IEAF: A Hybrid Method for Forecasting Short Life Cycle Spare Parts

Yeliang Fan, Jie Li
School of Economics and Management, Hebei University of Technology, Tianjin 300401, China, leo-van@hotmail.com, ljrsch@163.com

Chao-Hsien Chu
College of Information Sciences and Technology, Pennsylvania State University, PA 16802, USA, chu@ist.psu.edu

The demand of short life cycle products and their spare parts are often nonlinear and non-stationary, thus, traditional time series forecasting methods, such as Double Exponential Smoothing (DES) and Autoregressive Integrated Moving Average (ARIMA), have difficulty of getting accurate forecasting results for them. In this paper a novel hybrid model, IEAF, is proposed to forecast the demand of short life cycle spare parts. IEAF model hybrids the pre-processing process of data mining to clean data, the Ensemble Empirical Mode Decomposition (EEMD) method to decompose and remove data non-stationary, and the ARIMA method to predict the decomposed data, followed by post-processing process to arrive final forecast results. To overcome the undershoot and overshoot problems in standard EEMD, an improved method is developed to generate the envelopes in data decomposition. Our empirical test with 446 real data sets of spare parts proved that the proposed model has more accurate and stable forecasting results than two traditional forecasting methods and earlier version of model decomposed method. With IEAF model managers can make better decision on spare parts inventory management.

Key words: spare parts forecasting, short life cycle products, Ensemble Empirical Mode Decomposition, ARIMA, data mining

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1. Introduction

Tech-savvy products, such as mobile phones, laptops and pads, have short life cycle and are very difficult to forecast, plan and manage. Compared with other daily use products, the life cycle of these products are much shorter which vary from several months to less than three years (Kurawarwala and Matsuo 1958). The spare parts of short life cycle products for maintenance usually have the same short life cycle. When the sales of products increase, the demand of spare parts will also increase accordingly. In addition, short life cycle products and their spare parts have some special characteristics, such as being seasonal, lacking of historical data and having rapid random fluctuation (Kurawarwala and Matsuo 1958). As such, it is difficult for companies to get accurate forecasting results of spare parts to ensure daily maintenance. If current inventory level is low, too many repairing request will result in a shortage of spare parts. Customers' satisfaction will then drop down, as not all customers' repairing requests are met on time. On the other hand, when lots of spare parts are hold, it will increase inventory cost if there is few repairing request. As time goes by, new products will come out to replace the old ones. If there are still many spare parts of old products after their withdrawing from market, companies will suffer great losses.

Another challenge of spare parts forecasting caused by the delay between sales data recording and real repairing activities. Manufacturers often record sales data of spare parts once they are sold. But the spare parts may only be sold to the maintenance stations but they have not been used for repairing yet. This situation is similar to the sales of short life cycle products. Products may still be hold by distributors, wholesalers or retailers. They are not brought by customers but the sales data has been recorded. Thus, it is hard to find accurate relation between demand of short life cycle products and their spare parts, thereby, we cannot estimate spare part demand based on the product demand directly.

In order to plan the resources, make the pricing decision, and improve customer services, an appropriate inventory control point for spare parts is needed. Traditional forecasting algorithms, such as Double Exponential Smoothing (DES) and Autoregressive Integrated Moving Average (ARIMA), have difficulty of obtaining accurate forecasting results, due to the fact that most short life cycle data has significant amount of noise and is nonlinear and non-stationary in nature. Recent advances in data mining and model decomposition research have obtained promising results in analysing data with the mentioned features. The two key elements which contribute to the success of data mining are: data preprocessing and post processing. Data preprocessing techniques can be used to clean or repair the initial data to remove noise, missing, redundancy and invalid data which have bad influences on forecasting. Post-processing procedures usually include varied pruning routines, rule filtering, empirical adjustment or even knowledge integration (Bruha and Famili 2000). Data decomposition method, based on Ensemble Empirical Mode Decomposition (EEMD), can transform non-stationary data into stationary sub data sets (Wu and Huang 2009) which can then be properly handled by traditional forecasting methods.

In this paper, a novel forecasting method, named IEAF, based on a hybrid of data mining process, an improved EEMD and ARIMA forecast methods is proposed. We propose improvement over EEMD and integrate ARIMA into the middle of data mining process, starting with a preprocessing phase and ending with a post processing stage. We implemented the proposed approach and statistically evaluated the results with 446 real data sets. Empirical tests proved that IEAF method is more accurate than traditional forecasting methods and the improvements are statistically significant.

The novelty and main contributions of this paper lie in:

1. Hybrid data mining and EEMD processes. We integrate data mining process with EEMD to reduce data noise so as to improve forecast accuracy.

2. Improved EEMD Method: We developed a new way to generate envelopes during the process of EEMD which reduce the amounts of overshoot and undershoot.

To the best of our knowledge, this paper is the first to adopt and improve Hilbert-Huang Transform (HHT) process for non-stationary time series forecast. It is also one of the few studies that hybrid data mining with time series method to increase forecasting accuracy. The paper is organized as follows. Section 2 provides a literature review of related methods for spare parts forecasting. Section 3 describes the standard EMD and EEMD methods. Section 4 presents the technical details of the proposed IEAF algorithm. Section 5 presents details of experiment and implementation. Section 6 evaluates and compares the empirical test results between IEAF and other algorithms. Finally, conclusions are drawn and some directions for future works are presented in section 7.

2. Related Work

Extensive research has been done in spare part forecast (Willemain et al. 2004), however, the study of forecast for short life cycle spare parts is limited. We classify the related methods into six categories: 1) growth models, 2) analog methods, 3) time series methods, 4) decomposition methods, 5) data mining methods and 6) others.

2.1. Growth Models

Kurawarwala and Matsuo (1996) developed a growth model that uses information from past products histories and approximates them to entire life cycle sales to predict monthly demand. Xu and Song (2007) analyzed the characteristics of short life cycle products and proposed an improved Bass model for forecasting. They took into account the seasonal characteristics of demand and modified the Bass model with consideration of seasonal factors. Compared with the Bass model, the improved model was proved to have satisfying forecasting results for short life cycle products demand. But Xu et al. built the Bass model with all data, which is impracticable in real world when there is no similar or related spare part. When we predict the demand of next month, we can only use the historical data to build the Bass model. It is difficult to estimate the parameter m (m represents the total market potential) before the stage of maturity in product life cycle, thus, it is difficult to predict the demand with a growth model. According to Xu and Zhang (2008), the Bass model is more suitable for predicting the demand of durable products for particular product type or industry and is not appropriate for short life cycle products.

2.2. Analog Methods

Szozda (2010) proposed a new method that allows people to use life cycles of similar, analogous products to arrive at the initial forecasts for the products at hands. Green and Armstrong (2007) proposed a structured judgmental procedure with opinions of analogies from experts for forecasting.

However, their methods are only reasonable to predict products with similar ones which cannot be applied to any type of products. Wu et al. (2006) explore and compare several leading indicator methods for short life cycle product forecast. Using correlation values between leading indicators and products, they predict the cluster demand pattern two to eight months ahead of time. However, it is difficulty, if not impossible, to find leading indicators of spare parts when they are only designed for specific products.

2.3. Time Series Models

Time series models have been widely used in demand forecasting. For example, Johnson and Thompson (1975) and Ray (1982) dealt with inventory control problems using ARIMA model. Miller (1986) modelled product demand using an exponential smoothing model. However, time series methods have difficulty of getting accurate forecasting results when the data is nonlinear and non-stationary.

In this paper we compared the proposed IEAF method with two popular time series methods: Double Exponential Smoothing and Autoregressive Integrated Moving Average (ARIMA). Exponential smoothing is one of the most popular methods for time series forecasts. When there is a trend in the data, simple exponential smoothing model cannot do well (Croarkin et al. 2010). Therefore, double exponential smoothing (DES) model (Cooray 2008) was introduced and compared.

