

Intelligent Demand Forecasting for Sustainable Spare Parts Reuse in a Rational Consumption Environment

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Abstract—This study explores the development of intelligent demand forecasting methods in the context of the rise of rational consumption awareness, to establish the optimal spare parts reuse plan. As consumers pay more attention to sustainability and environmental protection, price and quality are no longer the only considerations; global inflation has also made consumer behavior more conservative, emphasizing budget control and long-term value. In response to the sluggish market demand, this study proposes a intelligent demand forecasting method to help companies understand consumer demand and design product reuse plans that are in line with their values. This study adopts the concept of "integrated forecasting" and designs two methods: (1) Hybrid Stacking (HS) Method: Combining traditional time series and machine learning techniques to improve forecast accuracy; (2) External Information Integration (EI-HS) Method: Incorporating external information into the HS model as an improvement baseline to further reduce forecast errors. Finally, the results of MASE and RGRMSE indicate that the methods proposed in this study hold strong application potential. The research results emphasize that the development of intelligent demand forecasting methods in the era of rational consumption is of key significance and points out the direction of sustainable improvement and expansion in the future, providing companies with more accurate forecasting tools and spare parts reuse decision-making basis.

Keywords: *Rational consumption; intelligent demand forecasting; spare parts; reuse*

1. Research Background and Motivation

All enterprises and terminal consumers will inevitably face cost pressures from rising prices. Coincidentally, this is also the best time for enterprises to implement ESG (Environment, Social, and Governance). Recycling cannot only reduce production costs but also protect the environment. For enterprises, recycling spare parts is one of the simplest projects when implementing ESG. In particular, for the production of spare parts for machinery and equipment, enterprises as sellers are willing to accept recycling provided that quality and functions are not impaired. However, more accurate demand forecasting is needed in the case of spare parts production. Unlike general consumables, spare parts belong to a niche market, and manufacturers must be cautious in controlling capacity and inventory.

Generally, "spare parts" refer to components or fittings used to maintain, replace, or repair damaged products or equipment. These may be original manufacturer parts or compatible parts produced by third-party manufacturers. The primary purpose of spare parts is to ensure normal equipment operation, extend service life, and repair or replace damaged parts. Spare parts are applicable across various products and industries and can be categorized by usage, functions, or application scenarios. The following provides a broad classification, although spare parts are further subdivided depending on the industry and application.

- Manufacturing machinery spare parts: Parts for industrial machinery and manufacturing processes, such as gears, screws, nuts, machine parts, and tools
- Electronics spare parts: Parts for electronic equipment, such as circuit boards, electronic elements, and connecting wires
- Transport vehicle spare parts: Parts for airplanes, ships, and vehicles, such as engine

parts, electronic equipment, and transport vehicle components

- Home appliance spare parts: Parts for home appliances, such as refrigerators, washing machines, and microwave ovens
- Building spare parts: Materials used for buildings and construction, such as bricks, cement, and pipelines
- Water and power spare parts: Parts for water and power systems, such as transformers, cables, circuit breakers, taps, pipelines, and pumps
- Medical spare parts: Parts used for medical equipment and instruments, such as surgical tools and inspection instruments

Spare parts recycling refers to the process of decomposing unused or damaged parts or products to recycle and reuse their materials or elements. This process helps reduce waste and promotes the reuse of resources. In general, spare parts recycling includes the disposal of old equipment, vehicle parts, and home appliances. Spare parts recycling not only benefits environmental protection but also provides enterprises with access to lower-cost parts. Some companies specialize in recycling spare parts and provide disposal and resource recovery services for waste. In the recycling process, materials can be classified, decomposed, and treated to ensure effective reuse. Spare parts recycling is a multi-layered and complex process that requires appropriate technology and equipment. Multiple countries and regions are working to formulate stricter regulations to promote sustainable recycling and waste management practices.

Spare parts demand forecasting plays a critical role in manufacturing equipment maintenance, management, and finished parts inventory. The availability of spare parts is vital for ensuring the smooth maintenance and operation of manufacturing equipment. Spare parts inventory is consumed by both preventive and corrective replacement operations, which result from equipment failure. However, equipment failure is a random process, making the demand for replacement parts uncertain. To address this issue, companies often overstock spare parts, since shortages can result in costly outcomes, such as a long-term shutdown or high expenses for emergency procurement. Nevertheless, spare parts are often expensive, and overstocking is not an ideal solution.

Time is money. An accidental equipment breakdown can cause significant loss to enterprises. In a period of fierce competition, recyclers must seek cost advantages wherever possible. Improper management of spare parts inventory will cause cost backlog, while a shortage of spare parts will

lead to a significant increase in production costs. Thus, the concept of “not too much, not too little” becomes both a challenge and a goal of spare parts management. There are many spare parts of specific models, and many of them are expensive, making it a challenge to decide which spare parts to stock. When considering stocking some spare parts as a potential way to save time, it may be worth adopting a strategic spare parts inventory. Maintenance personnel often find that they must wait several hours before obtaining replaceable articles from recyclers. This delay may cause significant productivity losses, and such costs are often higher than purchasing spare parts in advance. How should thousands of spare parts on a manufacturing site be evaluated and selectively managed? Identifying both common and uncommon replacements effectively is a critical production management issue, as it helps reduce downtime and maintain normal operations.

Accurate spare parts demand forecasting will help reduce inventory backlogs. However, forecasting spare parts demand effectively and selecting production projects that use spare parts remains a challenging task. The triggering factor, equipment failure, is random. Hence, spare parts demand generally shows a significant variation in both demand scale and demand intervals. Due to these features, spare parts are usually associated with intermittent or fluctuating demands. Demands are classified as fluctuating when two conditions are met: first, there is a significant difference in demand scale between periods; second, there are no demands in many periods. Therefore, this study aims to develop an intelligent method to cope with spare parts demands effectively and in real time, to understand the demand features of each spare part. The reuse solution for spare parts will then be optimized through principal element analysis, and the spare parts most suitable for recycling will be selected.

