing, respectively, ϕ_i and Φ_i are non-seasonal and seasonal parameters of the autoregressive part, respectively, θ_i and Θ_i are non-seasonal and seasonal parameters of the moving average part, respectively, $\{\varepsilon_t\}$ is a white noise process with mean zero and variance σ^2, and B is the backshift operator [23, 34].

When using the ARIMA model, it is difficult to select the model order appropriately, i.e., the values of p,d,and$q$. In this study, R was used to perform ARIMA method calculations. The *auto.arima()* function in the *forecast* package of R selects an appropriate model order as well as seasonal parameter values [34].

4 Results

4.1 Data

Time series analysis was applied to the alternator and starter sales records of Shin-Etsu Denso. The data was collected over a period of 12 years and 1 month, from December 2001 to December 2013. The company remanufactures over 7000 types of alternators and starters, and bly considered the alternator and starter types characterized by high sales numbers in the domestic market. Eighty types of alternators and 80 types of starters were selected among the products that registered sales of 100 or more units each year over the four most recent years of the data collection period (2010–2013). An example of the sales record data is shown in Fig. 2. It is the record of the number of sales of a certain alternator (referred to as Alternator A hereinafter).

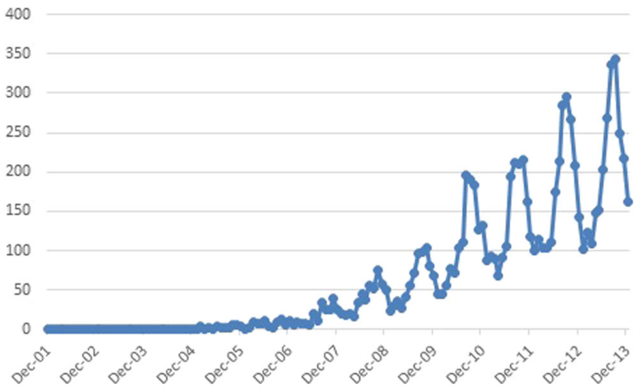


Fig. 2 Trend of monthly sales number of one type of alternator (*Alternator A*)

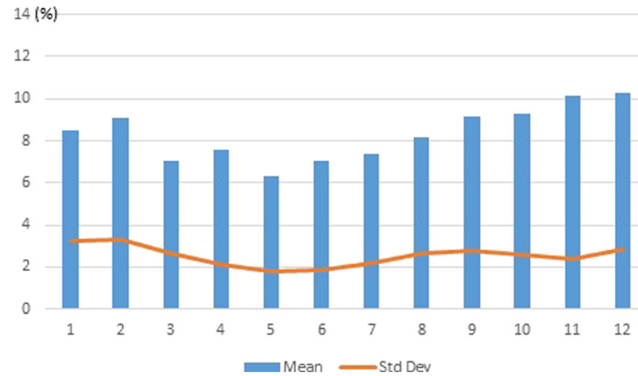


Fig. 4 Seasonal fluctuation in starter demand (sales per month as a percentage of sales per year; mean and standard deviation)

4.2 Demand seasonality characteristics

The demands for remanufactured alternators and starters are characterized seasonality, which affects forecasting accuracy. These features were investigated.

The seasonality arises because alternators are more likely to fail at high temperature, and starters are more likely to fail at low temperature. Figures 3 and 4 show the mean percentage of each month's sales within a year for the sample 160 products in the most recent 4 years. It can be inferred from Fig. 3 that the demand for alternators peaks in August–October. The demand for starters is high from October to February, as can be seen Fig. 4.

The periodicity of the seasonality was characterized by the following features. To measure the periodicity of the time series data, the autocorrelation coefficient at lag 12 was calculated. The lag-k autocorrelation coefficient (referred to as ACF(k) hereinafter) is defined as follows [35].

$$\mathrm{ACF}(k) = \frac{\sum_{i=1}^{N-k}\left(y_i-\overline{y}\right)\left(y_{i+k}-\overline{y}\right)}{\sum_{i=1}^{N}\left(y_i-\overline{y}\right)^2} \tag{6}$$

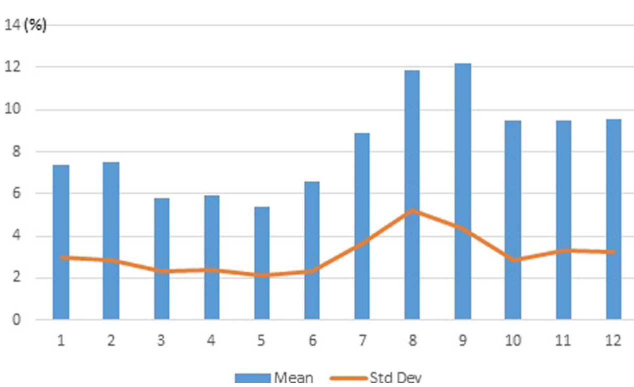


Fig. 3 Seasonal fluctuation in alternator demand (sales per month as a percentage of sales per year; mean and standard deviation)

The seasonal periodicity is high when the value of ACF(k) is close to 1. Because it is inappropriate to consider the demand record data to be stationary, the demand per month, expressed as a percentage of the total demand per year, was set as the time series, and ACF(k) was calculated according to Eq. (6).

To determine the demand seasonality of each product, for alternators, the average sales numbers for August, September, and October as a percentage of the total annual sales over the last 4 years were calculated. Hereinafter, this value is called the *Sum_ratio*. For starters, the average sales numbers for October, November, and December as percentages of the total number of annual sales over the last 4 years were calculated. Hereinafter, this value is called the *Fall_ratio*.