Let Y_{t+T} be the predicted value of tth term initial value after T terms. $S_t^{(1)}$ and $S_t^{(2)}$ are the first and second exponential smoothing value. x_t is the tth term initial value and α is the level of the series, then:

$$\begin{aligned} Y_{t+T} &= a_t + b_t \cdot T \\ a_t &= 2S_t^{(1)} + S_t^{(2)} \\ b_t &= \frac{\alpha}{1-\alpha}(S_t^{(1)} - S_t^{(2)}) \end{aligned} \tag{1}$$

where

$$\begin{aligned} S_t^{(1)} &= \alpha x_t + (1-\alpha)S_{t-1}^{(1)} \\ S_t^{(2)} &= \alpha S_{t-1}^{(1)} + (1-\alpha)S_{t-1}^{(2)} \end{aligned} \tag{2}$$

Parameter α of SES model is between 0 and 1. We choose 0.9 in this paper as it produces better results.

Autoregressive integrated moving average (ARIMA) model is another popular time series analysis method in statistics and econometrics, which was first proposed by Box and Jenkins (Box et al. 2008). In $ARIMA(p,d,q)$ model, p is the number of autoregressive items, q is the number of moving average items and d is times of difference to make the time series stationary. Thereby, $ARIMA(p,d,q)$ is the extension of $ARMA(p,q)$ model.

2.4. Decomposition Methods

Chung et al. (2012) proposed a sales forecasting model of movie and game products at Blockbuster Company. They assumed that the sales consist of three components: consumers who have rented or bought things already, consumers who will rent or buy things and the networking effect between related potential customers and previous customers. With empirical test, they showed that their sales model matched well with the real sales activities.

Hilbert-Huang Transform (HHT) is a popular method for modeling data with nonlinear and high non-stationary relation (Huang et al. 1996, 1998, 1999). Empirical Mode Decomposition (EMD), the first part of HHT, is a direct, intuitive and adaptive data decomposition method with an a posteriori-defined basis based on and derived from the data (Huang 2005). EMD can decompose a nonlinear and non-stationary signal into a series of Intrinsic Mode Functions (IMF) which represents different oscillatory modes. An IMF is defined as:

1. The number of zero-crossing and the number of extrema must be equal to or differ at most by one in the entire dataset.

2. The mean value of the lower envelope generated by the local minima and the upper envelope generated by the local maxima is zero at any point.

Compared with other methods, for instance Wavelet Transform (WT) and Short Time Fourier Transform (STFT), EMD can deal with nonlinear and non-stationary data much better. However, it still has some weaknesses (Rato et al. 2008). In this study, we propose an improvement and adapted it for spare part forecast.

2.5. Data Mining Methods

Xu and Zhang (2008) consider products' demand, season factor and demand predicted by Bass model and built a SVM forecasting model to predict the demand of short life cycle products. But from the forecasting result the normalized mean square error of the proposed model is 0.5826, which is higher than normal expected value.

Maaß et al. (2014) discussed how can data mining techniques improve the short-term forecasting method for short life cycle products. In this work, they found that data preparation is critical to the results. As discussed by Shearer (2000), data preparation contains five elements: 1) select data, 2) clean data, 3) construct data, 4) integrate data and 5) format data. In this study, we adopt data cleaning and data decomposition to decrease the uncertainty in data.

2.6. Other Methods

Zhu and Thonemann (2004) proposed an adaptive forecasting algorithm that uses structural knowledge to forecast the demand and develop an optimal inventory policy. Because it is difficult to apply optimal policy, they further proposed three heuristics to approximate the optimal inventory policy and shown that one of them had near optimal solutions. They implemented and evaluated the algorithm with data from a personal computer manufacturer in North America. Cakanyildirim and Roundy (2002) discovered that lots of demand forecasting algorithms are easily affected by the random errors. They proposed a scheme which can estimate the correlation and variance of forecasting errors and use it to model the evolution of forecasting over time. In this study, we apply simple data preprocessing method to deal with data noise or unexpected data issue.

3. Mode Decomposition of Hilbert-Huang Transform

In this section, we will use data sets 69 and 141 to illustrate the mode decomposition process of HHT and explore its strengths and weaknesses. The nature of these data sets are given in the appendix.

3.1. Empirical Mode Decomposition (EMD)

As discussed in section 2.4, EMD is a useful decomposition method for nonlinear and non-stationary data. The process of EMD, known as shifting process, can be preceded as follows:

1. Identify all the local maxima and minima points. In the EMD/EEMD matlab code written by Wu (2014), local maxima is defined as x_i where $x_{i-1} \leq x_i$ and $x_i \geq x_{i+1}$ and local minima is defined as x_i where $x_{i-1} \geq x_i$ and $x_i \leq x_{i+1}$. Using data set 141 as an example, we identify 6 local maxima points and 5 local minima points, as shown in Fig. 1.

2. Connects all local extrema points with a cubic spline interpolation to generate the upper and lower envelopes. For point $x \in [x_i, x_{x+1}]$, the cubic polynomial curve is defined as:

$$y = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i \tag{3}$$

a, b, c and d can be solved by:

$$\begin{aligned} a_i &= \frac{S_{i+1} - S_i}{6h_i} \\ b_i &= \frac{S_i}{2} \\ c_i &= \frac{y_{i+1} - y_1}{h_i} \\ d_i &= y_i \end{aligned} \tag{4}$$

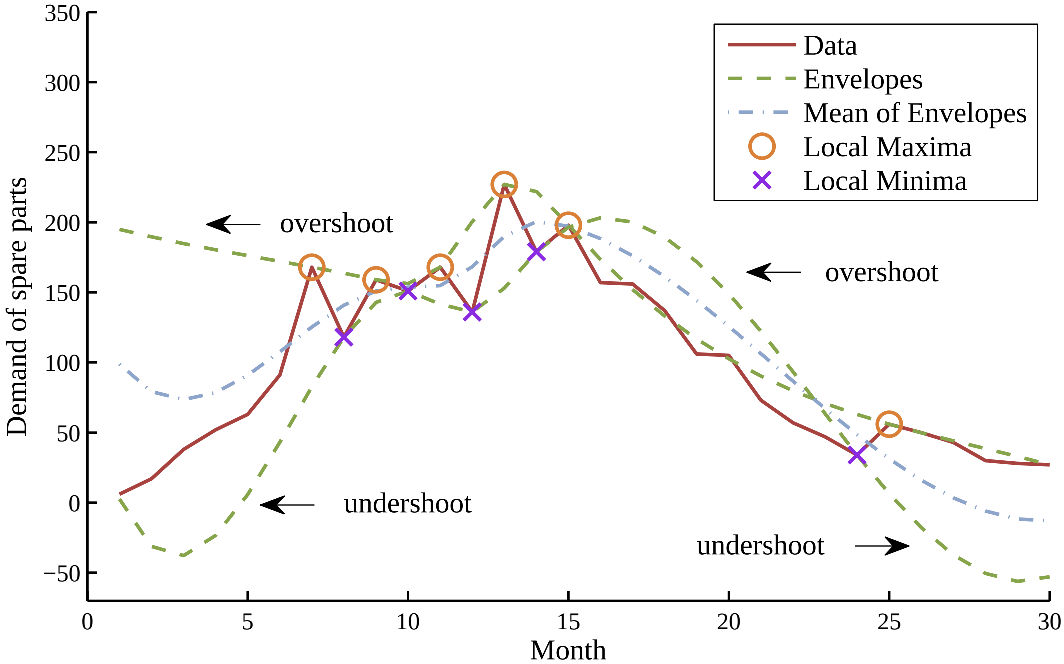
where

$$\begin{gathered} h_i = x_{i+1} - x_i \\ h_{i-1}S_{i-1} + (2h_{i-1} + 2h_i)S_i + h_i S_{i+1} = 6\left(\frac{y_{i+1} - y_1}{h_i} - \frac{y_i - y_{i-1}}{h_{i-1}}\right) \end{gathered} \tag{5}$$

In this study, we take ”not-a-knot” as boundary conditions, thus:

$$\begin{aligned} S_0^{'''}(x_1) &= S_1^{'''}(x_1) \\ S_{n-2}^{'''}(x_{n-1}) &= S_{n-1}^{'''}(x_{n-1}) \end{aligned} \tag{6}$$

Figure 1 **Upper and lower envelopes generated by EMD and the mean value of upper and lower envelopes (Dataset 141)**



3. Define m_1 as the mean value of upper and lower envelops generated at first time, as shown in Fig 1. Then the first component h_1 is defined as:

$$h_1(t) = x(t) - m_1 \tag{7}$$

where, $x(t)$ is the initial data.

