XGBoost modeling for sparse spare-parts demand forecasting

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ABSTRACT

Spare parts demand in many industrial systems is inherently sparse and intermittent. In practice, long periods of zero usage are common, even though inventory must still be maintained to ensure operational reliability. This situation increases holding costs and the risk of obsolescence, while also limiting the effectiveness of conventional forecasting techniques. This study demonstrates that a global XGBoost model trained across multiple spare-part items significantly outperforms item-specific models under sparse demand conditions. Using six years of historical spare-parts usage and procurement data from the energy sector, this study compares global and single-item extreme gradient boosting (XGBoost) modeling strategies. Forecast accuracy is evaluated using mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and median absolute error (MdAE), which is particularly suitable for zero-inflated demand patterns. The results consistently show that the global XGBoost model achieves lower errors across all metrics. In particular, the global model attains a markedly lower MdAE (0.00018), indicating greater robustness when demand is irregular and intermittent.

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1. INTRODUCTION

Spare-parts demand in many industrial settings is characterized by sparse and intermittent usage, where long periods of zero demand are common while inventory must still be maintained to ensure operational continuity [1]–[3]. This condition increases inventory holding costs and the risk of obsolescence, particularly for slow-moving and critical components [4], [5]. Conventional forecasting approaches, including classical time-series and intermittent-demand methods, often struggle under such conditions, especially when historical observations are limited [3], [5]. In the dataset analyzed in this study (2020–2025), approximately 90.6% of monthly observations correspond to zero demand, confirming the highly sparse nature of spare-parts usage. To address these challenges, machine-learning-based forecasting methods have been increasingly adopted due to their ability to model non-linear relationships and handle heterogeneous data structures [6]. Among these methods, tree-based ensemble algorithms, particularly extreme gradient boosting (XGBoost), have demonstrated strong performance in forecasting tasks involving irregular and zero-inflated demand [7]–[9].

Beyond algorithm selection, the modeling strategy itself plays a critical role when demand data are sparse. Global modeling approaches train a single model across multiple items, enabling shared demand patterns to be learned jointly, whereas single-item models are trained independently for each item [1], [2]. Prior studies report that global models often provide more robust forecasts when individual time series are short or highly intermittent [10]. However, empirical comparisons between global and item-specific XGBoost models for highly sparse spare-parts demand remain limited, particularly in industrial inventory contexts. Table 1 summarizes representative studies comparing global and single-item forecasting approaches across different application domains. This overview motivates the focus of the present study on comparing global and single-item XGBoost models for sparse spare-parts demand forecasting.

Table 1. Comparison of global and single-item forecasting approaches in previous studies

Ref.	Focus	Dataset / application domain	Methods / algorithms	Key contribution
[1]	Global modeling for grouped time series	Large-scale forecasting competition datasets	Global recurrent neural networks (RNN)	Demonstrated that global models outperform local models by sharing information across related time series, particularly when individual series are short or sparse
[2]	Global modeling under heterogeneous demand patterns	Diverse real-world forecasting datasets	Global probabilistic forecasting models	Reported that global models achieve more robust performance across series with varying demand characteristics
[5]	Single-item (local) modeling for intermittent demand	Spare parts and intermittent demand datasets	Croston-based local forecasting methods	Identified performance limitations of single-item models when historical demand observations are sparse and highly intermittent
[9]	Global modeling for energy demand forecasting	Energy consumption and smart-meter data	Global long short-term memory (LSTM) – XGBoost hybrid models	Reported that global learning across multiple series improves robustness and prediction accuracy under non-linear and fluctuating demand patterns
[10]	Global modeling for multiple time series	Retail and demand time-series data	Global machine learning–based forecasting models	Reported improved forecast accuracy and stability compared to single-item models under data scarcity

2. METHOD

2.1. Research workflow

This study adopts a quantitative research design to evaluate two forecasting strategies for sparse spare-parts demand based on a machine-learning model. Specifically, the strategies compare global and single-item modeling approaches using XGBoost. The workflow consists of data collection and preprocessing, feature engineering, model development, time-based data splitting, and model evaluation.

2.2. Dataset and feature engineering

The analysis uses monthly spare-parts usage and procurement records obtained from an energy-sector organization over a six-year period (2020–2025). A purposive sampling approach was adopted to concentrate on spare parts that exhibit sparse and intermittent demand, which is typical in industrial maintenance environments. Feature engineering was applied to convert raw transactional records into meaningful input variables for machine-learning modeling under sparse demand conditions. Temporal features were derived from historical usage and procurement data to capture recent demand behavior. In particular, two-month lag variables were included to represent short-term dependency, reflecting the limited memory commonly observed in intermittent demand. Rolling features were calculated to smooth irregular month-to-month fluctuations and provide a more stable representation of recent demand levels. To preserve the temporal order of observations, additional time-related indicators such as month and year were included. These indicators help the model distinguish between different periods in the historical data while avoiding the imposition of strong or predefined seasonal patterns. The final set of engineered features resulting from this process is summarized and discussed in the results section.

