Postprint: Decomposition-Ensemble Based Interval Prediction of Air Cargo Demand

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Abstract

Air cargo constitutes a crucial strategic resource for the nation and plays an indispensable role in domestic and international trade. Scientific forecasting of aviation freight demand serves as an important basis for airlines to formulate infrastructure planning and overall investment decisions. Addressing the uncertainty in aviation freight volume data and proceeding from practical needs, this paper introduces the Bootstrap method for uncertainty estimation and proposes a decomposition-ensemble based interval forecasting method. Specifically, first, the freight demand data is decomposed using the Seasonal-Trend decomposition using Loess (STL) method; second, the trend component and seasonal component are predicted by Support Vector Regression (SVR) and Seasonal Autoregressive Integrated Moving Average (SARIMA), respectively; third, the white noise component is innovatively extracted and resampled using the Bootstrap method; finally, the forecasting results and the processed white noise are integrated and reconstructed, and quantiles are used to construct intervals for uncertainty quantification. Experimental results on freight data from two major hub airports in China demonstrate that the constructed intervals can effectively quantify uncertainty in conjunction with forecasting results, providing a new research approach for interval forecasting.

Full Text

Preamble

Research on Interval Prediction of Air Cargo Demand Based on Decomposition Integration

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Abstract: Air cargo constitutes a crucial strategic resource for the nation and plays an indispensable role in domestic and international trade. Scientific forecasting of air cargo demand serves as a vital foundation for airlines to formulate infrastructure planning and overall investment decisions. Addressing the uncertainty inherent in air cargo volume data and grounded in practical requirements, this paper introduces the Bootstrap method for uncertainty estimation and proposes a decomposition-integrated interval prediction method. Specifically, the historical data is first decomposed using the Seasonal and Trend Decomposition using Loess (STL) method. The trend and seasonal components are then forecasted using Support Vector Regression (SVR) and Seasonal Autoregressive Integrated Moving Average (SARIMA), respectively. Thirdly, the white noise component is innovatively extracted and resampled using the Bootstrap method. Finally, the prediction results are integrated and reconstructed with the processed white noise to quantify uncertainty through quantile-based interval construction. Experimental results on cargo data from two major hub airports in China demonstrate that the constructed intervals effectively combine prediction results with uncertainty quantification, offering a novel research approach for probabilistic interval prediction.

Keywords: decomposition integration; interval prediction; STL; SVR; Bootstrap

0 Introduction

As China's economy transitions to a high-quality development stage, e-commerce and express logistics industries have experienced rapid growth, with the proportion of air cargo demand in the freight market increasing annually. Scientifically and accurately forecasting air cargo demand, monitoring its future dynamic trends, and implementing corresponding measures based on these trends constitute effective guarantees for the sustained and healthy development of the air transport industry. Such forecasting provides data support for aviation transport decision-makers at all levels to formulate development strategies and plans [1]. However, the high noise, uncertainty, nonlinearity, and non-stationarity characteristics of air cargo volume data make prediction extremely challenging. Consequently, developing a stable and accurate forecasting model for air cargo systems represents a valuable and critical task.

In recent years, extensive research has been conducted on freight volume forecasting models, primarily encompassing traditional forecasting models, artificial intelligence models, and combined forecasting models. Traditional models such as grey prediction [2,3], regression analysis [4], and system dynamics [5] were widely adopted in early freight demand forecasting due to their strong interpretability and satisfactory performance on linear data. Liu et al. [6] established a multiple linear regression model based on uncertainty theory to forecast national railway annual freight volume. Zhang et al. [7] constructed a system dynamics model to predict Haikou's external passenger demand from 2020 to 2035. Nevertheless, the non-stationary characteristics of data make precise modeling difficult for traditional models, and prerequisite assumptions such as stationary sequence modeling further limit their applicability [8].

With the rise of data mining technologies, artificial intelligence methods have attracted significant attention for their superior predictive performance on nonlinear data and have been widely applied across various forecasting domains. Zou et al. [9] developed a support vector regression model for short-term highway traffic flow prediction, achieving lower errors compared to backpropagation and autoregressive integrated moving average models. Zhang et al. [10] constructed a Long Short-Term Memory neural network for airport pavement traffic congestion prediction, demonstrating its practical value. However, whether traditional or AI-based, single models cannot fully capture the data characteristics of freight demand.