For the 80 types of alternators, the plots of ACF(12) and *Sum_ratio* are shown in Fig. 5. For the 80 types of starters, the plots of ACF(12) and *Fall_ratio* are shown in Fig. 6. In Figs. 5

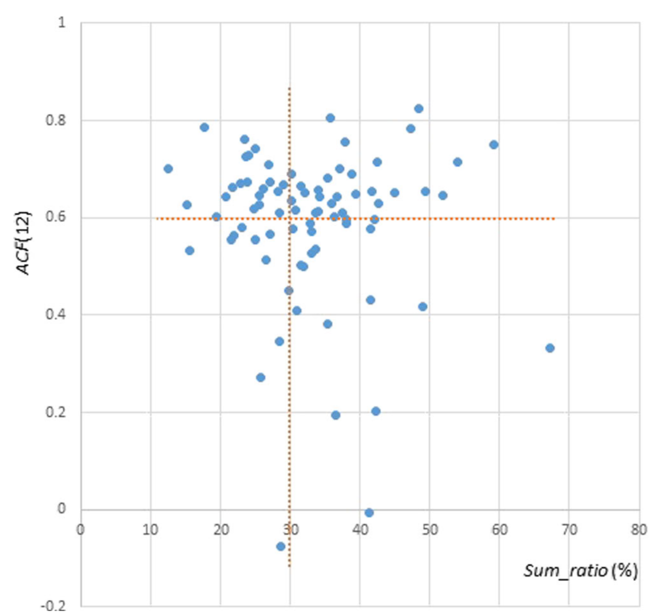


Fig. 5 Seasonality (percentage of demand during summer: *Sum_ratio*) and periodicity (lag 12 autocorrelation coefficient: ACF(12)) for 80 types of alternators

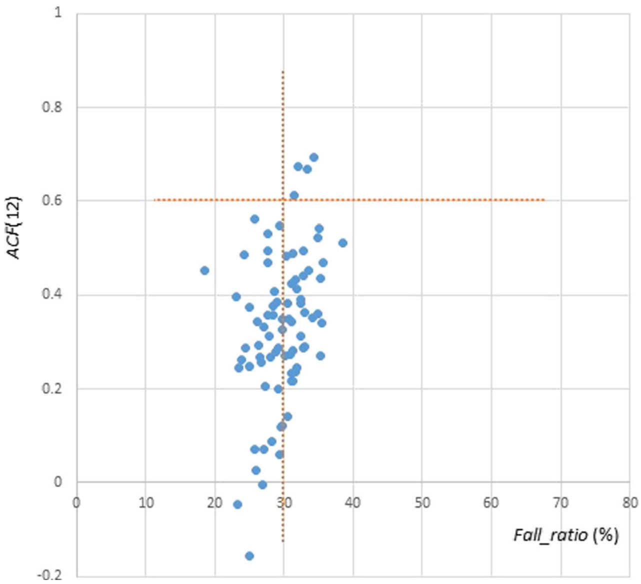


Fig. 6 Seasonality (percentage of demand during autumn: *Fall_ratio*) and periodicity (ACF(12)) for 80 types of starters

and 6, ACF(12)=0.6 and *Sum_ratio/Fall_ratio*=30 % were considered to be one criterion (shown as red lines in the figures), and four categories were created. From the figures, it can be observed that *Sum_ratio* for alternators is higher than the *Fall_ratio* for starters and that ACF(12) values are also higher for alternators. These findings indicate that the peak demand in summer for alternators is higher than that in the fall for starters and that, on average, the periodicity of seasonality is higher for alternators than that for starters.

Figure 7 shows an example of the transition of sales numbers for each category in Figs. 5 and 6. Figure 7a shows an example of the right-top category (strong periodicity and strong seasonality) of Fig. 5. The transition diagram shows the peaking of the sales numbers in summer as well as periodicity. The aforementioned Alternator A (Fig. 2) had *Sum_ratio*=37.8 %, ACF(12)=0.76, and fell in the same right-top category. Figure 7b shows an example from the right-bottom category (strong seasonality and weak periodicity) of Fig. 5. In this case, although the demand peaks in summer, the peak months are different for each year; thus, the seasonality changed, particularly in the last 4 years. Figure 7c shows an example from the left-top category of Fig. 5 (strong periodicity but low value of *Sum_ratio*). The demand peaks in seasons other than summer (September–November) and shows periodicity. Figure 7d shows an example from the left-bottom category of Fig. 5 (low in both seasonality and periodicity); the fluctuations are irregular. There were many starters with low periodicity, and many had seasonality with weaker peaks in autumn and winter compared with the summer peak of alternators. Figure 7e shows an example of a starter with strong seasonality and periodicity. This starter shows a strong peak in winter.