2.3. Modeling strategy and hyperparameter configuration

Forecasting models were developed using XGBoost, a tree-based ensemble learning algorithm that incrementally improves predictive performance through gradient boosting optimization [7]. Two modeling strategies were examined. In the global modeling approach, a single XGBoost model was trained on pooled observations from multiple spare-parts items, allowing the model to learn shared demand structures across items. In contrast, the single-item modeling approach trained independent XGBoost models for each spare part using item-specific historical data, which can limit model stability when observations are sparse [2], [5].

Traditional forecasting approaches commonly used for intermittent demand, such as autoregressive integrated moving average (ARIMA)-based models and Croston-type methods, are primarily designed for item-level analysis. While these methods are effective for individual time series with sufficient historical data, they have limited capability to capture shared patterns across multiple heterogeneous items. As a result, their performance often degrades when demand data are sparse and highly intermittent. Therefore, Croston-type and ARIMA-based methods are not included as numerical baselines in this study, as the primary objective is to isolate the effect of global versus single-item modeling strategies within a consistent machine-learning framework rather than to compare different classes of forecasting algorithms [3], [5].

In the global modeling approach, individual spare-part items are distinguished implicitly through their historical usage and procurement patterns rather than through explicit categorical encoding. Item identifiers are retained only to associate observations with the same item, while shared demand characteristics are learned from numerical features such as lagged usage, rolling aggregates, and inventory-related variables. This design allows the XGBoost model to generalize across multiple items without requiring explicit item-level encoding.

Zero-demand observations are fully retained during both training and evaluation to reflect the true intermittent nature of spare-parts demand. The proposed models generate point forecasts of exact demand quantities rather than probability-weighted outputs. Robustness to zero-inflated demand is therefore assessed through error-based evaluation metrics, particularly the median absolute error (MdAE), which provides a stable representation of typical forecasting error under sparse demand conditions.

Recent developments in machine-learning-based time-series forecasting suggest that complex temporal dynamics can be modeled more effectively when information is learned jointly across related series [11], [12]. Neural forecasting approaches further support this capability by capturing non-linear demand behavior in sparse and high-dimensional settings [13], [14]. Probabilistic forecasting models extend this idea by explicitly modeling uncertainty and variability in intermittent demand patterns [15], [16]. In addition, large-scale global learning frameworks have been shown to improve forecasting robustness in industrial and energy-related applications, particularly when individual time series are short or highly intermittent [17], [18]. Similar benefits of cross-series learning have also been reported in recent studies focusing on neural and state-space-based forecasting models [19]–[21], as well as in broader surveys of large-scale time-series forecasting methods [22]–[25]. Against this methodological background, the present study adopts XGBoost as a representative machine-learning model and focuses on comparing global and single-item modeling strategies. The conceptual difference between global and single-item modeling strategies adopted in this study is illustrated in Figure 1.

For the global XGBoost model, key hyperparameters were selected through preliminary tuning to balance model complexity and generalization under sparse demand conditions. The learning rate was set to 0.05, the maximum tree depth was limited to 4, and the number of boosting trees was fixed at 300. In addition, subsample and colsample_bytree ratios were set to 0.8 to improve robustness and reduce the risk of overfitting.

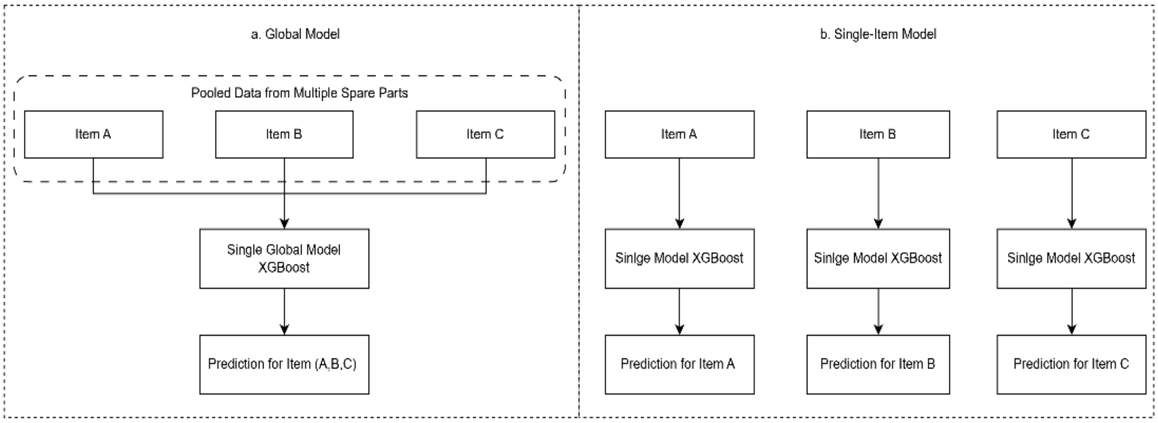

Figure 1. Comparison of global and single-item modeling strategies for sparse spare parts demand