All forecasting techniques have limitations, so the characteristics and applicability of relevant materials must be considered carefully before being applied. To address these limitations, the “intelligent demand forecasting methods” developed in this study are expected to enhance the accuracy and efficiency of forecasting by combining multiple artificial intelligence technologies with traditional demand forecasting methods.

The following are several time series forecasting methods that are commonly used in ensemble forecasting:

- Simple Moving Average (SMA)

SMA calculates the demand of the subsequent period by averaging the demands of previous periods. The goal of this method is to obtain a representative value that eliminates random fluctuations and disregards past uncorrelated data.

Although it is easy to use and understand by simply moving an average line, it has limitations, especially in rapidly changing and fluctuating markets. Dealers and analysts often address these limitations by combining different indicators and types of moving average lines to make more accurate forecasts and decisions.

● Single Exponential Smoothing (SES)

Unlike SMA, which assigns equal weight to previous periods, SES gives greater weight to the most recent period. It estimates the demand for the next period by adding a fraction of the difference between actual demands and estimated demands. SES is a simple and effective forecasting method, but it has limitations in handling complex or uncertain data. The nature and basic model of data must be considered before selecting SES as the forecasting technology. Moreover, users must carefully consider its limitations prudently and may use more advanced methods for accurate prediction in diversified and challenging forecasting scenarios.

● Croston's Method (CR)

CR is a forecasting technology specifically developed for intermittent and sporadic demand data, which can overcome the limitations of SES in handling such demands. Intermittent demands refer to situations where items are required only occasionally. This method estimates the demands of the next cycle by dividing the estimated demand size by the interval between the estimated demands of the next period.

● Syntetos-Boylan's Approximation (SBA)

SBA is also a forecasting method specifically designed for intermittent demand data, with its primary goal being to improve the demand estimation component of CR. Similar to the CR method, it calculates the demands of the next cycle by dividing the estimated demand size by the interval between the estimated demands of the next period.

● Teunter-Syntetos-Babai's Method (TSB)

TSB is a demand forecasting technique that combines the advantages of CR and SES. TSB addresses two issues existing in CR: deviation of the method and the inappropriateness of this method for outdated problems. It estimates the demands of the next period by multiplying the estimated demand scale by the probability of occurrence in the next period.

Table 1. Strengths and Weaknesses of Methods Often Used for Time Sequence Forecasting Methods (Source: Compiled by this study)

Demand Forecasting Method	Strengths	Weaknesses
SMA	➤ Intelligible: SMA is simple and easy to calculate. Users can use it without advanced mathematical skills. ➤ Smoothing effect: SMA helps smooth price or data fluctuations, making it easier to identify a trend in a specific period. This is particularly useful in financial analysis, where it can help identify long-term trends amid short-term fluctuations. ➤ Widely used : Due to its simplicity, SMA is commonly applied in various industries, including finance, economics, and signal processing. It has become a standard tool for analysts and dealers. ➤ Comparison baseline : SMA provides a baseline for comparing current data points with historical averages, assisting analysts and dealers to make informed decisions about market trends and potential reversals. ➤ Lagging indicator : While often seen as a weakness, the lagging nature of SMA can sometimes serve as a strength. It filters noise,	➤ Lagging indicator : In fast-paced markets, SMA's lagging nature is a drawback. It cannot quickly respond to recent price changes, which may result in delayed decisions. In rapidly changing conditions, such delays can result in missed opportunities or losses. ➤ Weighting limitation : In some situations, SMA is more suitable for weighing more recent data points. ➤ Not suitable for highly volatile markets: In highly volatile conditions, SMA may generate misleading signals. In the case of an instant price change, the SMA may generate death cross or golden cross signals which fail to accurately reflect real market trends. ➤ Not applicable for important market events: SMA relies solely on historical prices and does not account for important events or news that may affect the market. ➤ Inadaptability: The fixed cycle of SMA makes it difficult to adapt to constantly changing market conditions.
SES	➤ Simplicity: SES is easy to understand and implement. It requires minimal computation, making it accessible for beginners and useful for rapid forecasting. ➤ Flexibility: SES can be applied to time series data with linear trends, without assuming a specific type of underlying trend. It can adapt to models that change over time. ➤ Efficiency: SES offers high computational efficiency, making it suitable for large datasets and real-time applications that require quick forecasts. ➤ Adaptability: SES emphasizes recent observations while gradually reducing the influence of older data, allowing it to efficiently respond to short-term changes. ➤ Baseline forecasting: SES offers baseline forecasting, which serves as a starting point for more advanced forecasting methods. It is often used as a benchmark for comparison with more advanced forecasting methods.	➤ Limited only to simple modes: SES works well for data with linear trends but performs poorly with complex patterns (e.g., seasonal fluctuation or non-linear trends). ➤ Low sensitivity: SES does not respond strongly to sudden changes or abnormal values in data. ➤ Manual adjustment: SES requires manual adjustment of the smoothing parameter. This parameter determines the weight given to recent observations. Selecting an appropriate smoothing parameter might be challenging, and repeated tests or expert judgement are required. ➤ Not applicable for noisy data: In datasets with high noise levels, SES may produce unreliable forecasts. Noise information in data might cause misleading forecasting, especially when the noise level is equivalent to the amplitude of the signal used for forecasting. ➤ Not applicable for long-term scope: SES is generally used for short-term forecasting. Extending the forecast period may lead to inaccurate forecasting, especially when the data model undergoes significant changes over time.