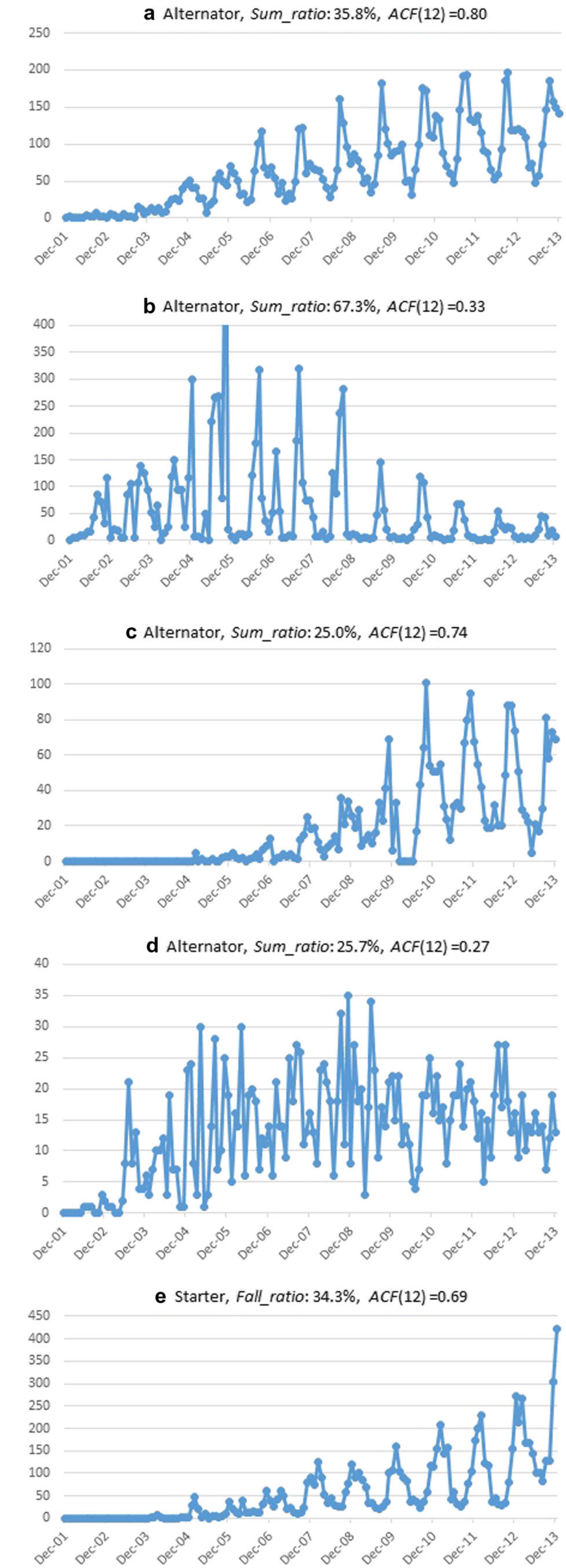


Fig. 7 Transition of number of sales (five cases)

From the abovementioned findings, the demand seasonality of the products was, on average, high in summer for the alternator and high in autumn and winter for the starter; however, there was significant variation among specific products.

4.3 Demand forecasting results

The demand forecasts were calculated using the recorded data. From the sales time series data of 12 years and 1 month (Dec. 2001–Dec. 2013), the data for the first 11 years and 1 month (Dec. 2001–Dec. 2012) were used to prepare forecasts for the last 1 year (Jan. 2013–Dec. 2013). The accuracy of the forecasts was verified by comparing the forecast value and the actual value in the forecast term (Jan. 2013–Dec. 2013). In this study, the focus is on the forecast accuracy for the 2 months that are important for production planning (Jan. 2013–Feb. 2013).

The ARIMA and Holt–Winters models were applied for forecasting. For the calculation, the *auto.arima()* and the *Holt-Winters()* functions in the *forecast* package of *R* were used. Two variations were set for the forecast calculation using the Holt–Winters model. One was the case where the *Holt-Winters()* function calculated all the parameters, and another was where parameter values of seasonal fluctuation for the same function were provided manually. The latter case was set because, on occasion, the forecasting calculation performed using the *Holt-Winters()* function did not properly extract the seasonal components (an example is shown below). This occurs when the smoothing parameter value of the seasonal component (value γ of Eq. (3)) is not calculated properly. In such cases, it is more appropriate to exogenously provide the value of γ. Here, we set γ=0.7, which implies that for forecasting, the seasonal fluctuation of the previous year (value s_t of Eq. (3)) was referenced with a weight of 0.7. The case where all the parameters are calculated using the *Holt-Winters()* function is expressed as "Holt–Winters (auto)," and the case where the *Holt-Winters()* function is applied when the value of γ is set to 0.7 is expressed as "Holt–Winters (γ=0.7)."

Defining "timeseries" as the vector that contains the sales time series data for the first 11 years and 1 month (Dec. 2001–Dec. 2012), the calculations using the ARIMA, Holt–Winters (auto), and Holt–Winters (γ=0.7) models were conducted by the following commands in *R*.

```
R> forecast ( auto.arima ( timeseries ), h=12) $mean
R> forecast.HoltWinters ( HoltWinters ( timeseries ), h=12) $mean
R> forecast.HoltWinters ( HoltWinters ( timeseries, gamma=0.7), h=12) $mean
```

For comparison with the forecast values of these three methods, the value of the same month previous year was considered as the forecast value, which was then compared with the actual value. Hereinafter, the forecast of same month previous year is considered as "*Previous Year.*" *Previous Year* was set because it is a common business practice to use the value of the same month previous year as a reference. Using the value of same month, previous year as forecast value is not bad in terms of average accuracy, as shown later.

Common measures for evaluating the forecasting accuracies include mean error (ME), mean percentage error (MPE), mean absolute percentage error (MAPE), and root-mean-square error (RMSE) [23]. Among these measures, MAPE and its variations were used in this study because the absolute value of the error is more important than the direction of the error. When the forecast at point T is set as $\hat{y}_T$ and the actual value as y_T, the absolute percentage error (APE) is defined as follows.

$$\mathrm{APE} = \left| \frac{\hat{y}_t - y_t}{y_t} \right| \times 100 \tag{7}$$

The MAPE is the average of the APEs. The MAPE for k months (MAPE(k)) is defined as follows.

$$\mathrm{MAPE}(k) = \frac{1}{k} \sum_{t=N+1}^{N+k} \left| \frac{\hat{y}_t - y_t}{y_t} \right| \times 100 \tag{8}$$

The APE between the cumulative forecast over k months from point N and the actual value is set as the cumulative APE for k months (CAPE(k)) and is defined as follows.

$$\mathrm{CAPE}(k) = \left| \frac{\sum_{t=N+1}^{N+k} \hat{y}_t - \sum_{t=N+1}^{N+k} y_t}{\sum_{t=N+1}^{N+k} y_t} \right| \times 100 \tag{9}$$

In this study, focus was placed particularly on the CAPE value over 2 months (CAPE(2)). This is because, as described in Sect. 3.3, the demand forecast over 1.5–2 months in future is important from the view point of production planning for alternator and starter remanufacture.