To effectively leverage the advantages of various models, Bates [11] proposed the concept of combined forecasting, which has gained increasing favor among researchers worldwide. Zhao et al. [12] built a convolutional neural network combined with a residual network model for forecasting metro station passenger flow, showing better predictive accuracy than traditional models. Zhao et al. [13] established a Modified Particle Swarm Optimization-Relevance Vector Machine (MPSO-RVM) combined model for short-term traffic flow prediction, confirming its superior performance on denoised data. Beyond direct combination forecasting on raw data, decomposition-integrated combination forecasting has emerged as an increasingly popular approach. Liang et al. [14] proposed a singular spectrum analysis-based decomposition-integrated forecasting model for air passenger demand, employing dual optimization algorithms combined with SVR or ARIMA models, yielding favorable prediction accuracy. Li et al. [15] introduced an air cargo forecasting model based on variational mode decomposition and empirical mode decomposition, combining ARIMA with a cuckoo search-optimized Elman neural network, achieving superior accuracy and robustness compared to benchmark models. These studies demonstrate that combined forecasting integrates the strengths of individual models and helps address suboptimal prediction accuracy.

The aforementioned methods essentially represent deterministic point predictions that contain limited information and struggle to characterize data uncertainty. To obtain more precise information about data variations and mitigate adverse effects on management systems, interval prediction research has gradually gained attention across various fields, including wind power forecasting [16,17], load forecasting [18], and metal price prediction [19]. Gan et al. [16] employed the Lower Upper Bound Estimation (LUBE) method to build a temporal convolutional network model that directly outputs prediction intervals for wind speed forecasting. Beyond LUBE methods that directly generate intervals through neural networks, a popular approach involves measuring uncertainty trends based on point predictions. Wang et al. [17] conducted statistical studies on prediction errors from point forecasts, proposing Gaussian distribution modeling of errors to expand point predictions into interval predictions. Serrano-Guerrero et al. [18] introduced pattern recognition into forecasting, constructing intervals for electric load prediction using data means and standard deviations. Wang et al. [19] utilized different distribution functions to analyze data distribution characteristics, achieving prediction interval construction based on point prediction results.

Existing literature has achieved considerable results in freight volume forecasting, yet three issues remain: (a) Research on air cargo demand forecasting still focuses on analyzing long-term freight demand changes [6,7] or macro-level national freight volume [20]. Compared to long-term national freight volume forecasting, decision-makers more urgently need short-term dynamic information to determine airport master planning. (b) Interval prediction research on freight volume is lacking. Effectively forecasting freight demand fluctuation intervals to formulate reasonable transport plans represents an effective means for airport profitability, and mastering these intervals enables airports to prepare risk response strategies in advance. (c) Few studies have effectively processed white noise in data. The randomness of white noise affects model performance in processing data information, and adopting effective methods to handle white noise can significantly improve prediction effectiveness.

Addressing these issues and inspired by interval prediction methods from other domains, this paper proposes, for the first time, an air cargo demand interval prediction method based on the Bootstrap (BT) approach. The method extracts the white noise component from data, processes it with Bootstrap, and combines it with combined forecasting results to construct Prediction Intervals (PIs), thereby reducing prediction difficulty, improving model accuracy, and quantifying uncertainty. The innovations of this study are:

a) We propose and validate the idea of constructing PIs using the data's inherent white noise and prediction results from denoised data. From a statistical analysis perspective, white noise holds no analytical value as it contains no useful information—no valuable patterns can be found in purely random data. Moreover, random data is unpredictable, making it time-consuming and ineffective as a prediction target. Therefore, our forecasting model excludes white noise during data preprocessing, predicting only the components containing effective information, which reduces prediction difficulty. For the white noise component, we randomly shuffle it and reconstruct it with prediction results, then construct intervals using quantiles.

b) We propose an interval prediction method that directly generates prediction intervals, ensuring reliability and stability. The proposed method involves no prior knowledge or distribution assumptions about prediction errors required by existing methods, thus achieving better prediction accuracy than indirect interval prediction approaches.

c) We establish a decomposition-integrated model combining STL, Bootstrap, and SVR-SARIMA combined forecasting to construct prediction intervals. This STL-SVR-SARIMA-BT model, guided by the "divide and conquer" principle, selects appropriate models based on the data characteristics of trend and seasonal components decomposed by STL. It leverages each model's advantages to extract maximum information and constructs intervals by incorporating the Bootstrap-processed white noise component.

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1 Methodology

1.1 STL Time Series Decomposition

Seasonal and Trend Decomposition using Loess (STL) is a nonparametric regression model based on locally weighted regression [21]. During iteration, it learns robustness weights for each data point, assigning relatively smaller weights to outliers when fine-tuning trends and seasonality to reduce their impact. The local weighted regression process in STL is essentially a nearest-neighbor kernel smoothing in a temporal context. The decomposition process allows users to specify the variation amounts of trend and seasonal components and the cycle length, which proves useful for analyzing time series with different temporal resolutions.

STL has three important parameters: the number of observations (or length) of the seasonal cycle; the smoothing window size of local weighted regression in seasonal smoothing; and the number of iterations for robustness in the outer loop. Other parameters can be determined accordingly or use default settings, such as the number of iterations for the inner loop, the smoothing window size of local weighted regression in trend smoothing, and the smoothing parameter for low-pass filtering.