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Table 1. (continued)

Demand Forecasting Method	Strengths	Weaknesses
CR	➤ Dispose of intermittent demands: The CR method is specifically designed to handle intermittent demand and is applicable to items that are demanded irregularly over time. ➤ Reduce forecasting error: It is effective in reducing forecasting error for intermittent demand data, which is challenging due to sporadic demands. ➤ Simple calculation: The calculation of the CR method is relatively simple. It is easy to implement compared with complex methods. ➤ Applicability to sparse data: CR can handle sparse data, as it does not require large amounts of historical data.	➤ Deviation occurs easily: The CR method often produces biased forecasts, especially when demand is not purely intermittent. This may lead to overestimation or underestimation. ➤ Sensitive to smoothing parameters: The performance of this method depends heavily on the selection of smoothing parameters. It is challenging to select the correct parameters. Inappropriate selection of parameters can cause inaccurate forecasting. ➤ Only suitable for the stationarity assumption: The CR method assumes that the intermittent demand model remains stable over time. Significant changes in demand patterns may reduce its accuracy. ➤ Not applicable for forecasting seasonal demands: The CR method is not designed to handle seasonal demand patterns. Seasonal variation may result in poor forecasting.. ➤ Lacking in context data: The CR method mainly relies on historical demand data and does not account for external factors (e.g., market trends, promotions, or economic changes). This might limit its accuracy in some situations. ➤ Not applicable for continuous demands: The CR method is not applicable for continuous demand. Other forecasting methods may be more appropriate in such cases.

Demand Forecasting Method	Strengths	Weaknesses
SBA	➤ Calculation is simple: The calculation of SBA is relatively simple and easy to understand. ➤ Handle intermittent demands accurately: SBA is designed to handle intermittent demands and typically provides accurate forecasts for sporadic demands. ➤ Minimize forecasting error: SBA minimizes the mean square error of forecasting, reducing forecasting inaccuracies and optimizing inventory levels. ➤ Consider lead time: SBA can incorporate lead time, enabling enterprises to consider the time required to receive inventory when generating forecasting data. ➤ Most applicable for inventory management: SBA focuses on intermittent demands, making it suitable for inventory management systems that require an optimal inventory level of merchandise with sporadic demands.	➤ Limited adaptability: SBA is tailored for intermittent demands and performs poorly for items with a regular demand mode. Therefore, its adaptability in situations with continuous demands is limited. ➤ Rely on historical materials: Like many forecasting methods, SBA relies on historical demand data. If historical materials are limited or unrepresentative, this may result in inaccurate forecasts. ➤ Sensitive to hypothesis: The performance of SBA can be influenced by assumptions about the distribution of basic demands. If these hypotheses are not valid, its forecasts might not be that accurate. ➤ Lacking in context data: SBA primarily focuses on historical demand patterns and may not account for external factors (e.g., market trends, promotions, or economic changes). ➤ Not applicable for trend demands: SBA struggles to handle trend demand patterns effectively. If intermittent demand data contain an underlying trend, SBA may not capture it accurately. ➤ As with any forecasting method, it is crucial for an organization to assess its specific demand characteristics, the features of demand data, and the method's limitations before adopting Syntetos-Boylan's Approximation (SBA) for forecasting.

Table 1. (continued)

Demand Forecasting Method	Strengths	Weaknesses
TSB	➤ Applicable for intermittent demands: TSB is designed to handle intermittent demand mode, i.e., periods without demands followed by periods with demands. ➤ More accurate: Compared to other traditional forecasting methods, TSB typically provides more accurate forecasts for items with intermittent demand. ➤ Cope with noise data: Intermittent demand data often contain noise and irregularity. TSB is effective at processing data with irregular patterns. ➤ Include lead time: TSB can incorporate lead time information, enabling it to adapt to inventory management and production plans where lead time is a key factor.	➤ Complexity: Compared with simple forecasting methods, implementing and understanding the TSB method can be more complex. It requires a solid understanding of basic principles of statistics. ➤ Data requirement: TSB requires historical demand data. For items with intermittent demand, these data may be sparse, making it difficult to generate accurate forecasts. ➤ Sensitive to parameters: Like many forecasting methods, the performance of TSB is susceptible to the selection of parameters. Testing and adjustment may be necessary to identify the correct parameters. ➤ Limited adaptability: TSB is tailored for intermittent demands. For items with a regular demand pattern, their performance may be poor. ➤ Stationarity Assumption: TSB assumes that the demand patterns remain stable over time. If the demand model changes significantly, this method may fail to produce accurate forecasting. ➤ As with any forecasting method, selecting the Teunter-Syntetos-Babai method should be based on the specific features of the data and the organizations' forecasting requirements.
ML	➤ Adaptability: This method can process a large amount of complex data and adapt to various types of demand forecasting issues. ➤ Accuracy: With appropriate data and feature engineering, an ML model can achieve very high forecasting accuracy.	➤ Data demand: This method requires large amounts of high-quality historical data for training. ➤ Explainability: Some complex ML models are difficult to interpret, which may be problematic in certain application scenarios. ➤ The selection of appropriate demand forecasting methods depends on the availability of data, problem complexity, time horizon, and the need for accuracy and explainability. In practice, organizations often obtain more accurate and reliable forecasts by combining multiple methods.

● Machine Learning Methods (ML)

With the popularity of big data analysis, ML is widely used. ML is a branch of Artificial Intelligence (AI). It enables computer systems to learn rules from large amounts of data and then forecast and make decisions automatically without explicit program design. Its core methods include four types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. By processing data with

algorithms, ML models can improve based on experience. It is widely applied in recommendation systems, medical diagnosis, financial analysis, and other fields.