4. Check if h_1 is an IMF. If it satisfies the definition of an IMF, then we get the first IMF. If it does not, we treat h_1 as the data. Repeat steps 2 and 3 until h_i become an IMF. As shown in Fig. 2, the number of zero-crossing is 11 and the number of extrema is 18. Therefore, h_1 is not an IMF.

Besides, there is another stoppage criterion, sd_i, that needs to be considered. If sd_i is smaller than a predetermined value, the shifting process will be stopped. Where,

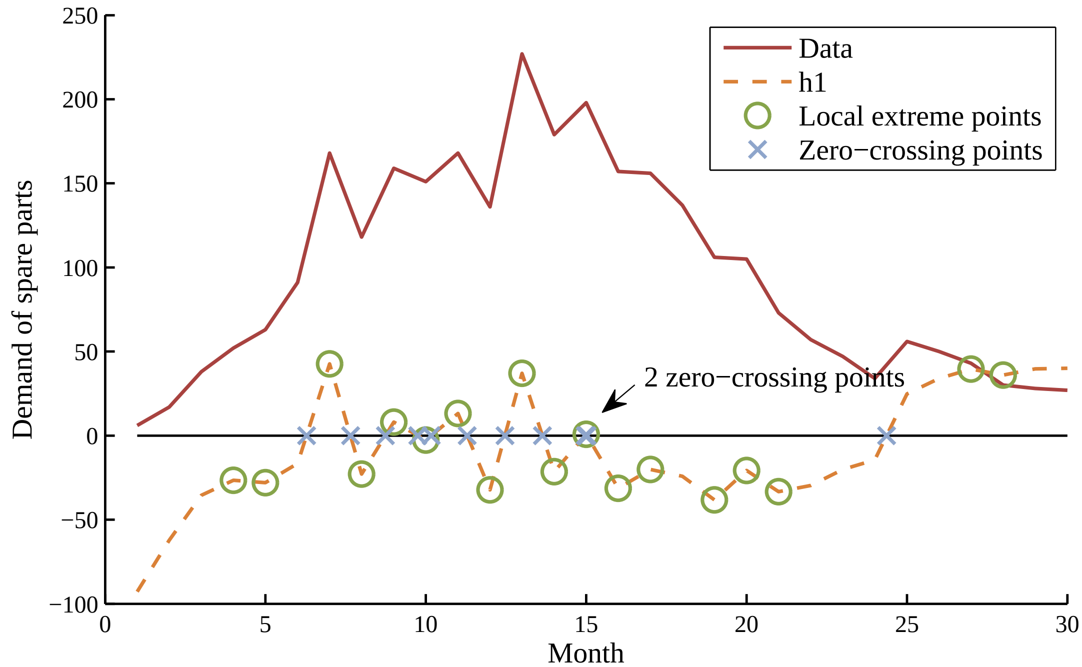
$$sd_i = \frac{\sum_{t=0}^{T} |h_{i-1}(t) - h_i(t)|^2}{\sum_{t=0}^{T} h_{i-1}^2} \tag{8}$$

5. When the first IMF c_1 is found, we remove it from the data by following:

$$x(t) = x(t) - c_1 \tag{9}$$

Repeat steps 2 to 4 to get all IMFs until $x(t)$ becomes smaller than the predetermined value or the residue is a monotonic function. At this time the remain $x(t)$ is called residue r and no more IMFs can be generated.

Figure 2 **Data and h_1 (Data set 141)**



6. Through steps 2 to 5 we can finally get

$$x(t) = \sum_{j=1}^{n} c_j + r \tag{10}$$

and the decomposition of the initial data based on strand EMD method is finished.

3.2. Ensemble Empirical Mode Decomposition (EEMD)

Although EMD was proved to be useful in many cases there are still many unsolved difficulties of using HHT in specific application domains (Wu and Huang 2009). In particularly, when the data is formed by both high and low frequency signals, the IMF generated by EMD may contains disparate scales signals or similar scale signals may appear in different IMF components. This phenomenon is known as mode mixing. The intermittency not only causes detrimental aliasing in the time-frequency distribution, but also makes the physical meaning of every IMF unclear. It is also likely resulted in serious overshoot and undershoot as shown in Fig. 1.

To fix the problems, a new noise-assisted data analysis method, named Ensemble Empirical Mode Decomposition (EEMD), is proposed by Wu and Huang (2009). The basic idea of EEMD is to add a series of uniformly distributed white noise to the initial signal which makes the signal continuous at different scales. The addition changes the characteristics of extreme points of signal and improves the ability to decompose the data without mode mixing. The standard EEMD procedure, works as follows:

1. Add uniformly distributed white noise $n_i(t)$ to the signal $x(t)$,

$$x_i(t) = x(t) + n_i(t) \tag{11}$$

where $x_i(t)$ is the signal after ith being added white signal.

2. Decompose the data with uniformly distributed white noise into IMFs.

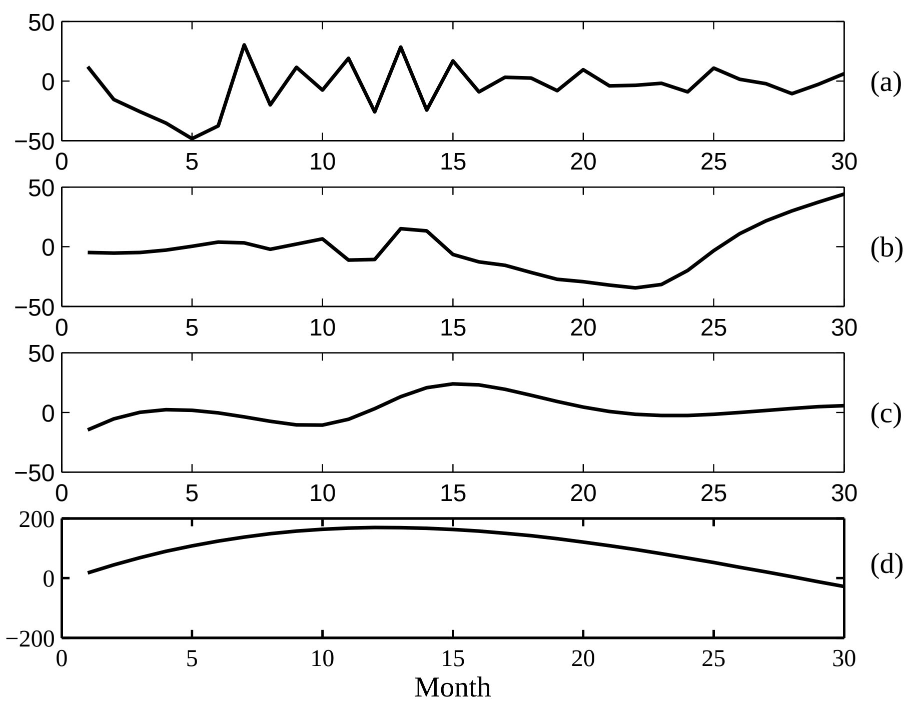
3. Repeat steps 1 and 2 with different white noises every time (repeated 20 times in this work).

4. Obtain the (ensemble) means of corresponding IMFs of the decompositions as the final result.

Fig. 3 shows the IMFs of data set 1 generated by standard EEMD method, where (a)-(c) are the IMFs and (d) is the residue. Since the corresponding IMFs of different series of white noise have no correlation with each other, the added white noise of the corresponding IMFs cancels each other eventually.

In the standard EEMD method, though it can identify all the local maxima and minima and connects them by a cubic spline interpolation with "not-a-knot" boundary conditions to generate the upper and lower envelopes, it still has some shortcomings such as having overshoot and undershoot near the beginning and end of period. In next section, we will propose our improvement over EEMD and discuss how it be integrated with a data mining schema for spare part forecasting.