Figure 8 shows the result of the forecast calculation for *Alternator A*, as shown in Fig. 2. In Fig. 8, the blue curve represents the transition of the actual value, whereas the four curves of different colors represent the forecast values of the ARIMA, Holt–Winters (auto), Holt–Winters (γ=0.7), and *Previous Year*. In this example, seasonality could not be extracted well with Holt–Winters (auto).

Table 1 lists the MPE for each month, MAPE for 12 months (MAPE(12)), and CAPE for each month, for

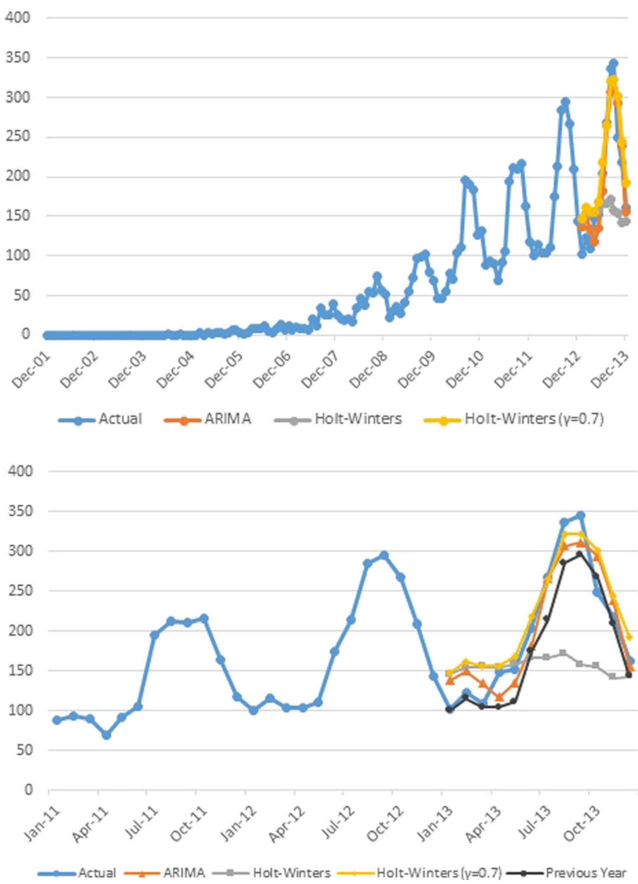


Fig. 8 Results of the demand forecast of *Alternator A* (Fig. 2) (*lower figure* is the blown up version of the *upper figure*)

each forecast result. From the table, the values of MAPE(12) were 14.4 % (ARIMA), 30.3 % (Holt–Winters (auto)), 17.3 % (Holt–Winters (γ=0.7)), and 13.1 % (*Previous Year*). In this example, the precision of *Previous Year* was the highest, followed by ARIMA, Holt–Winters (γ=0.7), and Holt–Winters (auto). A comparison of the cumulative values over 1 year (CAPE(12) values) reveals that ARIMA had an extremely good accuracy of 0.4 %, followed by Holt–Winters (γ=0.7) 9.9 %, *Previous Year* 12.1 %, and Holt–Winters (auto) 22.7 %.

For CAPE(2), in this example, *Previous Year* had the best accuracy of 4.4 %, followed by ARIMA 27.6 %, Holt–Winters (auto) 33.5 %, and Holt–Winters (γ=0.7) 37.4 %. The CAPE(2) of three other forecasts was poorer than that of *Previous Year*. As can be seen from Fig. 8, the alternator demand exhibits an increasing trend, and the demand in 2013 actually increased. However, there is slight change in actual demand in January and February compared to the same month previous year, and the three results that forecast increases are values with high error rates. In this particular case, it is more appropriate to assign the error to fluctuation in demand as opposed to issues with the forecasting methods.

The abovementioned evaluation was conducted for the 80 alternators and 80 starters considered here, and the results are listed in Tables 2 and 3. The values are averages of the 80 products. According to the tables, the MAPE over 12 months (MAPE(12)) was 40–50 % for both the alternators and starters. The MAPE(12) of *Previous Year* was good relative to the MAPE(12) of the other three forecasting methods.

In determining the CAPE(12), the errors of the three forecasting methods were 15–22 %, and the accuracy was relatively good compared to that achieved using *Previous Year.* Because CAPE(12) value was good but the individual monthly errors (MAPE values) were relatively large, the methods forecast the growth trend well but did not forecast the monthly fluctuation well, especially for alternators, for which the seasonal fluctuations are large.

Examining the 2-month forecast, the CAPE(2) values were good at 26–32 % for alternators and 16–21 % for starters. The corresponding values for *Previous Year* were 31.2 and 27.0 %, respectively. The Holt–Winters (γ=0.7) provided the best accuracy, which was better than *Previous Year* by 4.5 points for alternators and 8.6 points for starters.

As can be inferred from Tables 2 and 3, among the three forecast methods, the Holt–Winters (γ=0.7) yielded the best results overall. Figure 9 shows the distribution of the CAPE(2) values of the Holt–Winters (γ=0.7) and *Previous Year* methods for the 160 products considered here. For alternators, the average CAPE(2) value obtained using Holt–Winters (γ=0.7) was 26.7 %. In addition, Fig. 9 shows that two products had particularly high error rates, which affected the average values.

Figure 10 shows the forecast results obtained using Holt–Winters (γ=0.7) for the five products shown in Fig. 7. Among the five products, the forecast results were good for (a), (c), (d), and (e), but not for (b), and the lowest and highest CAPE(12) values were 8.7 % (Fig. 10e) and 19.9 % (Fig. 10c), respectively. The lowest and the highest CAPE(12) values were 1.0 % (Fig. 10a) and 29.3 % (Fig. 10e), respectively. In Fig. 10b, although one of the factors was that the forecast value was negative, the CAPE(2) value was 280.6 %, which is the highest error observed among the 160 products.