This technology is mainly classified into Multiple Linear Regression (MLR), Elastic Net (EN), Neural Network (NN), Support Vector Machine (SVM), and Random Forests (RFs), which are described as follows:

● Multiple Linear Regression (MLR)

MLR is a linear method used for modeling the relationship between one dependent variable (response variable) and multiple independent variables (forecasting variables).

● Elastic Net (EN)

EN is a penalized linear method. It combines the least absolute shrinkage and selection operator (LASSO) and penalized linear ridge regression (RR). This method selects variables through LASSO and shrinks the coefficients of RR for the relevant forecasting variables.

● Neural Network (NN)

Unlike the methods described above, a neural network employs a linear combination of forecasting variables as media (referred to as hidden units) for response modeling. These hidden units are generated by converting original forecasting variables using non-linear functions (e.g., the Sigmoid function).

● Support Vector Machine (SVM)

SVM aims to minimize the influence of abnormal values in response modeling. This method introduces a parameter to penalize samples with larger residual errors. Moreover, these samples may be converted with linear or non-linear functions (referred to as a kernel function).

● Random Forests (RF)

RF is different from the methods described above. In ML, RF is a classifier containing many decision trees, and its output category is determined by the mode of categories output by individual decision trees. It is an ensemble learning method based on bagging and fitting multiple classification and regression trees (CART). For regression problems, this method averages the forecasting results of each model to generate the final forecast. In addition, to reduce correlation, this method introduces randomness into the fitting process and randomly selects forecasting variables at each division. Strengths and weaknesses of the above forecasting method are summarized in the following table.

This study develops a new demand forecasting technology using a Hybrid Stacking (HS) method, which combines traditional time series forecasting methods with machine learning methods.

Table 2. Individual Strengths and Weaknesses of Widely Used Machine Learning Methods (Source: Compiled by this study)

Machine Learning Methods	Strengths	Weaknesses
MLR	➤ The model is simple, easy to understand, and explain. ➤ Computationally efficient and suitable for small -scale data. ➤ The output coefficients can directly explain the influence of variables.	➤ Assumes the existence of a linear relationship and does not apply to highly non-linear data. ➤ Sensitive to multicollinearity. ➤ Cannot perform variable selection automatically ; additional methods are required (e.g., stepwise regression).
EN	➤ Combines LASSO and Ridge regression, enabling both variable selection and handling of multicollinearity. ➤ Applicable to high-dimensional ($p \gg n$) problems. ➤ More stable than LASSO alone.	➤ Requires adjustment of two regularization parameters (α, λ), which is complex. ➤ Less interpretable than single linear regression.
NN	➤ Can capture highly non-linear complex relationships. ➤ Applicable to big and diversified data (e.g., images, voice, and text). ➤ Strong performance ; theoretically capable of approximating any functions (universal approximation).	➤ Requires large amounts of data and computational resources. ➤ Results are difficult to interpret (black box problem). ➤ Prone to overfitting ; requires regularization and cross-validation.
SVM	➤ Effective for processing non-linear data (through kernel functions). ➤ Performs well with high-dimensional data. ➤ Built on a solid mathematical foundation.	➤ Training time is lengthy and not suitable for large-scale datasets. ➤ Highly sensitive to the selection of hyperparameter s (C, γ) and kernel functions. ➤ Outputs are difficult to explain intuitively.
RF	➤ Can handle non-linear and high-dimensional data. ➤ Relatively insensitive to missing values and abnormal values. ➤ Automatically selects features and provides explanations for variable importance. ➤ Less prone to overfitting (more stable than a single decision tree).	➤ Less interpretable than linear models. ➤ Training and forecasting speed is slower than that of a single decision tree. ➤ For highly related variables, there might be a deviation in the importance assessment of variables.

TSB is selected as the time series forecasting method because it is suitable for the characteristics of reused spare parts, including intermittent

demand under a rational consumption trend, accurate forecasting, noisy and irregular data, and the inclusion of lead time information. RF is selected as the machine learning method because it can process non-linear, high-dimensional data and is relatively insensitive to missing values and abnormal values. It can also perform automatic feature selection, and the importance of variables is explainable. External information (EI) of enterprises is then incorporated into the above method to enhance the accuracy of forecasting.

2. Literature Review

Brown revealed the application of Simple Moving Average (SMA), SES, and other forecasting methods in inventory control. These methods are generalized forecasting approaches (i.e., they can be used to forecast the demand of any items) and are often applied to estimate the demand of parts [5]. Croston pointed out that SES is not suitable for intermittent or fluctuating demands (e.g., spare parts demands) and introduced a method named CR. This method calculates estimated demands based on the estimated demand scale and estimated demand intervals [7].

Syntetos et al. indicated that bias existed in the CR demand estimator [38]. Syntetos et al. proposed the Syntetos-Boylan Approximation (SBA), which modifies the demand estimator in CR [39]. Pour et al. proposed a method combining MLP with SES-based methods. Their method follows a two-stage process: at the first stage, MLP is used to calculate the estimated probability of demand occurrence; and at the second stage, if forecasted demand occurs, SES-based methods are applied to calculate the estimated demand size [35]. Gutierrez et al. reported that compared with the machine learning method NN, the traditional method CR performs worse but is less complex and requires less data. These two methods are accurate in different aspects, and each has its own advantages. They recommended combining ML and traditional forecasting methods [16]. This study was the first to use machine learning methods for forecasting intermittent or fluctuating demands. SES, CR, SBA, and MLP were employed to estimate daily spare parts demands in an electronic element distribution company. The dataset consisted of 24 time series, each containing 967 cycles.