Figure 3 IMFs generated with standard EEMD (Data set 141)



4. The Proposed IEAF Method

As can be seen from the above reviews, illustrations and discussions, none of the existing methods can fully address the challenges faced by forecasting the demand of short life cycle spare parts. Some of the unique characteristics we need to conquer include: random fluctuation (noise), nonlinearity, non-stationary, shortage of historical data (short life cycle). We proposed a model that hybrids data mining process, improved EEMD and ARIMA to address the issues.

The hybrid IEAF method can be divided into four phases (see Fig. 4):

1. Data cleaning, to reduce noise and unexpected data value.

2. Decomposition with an improved Ensemble Empirical Mode Decomposition (IEEMD) method, to remove data non-stationary.

3. Forecasting of every IMF with Autoregressive Integrated Moving Average (ARIMA) model.

4. Post-processing with removing negative values and rounding up values.

4.1. Data Cleaning

The very first step to be done in IEAF is data cleaning. A data set often consists of some noise, incorrect, inconsistent or invalid data. These problems can be caused by mistake of recording, special impact from other aspects, etc. Demand of short life cycle products spare parts is mainly associated with the sales of products themselves. Apparently demand of short life cycle products will be enhanced with increasing sales of these products. But it may also be affected by some other aspects. For instance, if one shop stops maintenance service for a day, then the demand of spare parts this day will definitely be zero. If today is weekend, office workers may go to the maintenance station to repair their own mobile phone because they have much more free time than as usual. So data cleaning must be applied first to fix these kinds of glitches.

Adopting the similar idea from quality control charting (Shewhart 1931), we check if the point satisfies the out of control condition:

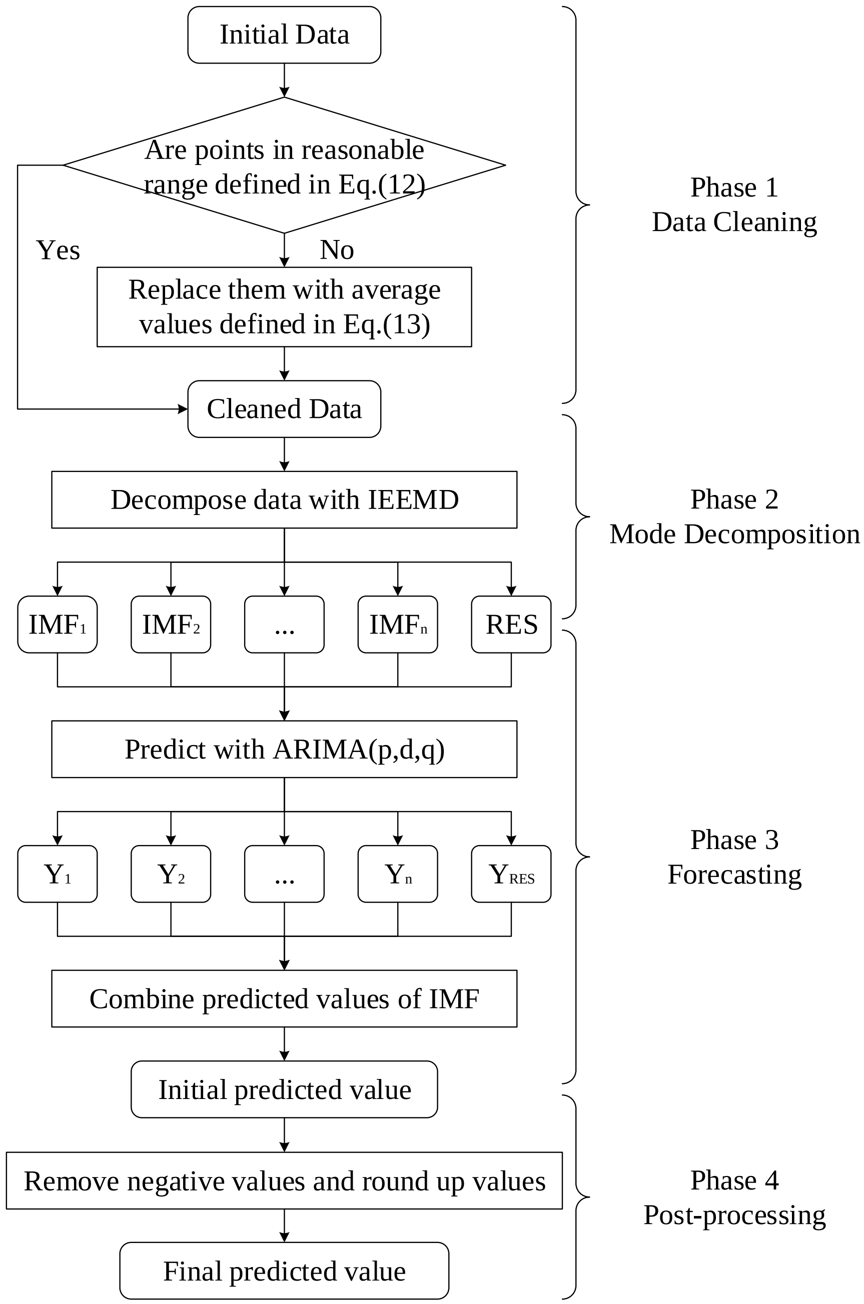
$$x_i \in [\bar{x} - 3\sigma, \bar{x} + 3\sigma] \tag{12}$$

where, $\bar{x}$ is the mean value of these six points, σ is the standard deviation of the left and right three points. If x_i does not satisfy (1), then it will be replaced by

$$\bar{X} = \frac{1}{7}\sum_{j=i-3}^{i+3} x_j \tag{13}$$

The reason why we replace it with $\bar{X}$ not $\bar{x}$ is that we also need to keep some increasing or decreasing trends. Using data set 69 as an example, the difference of initial data and cleaned data with this method is shown in Fig. 5. As shown, the data of month 16 was adjusted from 12 to 26.57, as it is much smaller than the values around neighborhood.

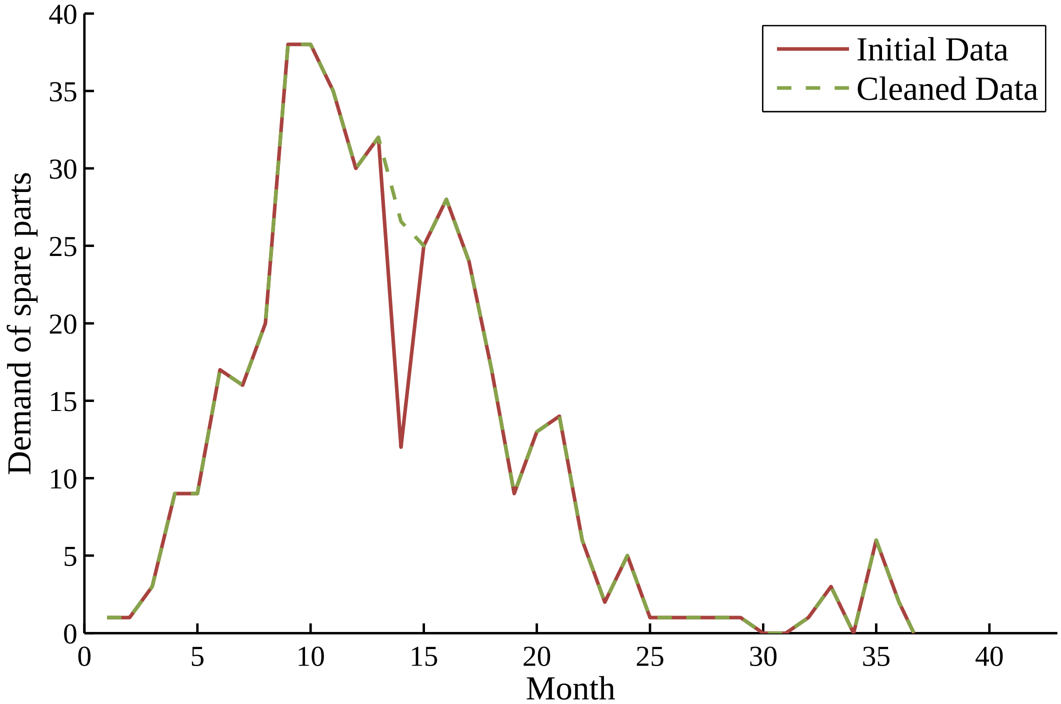
Figure 4 The process of IEAF method



4.2. Decomposition with Improved EEMD (IEEMD)

Though, at this stage, some unexpected values have been adjusted from initial data sets, the data are still nonlinear and non-stationary in nature. We apply IEEMD method to transform the cleaned data into stationary ones. Our proposed improvements in this phase focus on the convex points and the method used to generate the envelopes.