4.4 Analysis of forecasting errors

The reasons for the occurrence of forecast errors were examined evaluating the items with large forecast errors. By examining the items with 30 % or higher forecast errors over 2 months (CAPE(2)) as calculated with Holt–Winters (γ=0.7), shown in Figs. 9 and 10, the factors of forecast errors were investigated. This set included 21 of the 80 alternators and 12 of the 80 starters with CAPE(2) values of 30 % or

Table 1 Forecasting results for *Alternator A*

Month	Actual	Forecast values and APEs (%)				Actual cumulatives	Cumulative forecast values and CAPE(k) (%)			
		ARIMA	Holt–Winters (auto)	Holt–Winters γ=0.7)	*Previous Year*		ARIMA	Holt–Winters (auto)	Holt–Winters γ=0.7)	*Previous Year*
1	102	137.7 (35.0)	145.4 (42.6)	148.1 (45.2)	100 (2.0)	102	137.7 (35.0)	145.4 (42.6)	148.1 (45.2)	100 (2.0)
2	123	149.3 (21.4)	155.0 (26.0)	161.1 (31.0)	115 (6.5)	225	287.0 (27.6)	300.4 (33.5)	309.2 (37.4)	215 (4.4)
3	109	134.1 (23.0)	154.7 (42.0)	156.2 (43.3)	104 (4.6)	334	421.1 (26.1)	455.1 (36.3)	465.4 (39.3)	319 (4.5)
4	148	116.9 (21.0)	154.1 (4.1)	155.8 (5.3)	104 (29.7)	482	538.1 (11.6)	609.2 (26.4)	621.2 (28.9)	423 (12.2)
5	152	134.9 (11.2)	157.8 (3.8)	168.8 (11.0)	111 (27.0)	634	673.0 (6.1)	767.0 (21.0)	790.0 (24.6)	534(15.8)
6	204	181.9 (10.8)	165.5 (18.8)	218.4 (7.1)	175 (14.2)	838	854.9 (2.0)	932.6 (11.3)	1008.4 (20.3)	709 (15.4)
7	268	265.9 (0.8)	165.9 (38.1)	264.8 (1.2)	214 (20.1)	1,106	1120.8 (1.3)	1098.5 (0.7)	1273.3 (15.1)	923 (16.5)
8	336	306.3 (8.8)	171.4 (49.0)	320.7 (4.5)	285 (15.2)	1,442	1427.1 (1.0)	1269.9 (11.9)	1594.0 (10.5)	1208 (16.2)
9	344	311.0 (9.6)	157.7 (54.1)	322.3 (6.3)	295 (14.2)	1,786	1738.1 (2.7)	1427.6 (20.1)	1916.3 (7.3)	1503 (15.8)
10	249	293.6 (17.9)	154.7 (37.9)	301.6 (21.1)	267 (7.2)	2,035	2031.7 (0.2)	1582.3 (22.2)	2217.9 (9.0)	1770 (13.0)
11	218	238.6 (9.4)	141.4 (35.1)	244.7 (12.2)	209 (4.1)	2,253	2270.3 (0.8)	1723.7 (23.5)	2462.6 (9.3)	1979 (12.2)
12	162	155.4 (4.1)	143.0 (11.7)	192.4 (18.8)	143 (11.7)	2,415	2425.7 (0.4)	1866.7 (22.7)	2655.0 (9.9)	2122 (12.1)
MAPE(12)	45.2	49.5	42.7	42.5						

more. The factors causing forecast miss include the forecast error in the growth trend and in seasonal fluctuations. While the distinction between the two is vague, the CAPE(12) was used as the index for determining the forecast error in the growth trend, and the percentage difference between the forecast and actual values in the percentage of 2-month value within the 12 month value (hereinafter, expressed as DR(2)) was used as the index for determining the forecast error in

Table 2 Forecasting results for 80 alternators

Month	Average APE				Average CAPE(k)			
	ARIMA	Holt–Winters (auto)	Holt–Winters (γ=0.7)	*Previous Year*	ARIMA	Holt–Winters (auto)	Holt–Winters (γ=0.7)	*Previous Year*
1	32.8	28.1	30.3	39.9	32.8	28.1	30.3	39.9
2	22.3	20.0	21.9	27.8	20.2	16.6	18.4	27.0
3	42.2	31.7	31.9	35.9	22.8	16.4	16.4	24.4
4	39.9	36.4	37.7	38.9	22.2	17.2	16.3	22.1
5	54.4	47.2	41.8	37.9	23.9	18.0	16.6	21.5
6	49.2	43.4	44.7	38.8	23.2	18.6	17.5	20.4
7	48.7	43.7	45.2	38.9	22.6	19.2	18.2	19.9
8	60.2	54.7	55.2	49.8	22.6	19.7	18.8	21.2
9	43.7	41.8	43.1	44.5	21.2	19.6	19.0	21.9
10	68.8	63.1	65.3	54.1	21.4	19.9	19.3	21.7
11	47.3	45.1	44.8	48.5	20.9	19.4	18.8	22.8
12	60.1	57.1	58.6	58.5	21.7	20.5	19.8	23.4
MAPE(12)	45.2	49.5	42.7	42.5				

Table 3 Forecasting results for 80 starters

Month	APE average				CAPE(k) average			
	ARIMA	Holt–Winters (auto)	Holt–Winters (γ=0.7)	*Previous Year*	ARIMA	Holt–Winters (auto)	Holt–Winters (γ=0.7)	*Previous Year*
1	32.8	28.1	30.3	39.9	32.8	28.1	30.3	39.9
2	22.3	20.0	21.9	27.8	20.2	16.6	18.4	27.0
3	42.2	31.7	31.9	35.9	22.8	16.4	16.4	24.4
4	39.9	36.4	37.7	38.9	22.2	17.2	16.3	22.1
5	54.4	47.2	41.8	37.9	23.9	18.0	16.6	21.5
6	49.2	43.4	44.7	38.8	23.2	18.6	17.5	20.4
7	48.7	43.7	45.2	38.9	22.6	19.2	18.2	19.9
8	60.2	54.7	55.2	49.8	22.6	19.7	18.8	21.2
9	43.7	41.8	43.1	44.5	21.2	19.6	19.0	21.9
10	68.8	63.1	65.3	54.1	21.4	19.9	19.3	21.7
11	47.3	45.1	44.8	48.5	20.9	19.4	18.8	22.8
12	60.1	57.1	58.6	58.5	21.7	20.5	19.8	23.4
MAPE(12)	47.5	42.7	43.4	42.8				

seasonal fluctuations. DR(2) is expressed as the following equation with forecast values ($\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_{12}$) and actual values ($y_1, y_2, \cdots, y_{12}$).