Amin-Naseri et al. extended the scope by applying Generalized Regression Neural Network (GRNN) and Recurrent Neural Network (RNN). Their study used data from 30 time series (each including 67 cycles) to forecast the monthly spare parts demand for a petrochemical corporation [1]. Teunter et al. noted that, in addition to bias, CR is not well-suited for handling outdated issues. They proposed the Teunter-Syntetos-Babai's Method (TSB), which uses the probability of demand

occurrence to calculate estimated demands [42]. Sahin et al. demonstrated that machine learning methods, such as neural networks, are more accurate than traditional methods like CR in coping with spare parts demands by incorporating Time Delay Neural Network (TDNN) and Radial Basis Function Network (RBFN). These methods were used to forecast monthly parts demands for airplane maintenance companies based on 90 time series (each with 62 cycles) [40].

Wang et al. examined how to forecast parts demands using weather information and other EIs. The rationale is that temperature, humidity, and other weather conditions affect equipment operation, leading to equipment breakdown and eventually triggering demands for spare parts [44]. Support Vector Machine (SVM) was used to forecast monthly parts demands for airplane power companies based on 17 time series. The monthly highest temperature was included as one of the forecasts, with a threshold value set for this variable, to convert it into a binary variable. Each time series contained 108 cycles. This study also demonstrated how to convert forecasting results into an inventory policy.

Su proposed a decision optimization model for multiple parts and multiple equipment to assess the cost effectiveness and carbon dioxide emissions of the remanufacturing system. This provides a framework for remanufacturing decisions in the after-sales market [41]. Kin et al. (2014) proposed a product renovation process that is selected and planned based on the conditions of the old products. Fang et al. proposed a remanufacturability assessment framework for products and a comprehensive framework of remanufacturing process planning [12]. Jiang et al. proposed an optimization method for remanufacturing process planning that considers reliability and cost [22]. Lolli et al. retrospectively applied various NN-based methods to estimate the weekly spare parts demand of an automobile company using data from 24 time series (each containing 61~414 cycles) [29].

Wang et al. proposed an optimization method to represent the failure features of a remanufacturing program plan, aiming to obtain an optimal program plan [43]. Boone et al. demonstrated how Google Trends can help estimate the weekly food demands of a food retail company using EI [4]. Liu et al. extended Wang et al.'s study by including additional weather information, such as rain and snow [28]. In their study, information was repeatedly converted into these variables so that they could be used as ordinal variables. Yan et al. discussed a V-support vector machine and its application in sales forecasting [45]. Sridevi et al. developed an effective time series data forecasting system using a machine learning algorithm [37]. Peng et al. proposed a method to optimize and

assess the efficiency of the remanufacturing process, as efficiency plays a key role in remanufacturing systems [34]. Cui et al. examined working conditions of bearings, material selection, failure causes, and damage levels, and proposed an optimization method for bearing remanufacturing based on a failure model to address complex and diverse process issues [6]. Mayer and Grófa provided a broad comparison of models that forecast and calculate physical photovoltaic (PV) power using numerical weather prediction data [30], [32].

Kong et al. proposed a series of novel methods based on a deep all-sky image learning framework to forecast very short-term solar photovoltaic power generation [24],[31]. Huang et al. proposed a remanufacturing solution design method for the refactoring of waste parts with incomplete information [18]. Guo et al. developed a multi-objective model for remanufacturing operations that considers completion time, cost, load balance, and energy consumption, using the fuzzy theory [15]. Du Plessis et al. addressed short-term solar energy forecasting and used a deep learning model to capture the low-level behavior of utility-scale electro-optical systems [10]. Dong et al. developed a mixed forecasting model to improve the accuracy and stability of wind power forecasting [8],[11]. Konstantaras et al. proposed green supply chain management strategies, including closed manufacturing and carbon footprint reduction. These strategies enable companies to improve their environmental performance and comply with relevant environmental regulations. Their study presented a supply chain system that integrates manufacturing, remanufacturing, and maintenance activities (closed-loop manufacturing) to meet time-varying demand under a carbon tax regulation framework [25]. Nag et al. reviewed the literature on the recycling economy and noted a growing concern about environmental protection and excessive resource consumption, which has led to the development of new industrial production technologies and sustainable development activities. Remanufacturing technology helps preserve the value of waste products and reduce resource consumption and pollution, thereby contributing to sustainable development [33]. Ing. Kateřina Pitnerová concludes that the best tolls of demand management rely on specific needs and circumstances of a business [21].

Sareminia and Amini studied forecasting for slowly supplied spare parts, considering the development of reliable integrated data while accounting for management characteristics (e.g., service capability and irregular maintenance) and time consumed (order volume and time interval between two charges). They introduced a clustering management model for spare parts classification, which was used to sort and forecast 51,335

unmarketable spare parts of a steel company. The results showed that their proposed method and integrated model enhanced the reliability of spare parts inventory (accuracy increased by 80% and newly defined reliability rose by 10%) [36]. Babaveisi et al. proposed two mathematical models. The first model considered a quantitative model of definite inventory level, allocation of suppliers' spare parts orders, allocation of equipment repair, and planning time. The second model was an SVM-based forecasting model. To address demand uncertainty, demand estimation was conducted through piecewise linearization, with the target defined as the optimal number of intervals. They conducted an empirical study using spare parts supply chain data from an oil company, where demands were estimated using the piecewise method and costs were optimized through integrated decision-making to enhance the accuracy of forecasting and planning performance [3]. Arindam Mukherjee underscore the significance of Big Data in reshaping supply chain strategies and enhancing the responsiveness of modern businesses in a dynamic market environment [2].

This study examines how enterprises can implement efficient and accurate intelligent demand forecasting methods, as well as optimal recycling and reuse solutions. It is divided into two stages: (I) development of an intelligent demand forecasting method to design capacity and control inventory effectively; (II) establishment of an optimal recycling and reuse solution for spare parts. Two forecasting methods proposed successively were compared at the first stage to identify the most suitable approach, enabling enterprises to plan investment and allocate facilities, equipment, raw materials, inventory, and resources more accurately and deliver products and services more efficiently. The second stage simulates the identification of the most suitable spare parts production combination through in-depth interviews with enterprises and analysis of big data. Dimensionality reduction of variables was conducted using Principal Component Analysis (PCA) to rapidly identify and determine the most suitable combination of recycling and reuse.