Figure 5 Initial data and cleaned data (Data set 69)

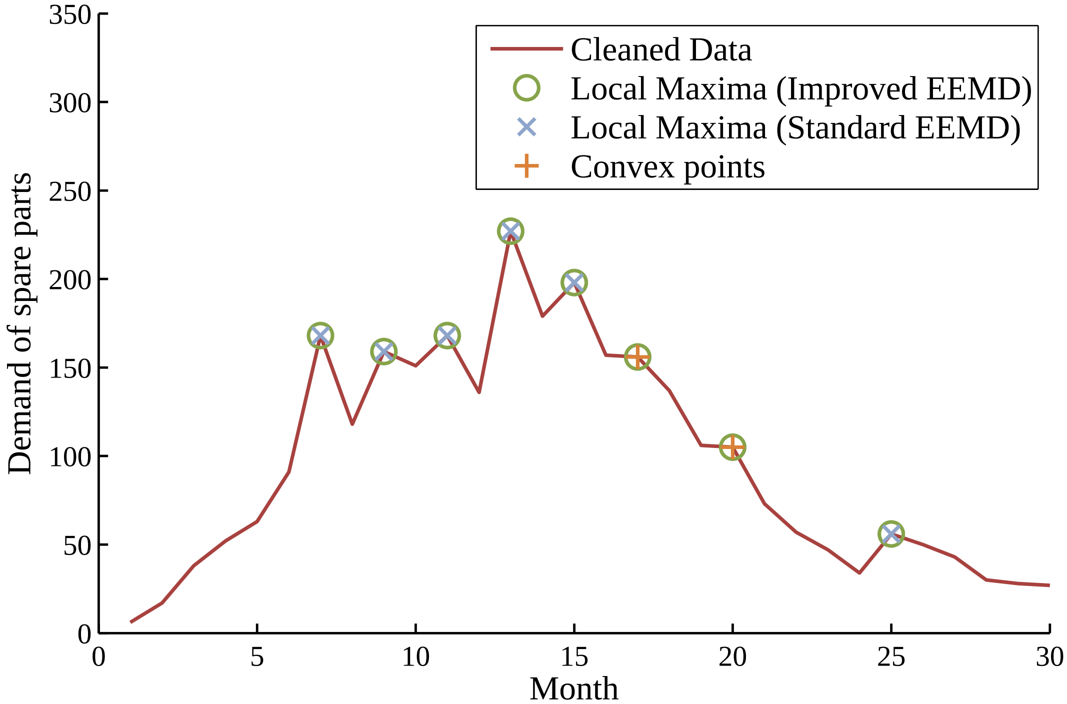


First, in the standard EEMD method, it identifies all the local maxima and minima, then connects them by a cubic spline interpolation with "not-a-knot" boundary conditions to generate the upper and lower envelopes. But it has some shortcomings, so here we not only take local maxima and minima points into consideration, but also consider some convex points, as showed in Fig. 6. Let p_i be the point we will check. p_{i-1} and p_{i+1} are the previous and next point of p_i. We define $\vec{a} = (x_a, y_a)$ as a unit vector pointing from p_i to p_{i-1} and $\vec{b} = (x_b, y_b)$ as a unit vector pointing from p_i to p_{i+1}. If the angle moved from $\vec{a}$ to $\vec{b}$ clockwise is between $7\pi/6$ and $3\pi/2$, then p_i is a convex point. As shown, points of month 16 and 28 are the convex points. These convex points, not local maxima or minima, were not used to generate the envelopes in the standard EEMD method, which will result in the difference of mode decomposition.

Second, in the standard EEMD method, it uses Cubic Spline Interpolation to produce envelopes of signals. Since the demand of short life cycle product spare parts changes rapidly, the Cubic Spline Interpolation does not make sure the interpolation curve between two local maxima or local minima points is monotonic. Thus, the standard EEMD method with Cubic Spline Interpolation may lead to the problems of undershoot and overshoot. As a result some spurious IMF components will be generated at the same time.

We propose to use Piecewise Cubic Hermite Interpolation which constructs a piecewise interpolation curve with consequent derivatives to produce envelopes. Piecewise Cubic Hermite Interpolation function meets the following conditions (Fritsch and Carlson 1980):

Figure 6 **Difference of points found by standard EEMD and IEEMD (Data set 141)**



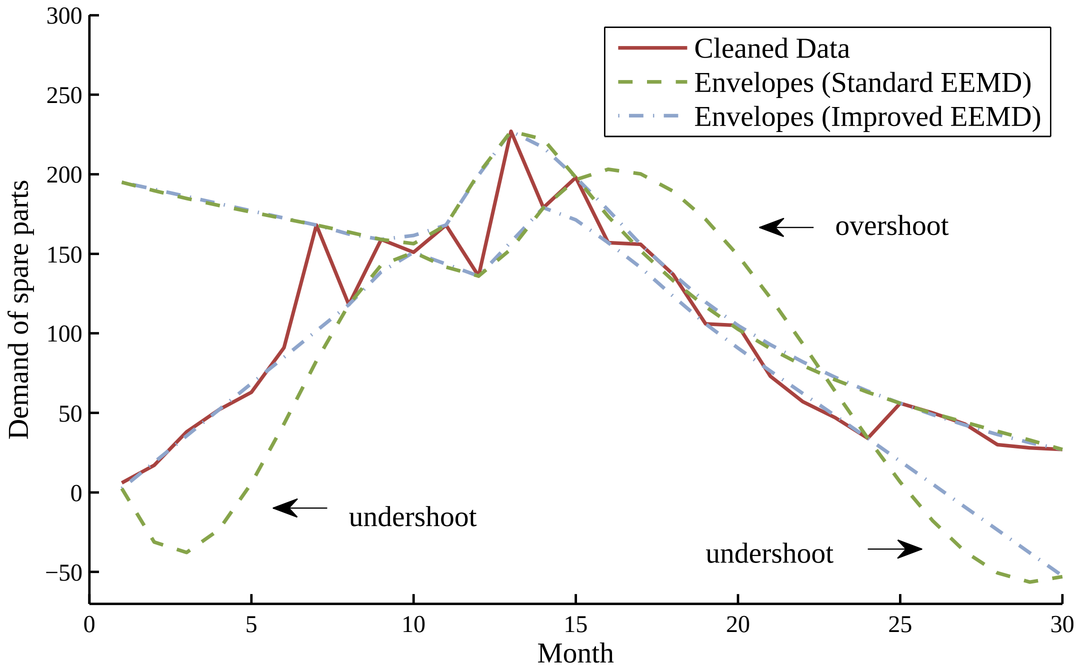
1. $I_h(x) \in C^1[a,b]$, where $C^1[a,b]$ is the function sets of consequent first derivatives in $[a,b]$.
2. $I_h(x_k) = f_k$, $I_k'(x_k) = f_k'$, where $k = 0, 1, ..., n$.
3. $I_h(x)$ is cubic polynomial in every $[x_k, x_{k+1}]$.