$$\mathrm{DR}(2) = \left| \frac{\widehat{y}_1 + \widehat{y}_2 \Big/ \sum_{i=1}^{12} \widehat{y}_i - y_1 + y_2 \Big/ \sum_{i=1}^{12} y_i}{y_1 + y_2 \Big/ \sum_{i=1}^{12} y_i} \right| \times 100 \tag{10}$$

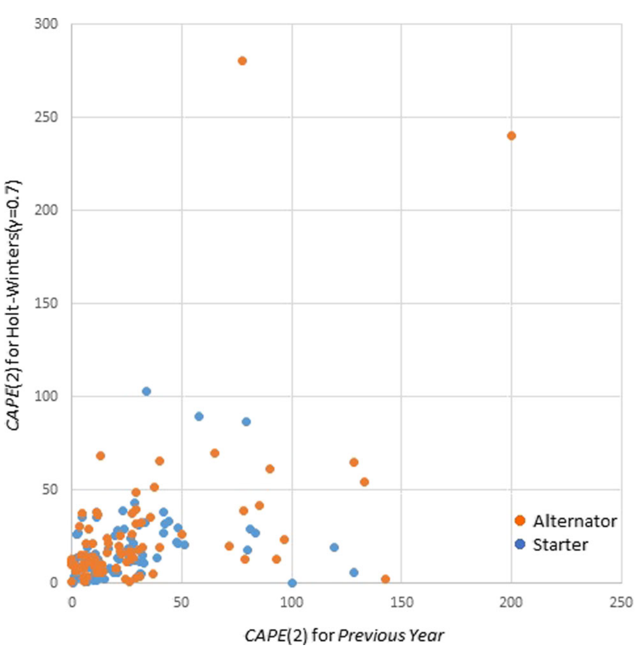


Fig. 9 Distribution of forecast error values (CAPE(2)) for Holt–Winters (γ=0.7) and *Previous Year* for 160 products

Table 4 shows the CAPE(2), CAPE(12), and DR(2) values of 33 products with a CAPE(2) value of 30 % or higher. In addition, the values of the ACF(12) used as the index of periodicity in Sect. 4.2 are shown as another index of seasonal features. The items with CAPE(12) and DR(2) of 20 % or higher are underlined. For the items with a large CAPE(12) (20 % or more), forecast error in the growth trend was the main factor causing the error in the 2-month forecast. The forecast error of seasonal fluctuations was regarded as the main factor causing the 2-month forecast error for items with a large DR(2) (20 % or more). In items with both large CAPE(12) and DR(2), both were considered to be factors of CAPE(2). According to this criterion, among the 33 products listed in Table 4, the main factor was the forecast error of the growth trend in nine cases, forecast error of seasonal fluctuation in 14 cases, and both in 9 cases. Furthermore, in one case, the forecast error occurred due to the combination of the two factors despite their small values.

Figure 11 shows the typical cases of each type. Figure 11a shows an example where the forecast error in the growth trend was the main factor (*1 of Table 4). The method forecasted that the demand volume would be approximately the same as that of the previous year, but the annual demand volume decreased than that in the previous year; the actual demand decreased for the first 2 months, which was the forecast error. In contrast, Fig. 11b shows an example where the forecast error in seasonal fluctuation was the main factor (*2 of Table 4). Although the cumulative total of the forecast for annual demand volume was only 0.4 % from the actual value, there was a gap between the fluctuation for each month in the forecast and actual values, and there was an error of 31.4 % for the first 2 months. *Alternator A* shown in Fig. 8 is an example where the forecast error of seasonal fluctuation was the main factor

Fig. 10 Forecast results for five cases (Fig. 7) using Holt–Winters (γ=0.7)