The comparison of key literature from recent years is presented below.

Table 3. Comparison between Differences of Important Literature of Recent Years ("V" means it is ever used)

Literature	Demand Forecasting Technology	Inventory Policy of Spare Parts	Reuse Solution	Empirical Study
Brown, R. G. (1959)	V			V
Croston, J. D. (1972)	V	V		
Syntetos, A. A. & Boylan, J. E. (2001)	V			
Syntetos, A. A. et al. (2005)	V			
Pour, A. N. et al. (2008)	V	V		
Gutierrez, R. S. et al. (2008)	V	V		V
Teunter, R. H. et al. (2011)	V			V
Sahin, M. et al. (2013)	V	V		V
Wang, Z. et al. (2014)	V	V		V
Su, T. S. (2014)		V	V	V
Kin, S. et al. (2014)			V	
Fang, H. C. et al. (2016)			V	
Jiang, Z. G. et al. (2016)			V	V
Lolli, F. et al. (2017)	V	V		V
Wang, H. et al. (2017)			V	
Boone, T. et al. (2018)	V			V
Liu, Y. et al. (2018)	V	V		V
Yan, H. et al. (2018)	V			
Sridevi, S. et al. (2018)	V			
Peng, S. T. et al. (2019)			V	V
Cui, X. et al. (2019)			V	V
Mayer M. J. & Grófa G. (2020)	V			V
Kong W. et al. (2020)	V			V
Huang, W. H. et al. (2020)			V	V
Guo, J. et al. (2020)			V	V
du Plessis A. A. et al. (2021)	V			V
Dong Y. et al. (2021)	V	V	V	V
Konstantaras, I. et al. (2021)			V	V
Nag, U. et al. (2022)			V	V
Sareminia, S. and Amini, F. (2023)	V	V		V
Babaveisi, V. et al. (2023)	V	V		V
This study	V	V	V	V

3. Modeling

3.1 Intelligent Demand Forecasting

This study developed a hybrid stacking demand forecasting method, which combines traditional time series forecasting techniques with machine learning approaches. Enterprise EI is then introduced into this method to enhance the accuracy of forecasting. A common issue with spare parts demand data in forecasting is its single-variable nature (i.e., the data do not contain

additional independent variables that can serve as additional forecasting variables). To address this problem, EI is employed as an additional forecasting factor. As shown in the study process figure, the main objective is to improve the forecasting capability for industrial spare parts demand through “ensemble forecasting”.

Intelligent demand forecasting not only improves the accuracy of forecasting but also strengthens the agility of enterprises, enabling them to respond effectively to market changes and customer demands. It is a crucial component of supply chain management, inventory optimization, and overall business planning, enabling organizations to make data-driven decisions and maintain competitiveness in a dynamic market. This study attempts to apply ensemble forecasting within intelligent demand forecasting methods. “Ensemble forecasting” is a method that combines multiple forecasting models to increase forecasting accuracy. The basic principle is to combine the results of several independent forecasting models to achieve more stable and precise outcomes. This approach is designed to handle complex issues that a single model cannot address effectively. Furthermore, it performs well when forecasting uncertainty is higher.

Stacking is an ensemble learning technique that aims to minimize the error of one or multiple forecasting methods. When multiple forecasting methods are used, the principle is to form a linear combination of these methods and then estimate the coefficients within the combination. The first method proposed in this study is called Hybrid Stacking (HS), which is designed to combine traditional methods with machine learning through a stacking approach. Its conceptual framework is shown in Figure 1.

This study employs TSB and RF, representing traditional and non-linear methods, respectively. Relevant literature has shown that their performance in specific aspects of this study may be more effective. The study will refer to the estimated demand in each period obtained from TSB and the estimated demand in each period obtained from RF. The possible HS of the two methods is presented as follows:

Meaning of symbols:

α_0 : the intercept

α_1 : coefficient of

α_2 : the coefficient of

ϵ_t : the random error in the period

$\hat{\alpha}_0$: the estimated intercept

$\hat{\alpha}_1$: the estimated coefficient of

$\hat{\alpha}_2$: the estimated coefficient of

λ_1 : the RR(ridge regression) penalty

λ_2 : the LASSO penalty

y_t : the demand in the period

$\hat{y}_t$: the estimated demand in the period

$\bar{y}_t$: the estimated demand size in period t

$\bar{y}_{t-1}$: the estimated demand size in period $t - 1$

$\hat{d}_t$: the estimated probability of demand occurrence in period t

$\hat{d}_{t-1}$: the estimated probability of demand occurrence in period $t - 1$

a, b : the smoothing constants in the range of $0 \leq a, b \leq 1$

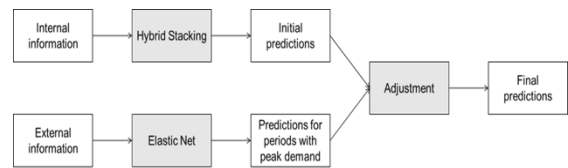


Figure 1. Framework of Hybrid Stacking Method

TSB (Teunter-Syntetos-Babai) is primarily used to address two issues in CR: the presence of deviation and CR's inability to resolve outdated problems. TSB estimates the demand for the next cycle by multiplying the estimated demand scale by the probability of demand occurrence in the next cycle. In this method, the estimated demand formula for the next cycle $\hat{y}_t$ to current cycle is:

$$\text{if } y_t = 0: \bar{y}_t = \bar{y}_{t-1}, \hat{d}_t = \hat{d}_{t-1} + b(0 - \hat{d}_{t-1}), \hat{y}_t = \bar{y}_t \hat{d}_t \quad (7)$$

$$\text{if } y_t > 0: \bar{y}_t = ay_t + (1-a)\bar{y}_{t-1}, \hat{d}_t = \hat{d}_{t-1} + b(1 - \hat{d}_{t-1}), \hat{y}_t = \bar{y}_t \hat{d}_t \quad (8)$$

For intelligent demand forecasting, the traditional time series forecasting method TSB and the machine learning method RF, are integrated into a demand forecasting method. Then, EI is incorporated into the above-mentioned method. HS technology is employed, and EI is introduced to capture the major peak value demand, thereby reducing forecasting error.