And the expression of $I_h(x)$ in $[x_k, x_{k+1}]$ is shown in (14).

$$
\begin{aligned}
I_h(x) = &\left(\frac{x - x_{k+1}}{x_k - x_{k+1}}\right)^2 \left(1 + 2\frac{x - x_k}{x_{k+1} - x_k}\right) f_k \\
&+ \left(\frac{x - x_k}{x_{k+1} - xk}\right)^2 \left(1 + 2\frac{x - xk + 1}{x_k - xk + 1}\right) f_{k+1} \\
&+ \left(\frac{x - x_{k+1}}{x_k - x_{k+1}}\right)^2 (x - x_k) f_k' \\
&+ \left(\frac{x - x_k}{x_{k+1} - xk}\right)^2 (x - x_{k+1}) f_{k+1}'
\end{aligned}
\tag{14}
$$

Fig. 7 shows the differences of envelopes generated by standard EEMD and IEEMD. The standard EMD method generates envelopes with Cubic Spline Interpolation cannot guarantee the curve between local maxima and local minima in monotonic. In fact, the problems of overshoot and undershoot, as shown in Fig. 7, are caused by using the Cubic Spline Interpolation. In which, the lower envelope may be higher than the upper envelope (See "overshoot" in Fig. 7) which will result in an inappropriate mean value to be removed from data. Fig. 8 shows the IMFs of data set 1

Figure 7 **Difference of envelopes generated by standard EEMD and IEEMD (Data set 141)**



generated by IEEMD method. Where, (a)-(c) are the IMFs and (d) is the residue. Basically, the resulted IMFs (a), (b) and (c) from EEMD and IEEMD look similar to each other except after months 20.

4.3. Forecasting with ARIMA

For every IMF, we can then predict the demand of next month using the ARIMA model. $ARIMA(p,d,q)$ model is defined as:

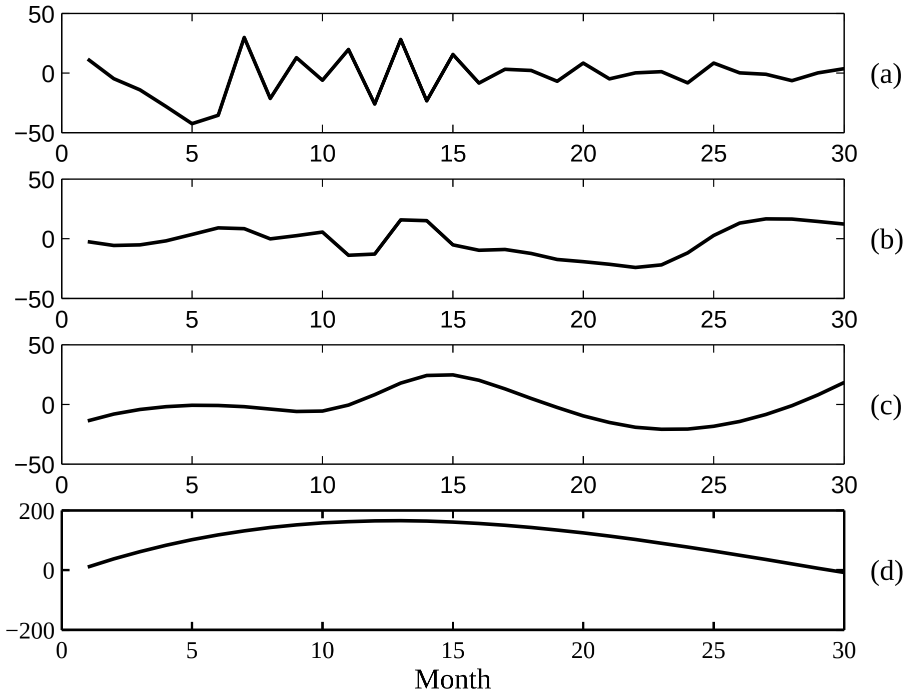
$$\left(1-\sum_{i=i}^{p}\phi_i L^i\right)(1-L)^d X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t \tag{15}$$

where, L is the lag operator, ϕ are the parameters of autoregressive, θ are the parameters of the moving average and d is the parameter of integrated process.

The parameter d is the times of difference to make the time series stationary. The parameters p and q in $ARIMA(p,d,q)$ are chosen by Akaike Information Criterion (AIC). AIC was first proposed by Akaike (Akaike 1974). Based on the information theory, AIC offers a new relative estimate method. The AIC value is defined as:

$$AIC = 2k - 2ln(L) \tag{16}$$

Figure 8 IMFs generated with IEEMD (Data set 141)



where k is the number of parameters in the model and L is the maximized value of the likelihood function for the model. After the forecasting of every IMF, we can then get real predicted value y by combining the results from IMFs:

$$y = \sum_{i=1}^{k} y_i \tag{17}$$

where k is the count of IMFs generated by IEEMD method and y_i is the predicted value of every IMF with ARIMA model.

4.4. Post-processing

Since the value we want to predict is the amount of spare parts needed in the future, it must be an integer and equal or greater than zero. Thus, we should replace the obtained negative values with zero and round up the values to the nearest integer values.

The complete set of pseudo code of IEAF method is defined in Algorithm 1.

5. Implementation and Experiment

In this paper, we aim to 1) compare the relative performance of the proposed hybrid model, IEAF, with two traditional forecast methods - DES and ARIMA 2) assess the impact of data cleaning process and 3) assess the effectiveness of the proposed improvements over standard EEMD. Five models - DES, ARIAM, EAF (standard EEMD + ARIMA), IEAF-NPRE (IEEMD + ARIMA, but without preprocessing) and IEAF (IEEMD + ARIMA) – were considered for comparison.

Algorithm 1 IEAF Method

input: S - The initial time sequence

output: V - The predicted value of next month

function IEAF(S)
  $I = \{\}, P = \{\}, V = \{\}$
  $S_c \leftarrow$ CLEAN(S) ▷ Clean the initial data
  $I \leftarrow$ IEEMD(S_c) ▷ Decompose cleaned data into IMFs with improved EEMD method
  for all $i \in I$ **do**
    $P \leftarrow$ ARIMA(i) ▷ Predict the value of next point of each IMF
    $V \leftarrow V + P$ ▷ Combine each P into the final forecasting value V
  end for
  $V \leftarrow$ NEGATIVETOZERO(V) ▷ Replace negative values with 0
  $V \leftarrow$ ROUND(V) ▷ Round up values to the nearest integer values
  return V
end function

All methods were coded in Matlab. We use the standard EEMD Matlab source code written by Wu (2014) and extend it for IEEMD. In the source code it evaluates TNM as total IMF number. TNM is defined as:

$$TNM = fix\left(\log_2\left(len\left(x\right)\right)\right) \tag{18}$$

Where $fix\left(x\right)$ rounds the elements of x toward zero and $len\left(x\right)$ returns the length of x. Besides, it shifts 10 times to get every IMF, which is different from the standard EMD method. The experiments were conducted on a laptop with 4 cored 2.3 GHz processor, 8G bytes memory and Windows 8.1 x64 based OS.

5.1. Performance Measures

Three performance measures - Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and standard deviation of MAPE (σ_{MAPE}) - were used for comparison. These measures have been extensively used in many forecasting studies (Kurbatsky et al. 2014, Wu et al. 2006).

1. Mean absolute error (MAE), which is a metric used to measure how close forecasts are to the actual outcomes. The smaller value means the lower forecast error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{p}_i - p_i\right| \tag{19}$$

where $\hat{p}_i$ is predicted value, p_i is the real value at time i and n is the number of predicted month.

2. Mean absolute percentage error (MAPE), which is a measure of forecasting accuracy as a percentage of error for a forecast method. The smaller value means the lower percentage of forecast error.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{p}_i - p_i}{p_i}\right| \cdot 100\% \tag{20}$$

where $\hat{p}_i$, p_i and n have the same meaning in MAE. When p_i is zero, we define MAPE as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{p}_i - p_i}{p_i + 1}\right| \cdot 100\% \tag{21}$$

3. Standard deviation of MAPE is used to measure the stability of forecasting method. Normally, the method with smaller standard deviation of prediction errors is more stable. σ_{MAPE} can be expressed as:

$$\sigma_{MAPE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(e_i - \bar{e})^2} \tag{22}$$

where

$$e_i = \frac{\hat{p}_i - p_i}{p_i} \tag{23}$$

and

$$\bar{e} = \frac{1}{n}\sum_{i=1}^{n} e_h \tag{24}$$

5.2. Hypotheses

We formulate three sets of null hypotheses to statistically test the difference between each pair of the five methods on the three performance measures:

1. *Hypothesis Set 1* $H_0^1 : MAE = MAE_0$. There is no difference in MAE between each pair of models.

2. *Hypothesis Set 2* $H_0^2 : MAPE = MAPE_0$. There is no difference in MAPE between each pair of models.