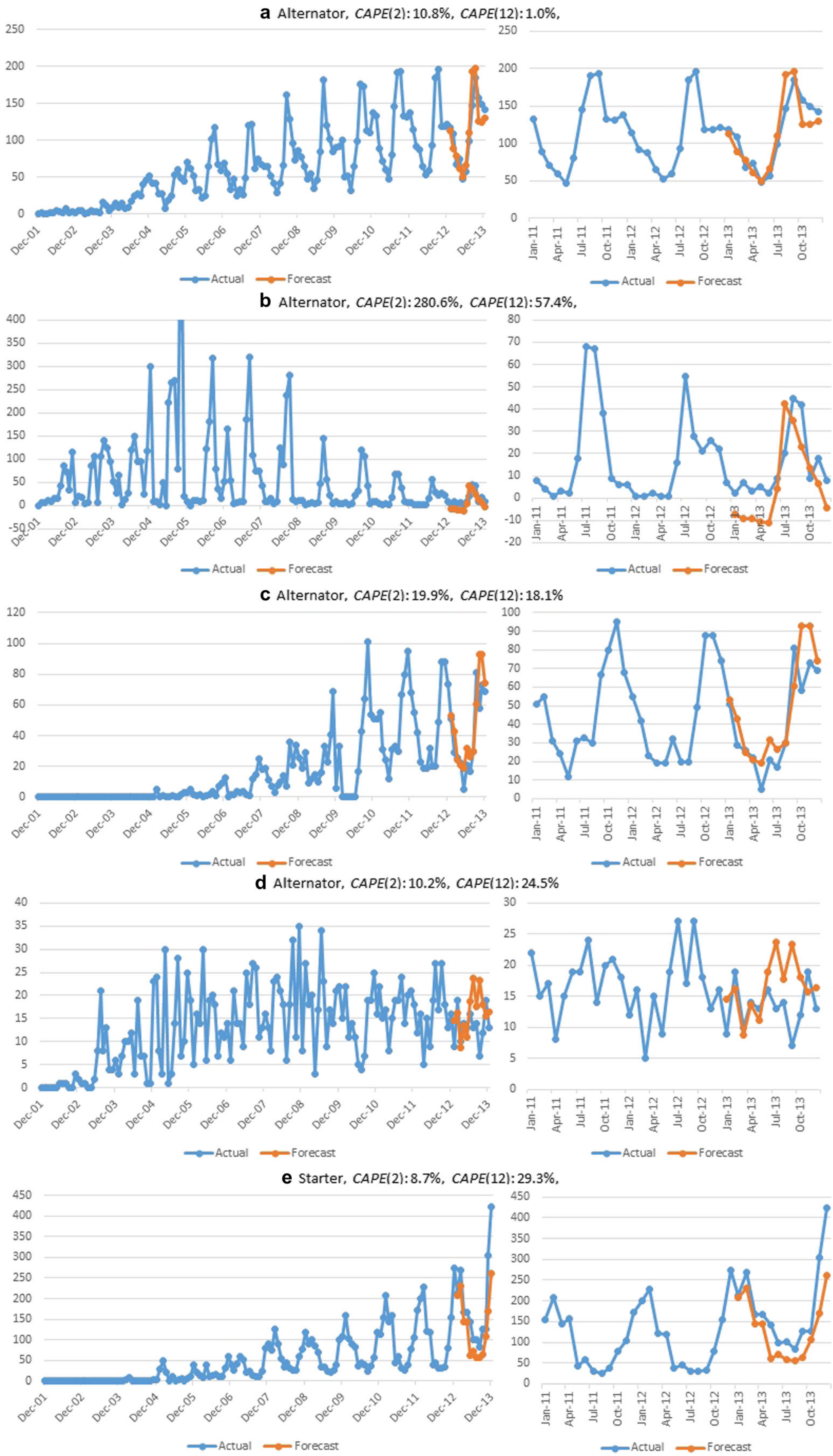


Table 4 Analysis of factors of forecast error

Product	CAPE(2)	CAPE(12) (trend)	RD(2) (seasonal)	ACF (12) (seasonal)	Product	CAPE (2)	CAPE(12) (trend)	RD(2) (seasonal)	ACF (12) (seasonal)
Alternator	30.2	5.6	26.1	0.71	Alternator	68.3	28.1	55.8	0.78
Alternator	31.9	24.5	9.8	0.65	Alternator	69.9	35.0	25.9	0.45
Alternator	32.4	1.2	33.2	0.61	Alternator *4	240.0	59.5	10.0	0.57
Alternator	35.4	11.0	22.0	0.70	Alternator	280.6	57.4	523.5	0.33
Alternator	36.5	48.1	7.8	0.65					
Alternator	37.4	20.5	21.3	0.58	Starter	31.2	10.6	23.1	0.29
Alternator *3	37.4	9.9	25.0	0.76	Starter *2	31.7	0.4	31.4	0.07
Alternator	38.5	99.2	30.5	−0.08	Starter	32.3	147.1	46.4	0.40
Alternator	38.8	8.8	27.5	0.69	Starter	33.1	7.0	24.3	0.06
Alternator	39.3	31.8	11.0	0.63	Starter	35.4	7.1	26.5	0.43
Alternator	41.5	28.9	9.7	0.41	Starter	35.7	17.7	15.3	0.36
Alternator	48.9	11.2	33.9	0.66	Starter	38.5	9.6	26.3	0.38
Alternator	51.5	18.3	85.3	0.60	Starter	38.7	27.1	15.8	0.12
Alternator	54.5	12.7	76.9	0.72	Starter	43.2	39.0	7.0	0.35
Alternator	61.7	31.6	22.9	0.42	Starter *1	87.0	107.8	10.0	0.45
Alternator	64.8	2.0	68.2	0.63	Starter	89.9	29.2	47.0	0.52
Alternator	65.4	24.0	33.4	0.65	Starter	102.9	81.4	11.8	0.51