2.4. Model evaluation

A time-based data-splitting strategy was employed to preserve temporal structure and prevent information leakage. Data from 2020 to 2024 were used for training, while 2025 data were reserved for testing. Forecast accuracy was assessed using mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and MdAE. MdAE was selected to represent typical error under sparse and zero-inflated demand conditions [26].

3. RESULTS AND DISCUSSION
3.1. Feature engineering outcome and model performance
Following the feature engineering process described in the method section, Table 2 presents the final set of features used for machine learning modeling. The constructed features represent item identity, basic temporal information, and short-term demand dynamics derived from historical usage and procurement data. Lagged usage and purchase variables provide localized temporal signals, while rolling averages offer a smoothed representation of recent demand intensity. Together, these features enable the global XGBoost model to generalize across items with limited historical observations, which is essential under sparse and zero-inflated demand conditions.

Table 2. Final feature set for machine learning modeling

Feature	Description
Item spare part	Unique identifier of the spare parts item
Month	Month index covering a six-year period
Year	Year index covering a six-year period
Spare part usage	Monthly spare parts usage over a six-year period
Lag1 spare part usage	Spare parts usage one month prior
Lag2 spare part usage	Spare parts usage two months prior
Rolling2 spare part usage	Rolling average of spare parts usage over the previous two months (Lag1 and Lag2)
Spare part purchased	Monthly spare parts purchase quantity over a six-year period
Lag1 spare part purchased	Spare parts purchase quantity one month prior
Lag2 spare part purchased	Spare parts purchase quantity two months prior
Rolling2 spare part purchased	Rolling average of spare parts purchase quantity over the previous two months (Lag1 and Lag2)

3.1.1. Model performance
Global and single-item XGBoost models were trained using data from 2020 to 2024 and evaluated on out-of-sample demand in 2025. Across all evaluation metrics, the global model consistently outperformed the single-item model. As reported in Table 3, the global model achieved substantially lower MAE (0.0162 vs. 0.1980), RMSE (0.1336 vs. 0.3538), and MAPE (7.90% vs. 29.41%), indicating more accurate average demand estimation. In addition to mean-based metrics, robustness under sparse demand conditions is further reflected by the MdAE. Given the zero-inflated nature of spare-parts demand, where many observations are close to zero, MdAE provides a more representation measure of typical prediction error. The global model attained a markedly lower MdAE (0.00018) compared to the single-item model (0.00181), indicating greater stability under highly intermittent demand conditions.

Table 3. Metric evaluation results

Metric evaluation	Global model	Single-item model
MAE	0.01616	0.19804
RMSE	0.13364	0.35378
MAPE	7.90307	29.41195
MdAE	0.00018	0.00181

These results are further illustrated in Figure 2, which compares actual spare-parts usage in 2025 with forecasts generated by both modeling strategies. The global model shows closer alignment with observed demand across most items, while the single-item model exhibits larger deviations, particularly for low-usage and highly intermittent items. Overall, the findings indicate that the global modeling approach provides more accurate and stable forecasts under sparse demand conditions.

3.2. Discussion
Before discussing the implications of model performance, it is useful to clarify how the engineered features contribute to the forecasting results. The combination of item identifiers, time-related indicators, and short-term lag and rolling features enables the global model to capture both similarities across items and recent demand behavior under sparse conditions. Lagged usage and procurement features provide localized temporal signals, while rolling averages help smooth irregular fluctuations that are typical of intermittent demand. Together, these feature representations support more effective generalization when historical observations are limited, which is reflected in the superior performance of the global model.