This study assumes a linear relationship between $\hat{y}_{TSB,t}$ and $\hat{y}_{RF,t}$, $t=\{1,2,\dots,n\}$. Thus, the demand function can be expressed as:

$$y_t = \alpha_0 + \alpha_1 x_{1,t} + \alpha_2 x_{2,t} + \dots + \alpha_p x_{p,t} + \epsilon_t$$

With an estimated value $\alpha_j = \{\alpha_1, \alpha_2, \dots, \alpha_p\}$, the demand estimation function for a given period can be expressed as:

$$\hat{y}_t = \hat{\alpha}_0 + \hat{\alpha}_1 x_{1,t} + \hat{\alpha}_2 x_{2,t} + \dots + \hat{\alpha}_p x_{p,t}$$

As in EN, regularization is employed in SSER to address issues arising when $n_p \gg n_n$. The formula

to estimate the minimum SSR (sum of squared residuals) is as follows:

$$SSR = \sum_{t=1}^n (y_t - \hat{y}_t)^2 + \lambda_1 \sum_{j=1}^p \alpha_j^2 + \lambda_2 \sum_{j=1}^p |\alpha_j|$$

3.2 Forecasting Error

Mean absolute scaled error (MASE) is a forecasting error indicator based on scaled error. It addresses limitations of error indicators based on relative error and relative measures. MASE scales forecasting error against the in-sample Mean Absolute Error (MAE) forecasted randomly. The formula for this indicator is as follows:

$$MASE = \frac{1}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{\frac{1}{n-1} \sum_{i=2}^n |y_i - y_{i-1}|} \right|$$

where n is the number of cycles included in the calculation, y_t is the demand of cycle t , and $\hat{y}_t$ is the estimated demand of cycle $t-1$. y_i and y_{i-1} are the demands of cycle i and cycle $i-1$, respectively. MASE is considered an optimal forecasting error indicator when handling intermittent or uneven demands.

Relative Geometric Root Mean Square Error (RGRMSE) is a forecasting error indicator based on relative measurement, which aims to overcome issues with the RMSE. This indicator scales forecasting error against the Geometric Root Mean Squared Error (GRMSE). This study adjusted MASE and used GRMSE of out-of-sample naive forecasting as the denominator of this indicator. Therefore, this indicator can be expressed as:

$$RGRMSE = \frac{(\sum_{t=1}^n (y_t - \hat{y}_t)^2)^{\frac{1}{2n}}}{(\sum_{i=2}^n (y_i - y_{i-1})^2)^{\frac{1}{2n}}}$$

where, y_t is the demand of cycle t , $\hat{y}_t$ is the demand estimation of cycle t at cycle $t-1$. For demands estimation at cycle t , n is the number of cycles contained in the calculation. y_i and y_{i-1} are the demands of cycle i and cycle $i-1$, respectively. GRMSE is considered a suitable indicator of forecasting error when dealing with intermittent or block demands.

4. Case Study

The case study examines spare parts for the equipment of an unnamed company in China. The spare part is a recycled component of a power module used in industrial surface treatment, which contains both Type-A and Type-B components. This part belongs to the generator module shaft seal, as shown in Figure 2.



Figure 2. Spare Part of Generator Shaft Seal

Table 4. Comparison between Forecasting Errors of Different Methods

Method	MASE		RGRMSE	
	Type-A	Type-B	Type-A	Type-B
Anonymous Company's	0.9263	1.2602	0.9564	0.9754
SMA	0.9263	1.2602	0.9564	0.9754
SES	0.8404	1.2202	0.9661	0.9752
CR	0.7104	1.0975	0.9480	0.9652
SBA	0.8457	1.1291	0.9488	0.9633
TSB	0.6922	0.9910	0.9497	0.9588
MLR	0.6763	1.0189	0.9356	0.9571
EN	0.5562	0.7300	0.9344	0.9479
NN	0.7710	1.3811	0.9495	0.9810
SVM	0.6744	1.0940	0.9508	0.9617
RF	0.5693	0.8522	0.9366	0.9479
HS	0.5552	0.7963	0.9366	0.9423
HS+EI	0.3911	0.4990	0.9016	0.9037

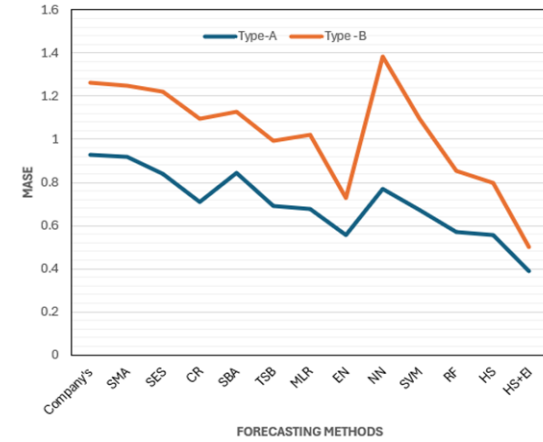


Figure 3. Comparison between Forecasting Errors (MASE) of Different Forecasting Methods