3. *Hypothesis Set 3* $H_0^3 : \sigma_{MAPE} = \sigma_{MAPE0}$. There is no difference in standard deviation of MAPE between each pair of models.

We use paired t-test to compare the MAE, MAPE and the standard deviation of MAPE (σ_{MAPE}) among the methods. The significance level is set at 0.05.

5.3. Data Sets

We obtain the historical data of spare parts from a major smart phone manufacturer in China for analysis. The mobile phones have 17 kinds of spare parts (see Table 1). A total of 459 real data sets were originally collected from Jan. 2007 to Aug. 2011. However, since 12 data sets have missing data and one data set only has five data points, they were removed from analysis. Thus, we only have 446 usable data sets.

Table 1 **Number of data sets of every kind of spare part**

Spare parts	Number of data sets*
Accessories	11 (1)
Battery	10 (0)
Camera	7 (0)
Charger	2 (1)
Consumptive materials	64 (0)
Data cable	6 (0)
Electroacoustic device	36 (2)
Electronic components	23 (1)
Flexible circuit	11 (0)
Headphone	4 (2)
LED module	15 (0)
Mainboard	18 (0)
Small circuit board	8 (1)
Structure materials	209 (1)
Touch screen	2 (0)
Wrapping materials	32 (3)
Others	1 (1)
Total	**459 (13)**

* The number in parenthesis represents the number of data sets with data missing problem or too short to be analysed.

6. Results and Analyses

In this section, we review the behavior of each forecasting method and compare the performance of these methods in terms of the three measures.

6.1. A Close Look at the Forecast Results

Table 2 shows the final predicted values and measurement results from data set 141 in terms of MAE and MAPE for the five methods we evaluated. For easy comparison, we also plot the results in Fig. 9.

As shown in Table 2, based on the results of MAE and MAPE, we can see that IEAF performs the best, followed by ARIMA and DES is the worst method. Two interesting results regarding this particular data set can be observed:

1) ARIMA model performs better than EAF method, as EAF tends to overshoot or undershoot the results in this data set.

2) The forecast results of DES lag one period behind the actual, which is common for most time series forecasting method, because they perform forecast based on the data from previous periods.

6.2. Comparison of Forecasting Error

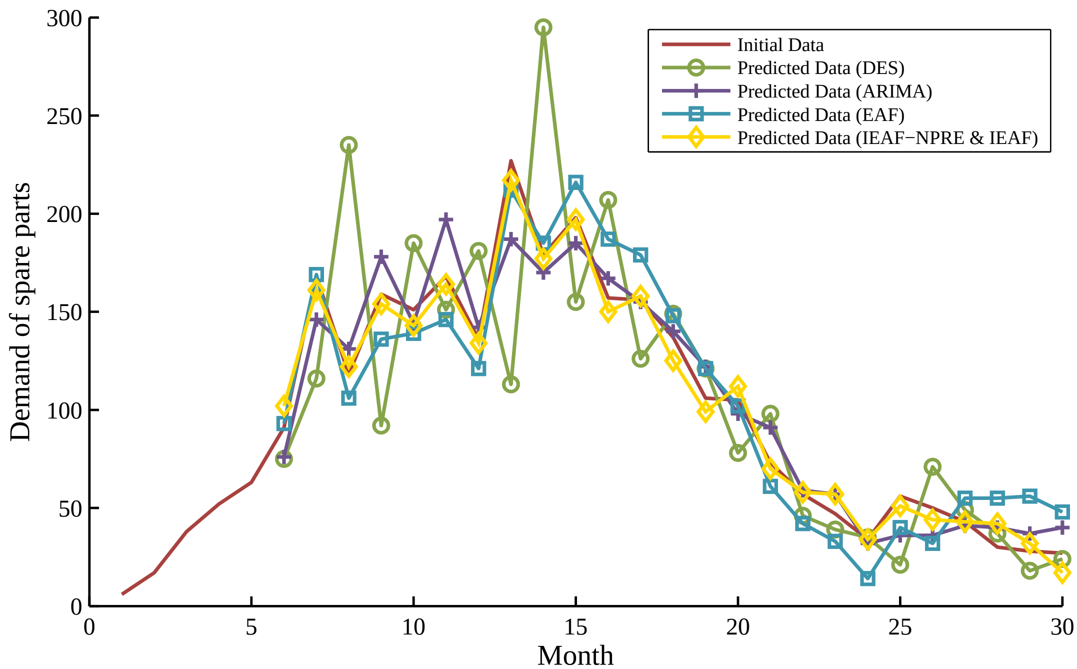
Tables 3 summarizes the paired t-test results of MAE. As shown, all $P(T \leq t)$ for one-tail values of MAE are less than 0.05 except that between IEAF and IEAF-NPRE. Thus, we reject the first set of null hypotheses except that between IEAF and IEAF-NPRE and prove that:

Table 2 Predicted data of DES, ARIMA, EAF and IEAF and the initial data (Data set 141)

	Predicted data of data set 141															
Month[1]	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Initial Data	6	17	38	52	63	91	168	118	159	151	168	136	227	179	198	157
Predicted Data (DES)	-	-	-	-	-	75	116	235	92	185	151	181	113	295	155	207
Predicted Data (ARIMA)	-	-	-	-	-	76	146	131	178	144	197	142	187	170	185	167
Predicted Data (EAF)	-	-	-	-	-	93	169	106	136	139	146	121	212	185	216	187
Predicted Data (IEAF-NPRE)[4]	-	-	-	-	-	102	161	122	154	143	164	121	217	177	184	150
Predicted Data (IEAF)	-	-	-	-	-	102	161	122	154	143	164	121	217	177	184	150
Month[1]	17	18	19	20	21	22	23	24	25	26	27	28	29	30	MAE[2]	MAPE[3]
Initial Data	156	137	106	105	73	57	47	34	56	50	43	30	28	27	-	-
Predicted Data (DES)	126	149	121	78	98	46	39	35	21	71	49	37	18	24	35.28	0.3016
Predicted Data (ARIMA)	155	140	122	98	91	59	57	32	36	36	41	40	37	40	12.40	0.1505
Predicted Data (EAF)	179	148	121	102	61	42	33	14	40	32	55	55	56	48	15.56	0.2490
Predicted Data (IEAF-NPRE)[4]	158	125	99	112	70	58	57	31	51	44	40	42	32	17	6.88	0.0948
Predicted Data (IEAF)	158	125	99	112	70	58	57	31	51	44	40	42	32	17	6.88	0.0948

[1] Month 1 is April, 2009.
[2] MAE of month 6 to 30 (The demand of beginning months cannot be predicted with IEAF).
[3] MAPE of month 6 to 30 (The demand of beginning months cannot be predicted with IEAF).
[4] There is no noise points to be cleaned in this dataset, thus the result of IEAF-NPRE is same as IEAF.

Figure 9 Predicted data of DES, ARIMA, EAF and IEAF and the initial data (Data set 141)



1) The average MAE of IEAF are significantly less than those of DES, ARIMA and EAF. That means our proposed method performs better than the two traditional time series methods, DES

Table 3 Paired T-test Results of MAE

	Mean	Variance	Sample	DES	ARIMA	EAF	IEAF-NPRE	IEAF
DES	19.327774	1315.691558	446	-	11.912310	11.412231	11.658523	11.353989
ARIMA	10.528319	529.860823	446	0.000000	-	8.155884	8.777948	8.143444
EAF	5.733946	139.286272	446	0.000000	0.000000	-	3.180331	2.985641
IEAF-NPRE	5.277700	133.561103	446	0.000000	0.000000	0.000787	-	**-0.039382**
IEAF	5.283199	111.360228	446	0.000000	0.000000	0.001493	**0.484302**	-

Upper right: Critical differences in mean between group pairs (T value).
Lower left: Calculation of significances (P value) at 0.05 levels.

and ARIMA and the standard model decomposition method (EAF) in forecasting the demand of spare parts.

2) The average MAE of IEAF-NPRE are significantly less than those of DES, ARIMA, EAF. That means IEAF-NPRE performs better than the two traditional time series methods, DES and ARIMA and the standard model decomposition method (EAF) in forecasting the demand of spare parts.