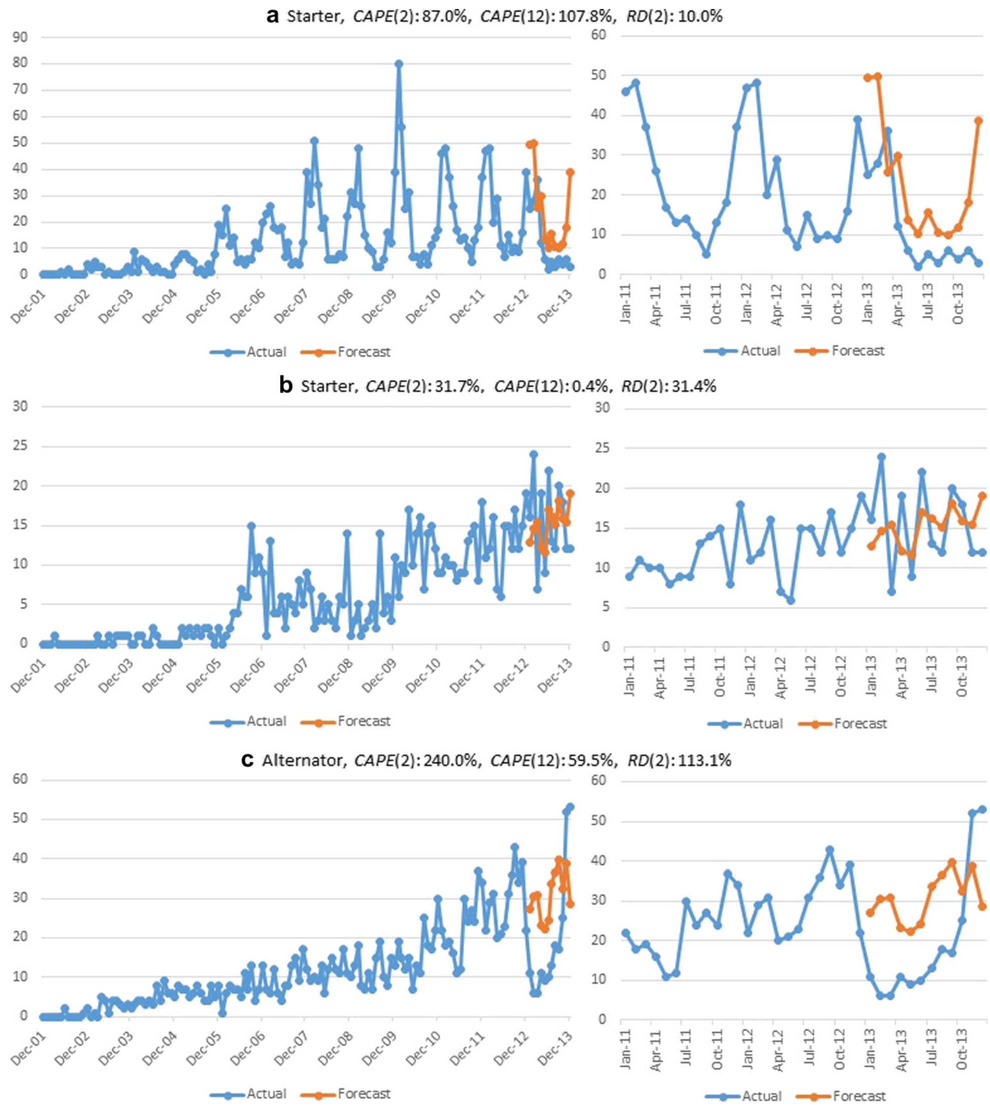
(*3 of Table 4). Figure 10c shows an example where both the forecast errors of growth trend and seasonal fluctuation are large (*4 of Table 4). The forecast error occurred because the demand transition shifted considerably from the normal trend. Among the 160 products, it had the second-largest CAPE(2) value (see Fig. 9). Major shifts in the demand trend do occur, and the forecasting in such cases is difficult.

5 Conclusions

The current study investigated the effectiveness of demand forecasting by time series analysis in auto parts remanufacturing. The study used the ARIMA and the Holt–Winters models. To investigate the effectiveness of these models, we used the time series data for the sales of 160 types of remanufactured alternators and starters made by a real independent remanufacturer (IR) of auto parts. The features of seasonality were investigated first, and the variation of seasonality and periodicity by products was shown (Figs. 5 and 6). As for the results of the forecasting calculations, the average errors of the forecasts over 12 months measured in terms of mean absolute percentage error (MAPE(12)) ranged from 40 to 50 %. The average cumulative absolute percentage errors in the forecasts over 2 months (CAPE(2)), which are often considered in production planning in auto parts remanufacturing, were 26.7 and 18.4 % for alternators and starters, respectively. Compared with the values of same month previous year (*Previous Year*), the results were better by 4.5 points for alternators and by 8.6 points for starters. Demand forecasting is critical for process optimization in remanufacturing, and these results are expected to provide a benchmark for future studies targeting demand forecasting in auto parts remanufacturing. The factors of the errors for forecasts over 2 months were investigated by distinguishing the errors in estimating the growth trend from the errors in estimating the seasonal fluctuations. Among the 33 cases with large forecasting errors, the errors in estimating the growth trend were the main cause of the overall errors in 9 cases, and errors in estimating the seasonal fluctuations were the main cause of the overall errors in 14 cases. The errors in estimating both the growth trend and seasonal fluctuations caused the overall error in ten cases.

Future steps with respect to the present study are as follows. First, by designating the forecasting accuracies via time series analysis that were clarified in this study, as the starting point, methods for increasing the forecasting accuracy should be explored. Although time series analysis is an effective method for forecasting, it does not include cause–effect mechanisms in its forecasts. Hence, the incorporation of any factor that explicitly affects demand into the forecast may increase the forecasting accuracy. Therefore, it is worth exploring such factors. Moreover, it is critical to address methods for incorporating the said factors into the forecasts. One such factor is weather conditions because as mentioned previously, temperature and humidity affect the failure rate of alternators and starters. If the influence of weather on alternator and starter demands is clarified and reflected in demand forecasting, the forecasting accuracies, especially forecasting accuracies of

Fig. 11 Categories of forecast errors



seasonal fluctuations, may improve. Another candidate is the information regarding the number of years passed since the year when the product was first manufactured, which may be helpful to project whether the demand would exhibit an increasing trend or a decreasing trend. In other words, it may be helpful to forecast the growth trend of demand. Although IRs do not have accurate information regarding the time distribution of new product sales, they have information about some types of products for the durations of their manufacture. In addition to these two factors, various pieces of information such as product-specific marketing material and product architecture may increase the forecasting accuracies. It is critical to specify the factors that increase the forecasting accuracies. With respect to the methods for reflecting the said information in demand forecasting, as described in Sect. 2, the methods presented in previous studies that integrated regression analysis and time series analysis may serve as useful references. Second, investigating the ways in which the forecast results can be reflected effectively in production planning is another significant next step. Depending on the available forecasting accuracy, the effective means of reflecting the results may differ. It is important to develop methods that can accurately reflect demand forecasting in remanufacturing process optimization. Production planning in remanufacturing is more complex than that in traditional manufacturing. It is crucial to develop a demand forecasting method that enables effective production planning in remanufacturing.

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