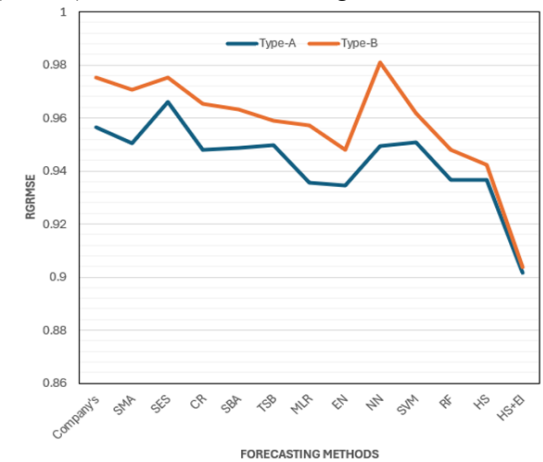


Figure 4. Comparison between Forecasting Errors (RGRMSE) of Different Forecasting Methods

The methods adopted in the case study, along with their corresponding forecasting error results, are presented in Table 4. The improved method achieved the lowest MASE and RGRMSE in both situations. Moreover, in the case of demand fluctuation (i.e., demand for spare part A), the MASE ranking of the basic method was the second smallest, although its RGRMSE performance is not similar. In contrast, when demand was unstable (i.e., demand for spare part B), the RGRMSE ranking of the improved method was the second smallest, although its MASE performance is not similar. These results demonstrate that combining traditional methods with machine learning methods can yield more accurate spare parts demand forecasting. Furthermore, these results indicate that incorporating EI can further enhance these forecasts. In summary, the findings suggest that the methods proposed in this study are promising. From a management perspective, compared with the actual forecasted MASE and RGRMSE values, when EI is not used, the proposed methods can reduce error values by 40.062% (36.812%) and 2.070% (3.393%) for irregular demand (unstable demand). When EI is used, the proposed methods can reduce error values by 57.778% (60.403%) and 5.730% (7.351%).

Table 5. Error Value Improvement Rate of Different Forecasting Methods (%)

Method	MASE		RGRMSE	
	Type-A	Type-B	Type-A	Type-B
Anonymous Company's	0.000	0.000	0.000	0.000
SMA	0.659	0.809	0.606	0.502
SES	9.273	3.174	1.014	0.021
CR	23.308	12.911	0.878	1.046
SBA	8.701	10.403	0.795	1.241
TSB	25.273	21.362	0.701	1.702
MLR	26.989	19.148	2.175	1.876
EN	39.955	42.073	2.300	2.819
NN	16.766	9.594	0.721	0.574
SVM	27.194	13.188	0.586	1.405
RF	38.540	32.376	2.070	2.819
HS	40.063	36.812	2.070	3.393
HS+EI	57.778	60.403	5.730	7.351

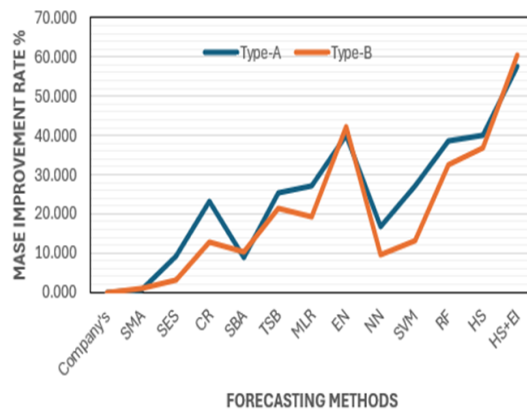


Figure 5. Error Value Improvement Rate (MASE) of Different Forecasting Methods (%)

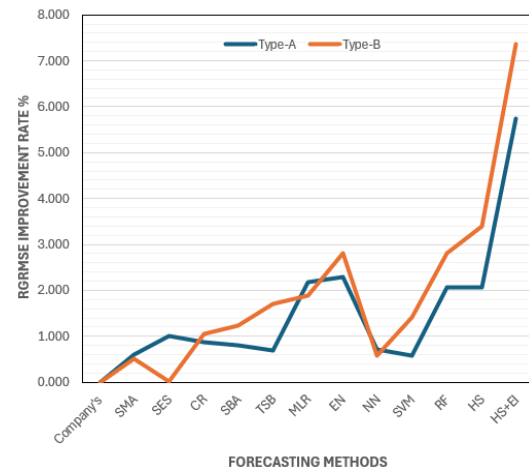


Figure 6. Forecasting Error Value (RGRMSE) Improvement Rate of Different Forecasting Methods (%)

5. Conclusions

The accuracy of spare-parts demand forecasting is a critical determinant of effective maintenance and inventory management. Nevertheless, such forecasting remains inherently challenging due to the highly intermittent and volatile nature of parts demand, which often exhibits substantial fluctuations in both demand magnitude and inter-arrival intervals. To address these complexities, literature has proposed a variety of specialized forecasting techniques. This study introduces two methods designed to improve forecasting performance under such conditions. The baseline approach is a Hybrid Stacking (HS) framework that integrates classical time-series models with contemporary machine-learning algorithms in a multi-layer structure. The enhanced approach extends the HS method by incorporating External Information (EI), enabling the model to capture exogenous factors that may influence demand dynamics. Both methods were empirically evaluated through a case study involving monthly demand forecasts for two types of spare parts characterized by irregular and sparse consumption patterns. For benchmarking purposes, multiple traditional and machine-learning forecasting methods were also implemented. Comparative analyses using Mean Absolute Scaled Error (MASE) and Relative Gradient Root Mean Squared Error (RGRMSE) demonstrate that the proposed methods achieve superior forecasting accuracy and exhibit strong potential for practical application in spare-parts demand management..

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