3) The average MAE of IEAF-NPRE is less than that of IEAF, but not significantly. Thus, it means the data cleaning process has impact on the forecasting error but we cannot proves that it is statistically significant. This is due to the fact that data cleaning has positive or negative impact on different data sets. In these 446 data sets, it has negative impact on data sets with large demand per month which leads to this result. However, from the results of MAPE shown below, we can still draw the conclusion that data cleaning do improve the forecasting accuracy.

4) The average MAE of EAF are significantly less than those of DES and ARIMA. That means the standard EEMD method performs better than the two traditional time series methods in forecasting the demand of spare parts.

5) The average MAE of ARIMA is significantly less than that of DES. That means ARIMA performs better than the traditional DES time series method in forecasting the demand of spare parts.

In specific, as shown in the Table 3, ARIMA can reduce the MAE of DES from 19.3 to 10.5 and EAF can further reduce the MAE to 5.73. The proposed IEAF method finally reduce the MAE to 5.28 and the result is proved to be statistically significant.

6.3. Comparison of Forecasting Accuracy

Tables 4 summarizes the paired t-test results of MAPE. As shown, all P(T≤t) for one-tail values of MAPE are less than 0.05. Thus, we reject the second set of null hypotheses and prove that:

1) The average MAPE of IEAF are significantly less than those of DES, ARIMA, IEAF-NPRE and EAF. That means our proposed method can obtain higher forecasting accuracy than the two traditional time series methods, DES and ARIMA and the standard model decomposition method

(EAF) in forecasting the demand of spare parts. Besides, the preprocessing of IEAF can improve the forecasting accuracy by adjusting the noise data.

2) The average MAPE of IEAF-NPRE are significantly less than those of DES and ARIMA. That means IEAF can still obtain higher forecasting accuracy than the two traditional time series methods, DES and ARIMA and the standard model decomposition method (EAF) in forecasting the demand of spare parts without preprocessing.

3) The average MAPE of EAF are significantly less than those of DES and ARIMA. That means the standard EEMD method can obtain higher forecasting accuracy than the two traditional time series methods in forecasting the demand of spare parts.

4) The average MAPE of ARIMA is significantly less than that of DES. That means ARIMA can obtain higher forecasting accuracy than the traditional DES time series method in forecasting the demand of spare parts.

Table 4 Paired T-test Results of MAPE

	Mean	Variance	Sample	DES	ARIMA	EAF	IEAF-NPRE	IEAF
DES	1.181301	1.104180	446	-	12.744251	20.294880	19.690304	21.341788
ARIMA	0.725503	0.579468	446	0.000000	-	13.607557	14.368078	14.632896
EAF	0.368394	0.165397	446	0.000000	0.000000	-	**-3.379460**	2.423588
IEAF-NPRE	0.415941	0.226612	446	0.000000	0.000000	0.000395	-	5.458413
IEAF	0.337879	0.161910	446	0.000000	0.000000	0.007883	0.000000	-

Upper right: Critical differences in mean between group pairs (T value).
Lower left: Calculation of significances (P value) at 0.05 levels.

In general, as shown in Table 4, the forecasting accuracy of DES is very bad as its mean MAPE is far larger than 1 (i.e., 1.18). ARIMA is better but it still only has 27%(=100%-72.6%) forecast accuracy. On the other hand, EAF can have 73%(=100%-36.8%) forecast accuracy and IEAF can obtain 76%(=100%-33.8%) forecast accuracy. However, without preprocessing IEAF can only obtain 58%(=100%-41.6%) forecast accuracy.

6.4. Comparison of Forecasting Stability

Table 5 summarizes the paired t-test results of σ_{MAPE}. As shown, all P(T≤t) for one-tail values of σ_{MAPE} are less than 0.05 except that between IEAF and EAF. Thus, we reject the third set of null hypotheses except that between IEAF and EAF and prove that:

1) The average σ_{MAPE} of IEAF are significantly less than those of DES, ARIMA and IEAF-NPRE. That means our proposed method has stable forecasting capability than the two traditional time series methods, DES and ARIMA in forecasting the demand of spare parts. It also proves that the preprocessing of IEAF can improve the forecasting stability. The average σ_{MAPE} of IEAF is less than that of EAF but not significantly.

2) The average σ_{MAPE} of IEAF-NPRE are significantly less than those of DES and ARIMA. That means IEAF can still obtain higher forecasting stability than the two traditional time series methods, DES and ARIMA in forecasting the demand of spare parts without preprocessing.

3) The average σ_{MAPE} of EAF are significantly less than those of DES and ARIMA. That means the standard EEMD method has stable forecasting capability than the two traditional time series methods in forecasting the demand of spare parts.

4) The average σ_{MAPE} of ARIMA is significantly less than that of DES. That means ARIMA has stable forecasting capability than the traditional DES time series method in forecasting the demand of spare parts.

Table 5 Paired T-test Results of Standard Deviation of MAPE (σ_{MAPE})

	Mean	Variance	Sample	DES	ARIMA	EAF	IEAF-NPRE	IEAF
DES	1.661336	4.272579	446	-	9.132085	12.988808	12.997008	13.776000
ARIMA	0.967028	1.449640	446	0.000000	-	10.379620	10.162159	11.101864
EAF	0.521873	0.327525	446	0.000000	0.000000	-	**-2.885295**	1.595703
IEAF-NPRE	0.600878	0.633918	446	0.000000	0.000000	0.002050	-	4.482508
IEAF	0.480164	0.436822	446	0.000000	0.000000	**0.055632**	0.000000	-

Upper right: Critical differences in mean between group pairs (T value).
Lower left: Calculation of significances (P value) at 0.05 levels.

As shown in Table 5, IEAF method has the lowest standard deviation of MAPE among four methods, which proves that IEAF method has the most stable forecasting results.

7. Conclusion

As discussed above, the demand of spare parts of short life cycle products has large random fluctuation and the data is nonlinear and non-stationary, thus, the traditional forecasting methods, such as DES and ARIMA, have difficulty of obtaining good forecasting results when applied. In this study, a new forecasting algorithm that hybrids data mining process with our improvement over EEMD and ARIMA was proposed to predict the demand of spare parts for short life cycle products. IEAF decomposes the initial data into IMFs first. It then combines the result after the forecasting of every IMF. Our empirical tests show that IEAF method can produce more accurate final forecasting results than two popular time series forecasting methods. IEAF also reduce the amount of undershoot and overshoot in the standard EEMD method which improve the accuracy of the forecasting method. With more accurate forecasting values, it offers better decision supports for managers with the management of spare parts inventory.

Future work should focus on finding the relations between the demand of spare parts and the related sales of short life cycle products with the delay between data recording and real selling and repairing activities. In this regards, we can divide the initial data into two phases. In the first phase, predict the sales of the short life cycle products with some correlation methods and then apply the IEAF to forecast the demand of spare parts in the second phase, which may lead to more accurate forecasting results.

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Appendix. Data set 69 and 141

Data set 69 which was used to illustrate the initial data and cleaned data is shown in Table. 6. The data set is the demand of small circuit board No. 100001568 and the first months of it is December, 2007. Data set 141 which was used to illustrate the process of standard EMD, EEMD and IEAF method is shown in Table. 7. The data set is the demand of electroacoustic device No. 182000476 and the first months of it is April, 2009.

Table 6 Data set 69

Month	1	2	3	4	5	6	7	8	9	10
Value	1	1	3	9	9	17	16	20	38	38
Month	11	12	13	14	15	16	17	18	19	20
Value	35	30	32	12	25	28	24	17	9	13
Month	21	22	23	24	25	26	27	28	29	30
Value	14	6	2	5	1	1	1	1	1	0
Month	31	32	33	34	35	36				
Value	0	1	3	0	6	2				

Table 7 Data set 141

Month	1	2	3	4	5	6	7	8	9	10
Value	6	17	38	52	63	91	168	118	159	151
Month	11	12	13	14	15	16	17	18	19	20
Value	168	136	227	179	198	157	156	137	106	105
Month	21	22	23	24	25	26	27	28	29	30
Value	73	57	47	34	56	50	43	30	28	27

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