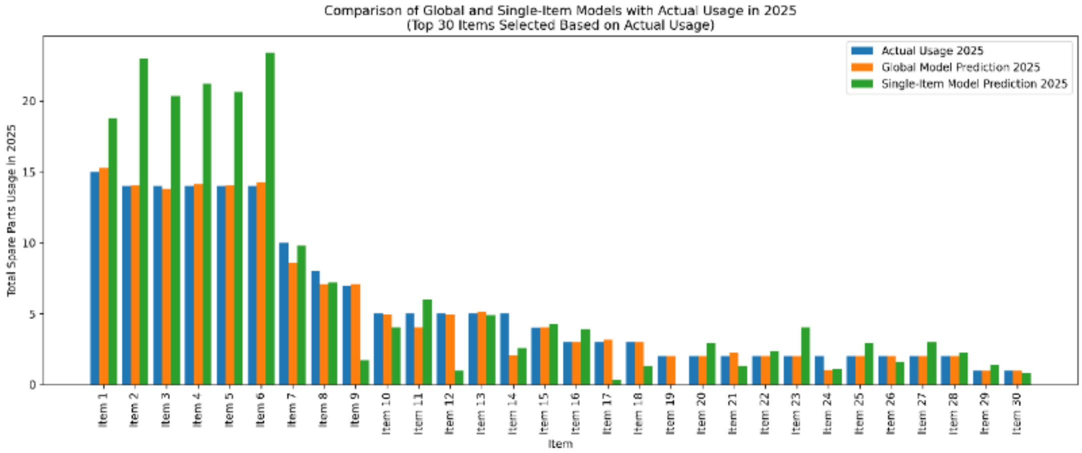

Figure 2. Comparison of global and single-item modeling strategies for sparse spare parts demand

The superior performance of the global model can be attributed to its ability to leverage shared temporal structures and cross-item demand characteristics. By pooling information across multiple spare-parts items, the global model is able to capture weak but consistent demand signals that are difficult to learn when models are trained independently for each item. In contrast, single-item models rely solely on item-specific histories and are therefore more susceptible to overfitting and unstable parameter estimation when data are limited. This finding is consistent with prior studies on global time-series forecasting models, which highlight the benefits of cross-series learning under sparse and heterogeneous demand conditions [10], [15]. From an operational standpoint, improved forecast stability is particularly relevant for critical spare parts with low usage frequency. More reliable demand estimates can reduce the tendency toward excessive safety stock while supporting timely replenishment decisions during unplanned maintenance events. This is especially important for slow-moving and high-value spare parts, where both overstocking and stock-out risks carry significant operational and financial consequences. A more detailed analysis of item-level failure cases and explicit cost quantification is left for future work, as it requires additional operational data beyond the scope of this study.

Although the global modeling approach consistently outperforms the single-item model on average, its effectiveness varies with the degree of demand sparsity. For items with moderate sparsity, where occasional non-zero demand provides informative signals, global modeling benefits from cross-item learning and produces more stable forecasts. However, for items exhibiting extreme sparsity, characterized by prolonged sequences of zero demand and very limited non-zero observations, the advantage of global modeling becomes less pronounced. In such cases, both global and single-item models tend to generate near-zero forecasts, resulting in similar predictive performance. Under these conditions, percentage-based error measures such as MAPE are only informative during non-zero demand periods, while absolute-error metrics provide a more consistent indication of model behavior across highly sparse series. This limitation under extreme sparsity is also consistent with findings in intermittent-demand forecasting literature [3].

These observations highlight potential failure scenarios for global modeling, particularly when demand information is insufficient even after pooling data across items. Under extreme sparsity, shared patterns across items provide limited additional guidance, and the global model may offer only marginal improvement over item-specific approaches. This limitation suggests that the benefits of global learning are most evident when sparse demand still contains weak but informative temporal signals.

From a practical standpoint, improvements in forecasting accuracy and stability have direct implications for inventory decision-making. Lower typical forecasting errors reduce uncertainty in demand estimates, which can help prevent excessive safety stock allocation, particularly for slow-moving and high-value spare parts. More stable forecasts also support better timing of replenishment decisions, thereby lowering inventory holding costs and reducing the risk of obsolescence. These findings are consistent with prior research on intermittent-demand inventory control and spare-parts management [5].

In addition, improved forecast reliability contributes to service level performance by reducing the likelihood of stockouts during unplanned maintenance events. While this study does not explicitly quantify cost savings or service level improvements, the observed reduction in forecasting errors suggests meaningful potential benefits in terms of inventory efficiency, safety stock optimization, and operational reliability in industrial maintenance environments.

4. CONCLUSION

This study shows that global XGBoost modeling provides more accurate and robust forecasts than single-item modeling under sparse and intermittent spare-parts demand conditions. By learning shared demand patterns across multiple items, the global model consistently achieves lower average and typical errors across all evaluation metrics, including MdAE. From a practical perspective, the improved stability of global forecasts supports more reliable inventory planning by reducing uncertainty in procurement decisions. This can help organizations balance spare-parts availability with inventory holding costs, particularly for critical and slow-moving items. Overall, global modeling offers a scalable and data-efficient foundation for intermittent-demand forecasting in industrial inventory systems. Beyond spare-parts applications, the proposed global modeling framework is also applicable to other sparse-demand forecasting domains, such as energy consumption, retail inventory management, and IoT-enabled systems. Future research may extend this work by incorporating longer historical datasets, multi-industry validation, rolling-origin evaluation, and the integration of transfer learning and explainable machine-learning techniques to further enhance robustness and interpretability.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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