In this study, STL decomposition is employed to decompose the air cargo volume time series into three components: trend, seasonal, and residual, reducing mutual interference among different components and thereby improving prediction accuracy. The STL decomposition result can be expressed using an additive model:

$$Y_t = T_t + S_t + R_t$$

where Y_t represents the original time series at time t, and T_t, S_t, and R_t denote the trend, seasonal, and residual components, respectively. $T_t + S_t$ are referred to as deterministic or predictable components. After removing the trend and seasonal components, the randomness in the residual component becomes more apparent.

1.2 Ljung-Box Test (LB Test)

To infer the randomness of a sequence, Ljung and Box proposed the LB test [22]. The constructed statistic is:

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{r_k^2}{n-k}$$

where n is the sample size, r_k is the sample autocorrelation coefficient at lag k, and the statistic follows a chi-square distribution with m degrees of freedom, where m is typically taken as $[n/4]$. Given a significance level α, the null hypothesis is rejected if $Q_m > \chi^2_{1-\alpha}(m)$. Accepting the null hypothesis indicates that the original sequence is a white noise sequence; otherwise, the sequence exhibits correlation [23]. The LB test serves as a method to verify whether relationships exist between time series values. Only sequences with strong correlations between values, where historical data influences future development, warrant mining historical data for effective information to forecast future trends [24].

1.3 SVR Model

Support Vector Regression (SVR) [25] represents an important application of support vector machines in regression tasks. Its fundamental idea involves mapping the original data sample set to a high-dimensional feature space H through a nonlinear mapping function and searching for a hyperplane to perform linear regression. In subsequent steps, the function is simplified as much as possible to reduce complexity while enabling broader generalization.

Assuming the given sample is $\{(x_i, y_i), i = 1, 2, ..., l\}$, the regression form can be expressed as:

$$y = \omega^T \phi(x) + b$$

where ω represents support vectors and b is the bias term. Introducing slack variables ξ_i and ξ_i^* can better address uncertainty, allowing SVR to be formulated as:

$$\min_{\omega,b,\xi,\xi^*} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*)$$

$$\text{s.t.} \begin{cases} y_i - \omega^T\phi(x_i) - b \le \varepsilon + \xi_i \\ \omega^T\phi(x_i) + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, \quad i = 1, 2, ..., l \end{cases}$$

where C is the penalty factor, ε is the empirical error, and C controls the empirical risk error of the SVR model. A larger C imposes greater penalties on samples with larger errors ξ_i during training.

1.4 SARIMA Model

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model extends the ARIMA model to improve its performance in modeling seasonal time series. The ARIMA model, popularized by renowned statisticians Box and Jenkins [26], is a class of linear non-stationary time series models based on the principle that past and present conditions will continue into the future.

The SARIMA(p, d, q)(P, D, Q)[S] model comprises seven parameters: non-seasonal autoregressive order p, seasonal autoregressive order P, common differencing order d, seasonal differencing order D, non-seasonal moving average order q, seasonal moving average order Q, and the seasonal period S. The mathematical expression is:

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D Y_t = \theta_q(B)\Theta_Q(B^S)\epsilon_t + \theta_0$$

where $\phi_p(B)$ and $\theta_q(B)$ are the characteristic polynomials of the autoregressive and moving average parts in the non-seasonal component of orders p and q, respectively. $\Phi_P(B^S)$ and $\Theta_Q(B^S)$ represent the characteristic polynomials of the autoregressive and moving average parts in the seasonal component of orders P and Q, respectively. $(1-B)^d$ and $(1-B^S)^D$ are the regular and seasonal differencing operators. d and D denote the orders of differencing applied to eliminate trend and seasonal effects, respectively. Y_t is the observed value at time t, θ_0 is a constant term, and ϵ_t is random error.

1.5 Bootstrap Method

The Bootstrap method was first proposed by statistician Efron [27]. Essentially, it is a nonparametric data-driven statistical sampling method based on simulation and resampling with replacement. Its fundamental idea involves constructing bootstrap samples through random sampling with replacement from the original sample data and using these samples for statistical inference about the population distribution. This method relies solely on the given original observations without additional assumptions, fully exploiting the population information carried by the original sample data, and demonstrates greater advantages with small samples.

Typically, each Bootstrap dataset is resampled to contain N data points, matching the size of the original dataset. The number of Bootstrap replications B is commonly set to 100, 500, 1000, 2000, 5000, and 10000, and it is known that increasing B enables more accurate parameter estimation. Since computational costs increase proportionally with B, it is necessary to consider computer performance and available time to select an appropriate B value.

2 STL-SVR-SARIMA-BT Model

To forecast air cargo demand while accounting for its nonlinear characteristics and small sample size, this study constructs an interval prediction model based on STL and Bootstrap. The model comprises four modules: data preprocessing, forecasting, Bootstrap processing, and interval construction. The implementation steps are as follows:

Step 1: Data Decomposition Module. STL is used to decompose raw cargo data into trend, seasonal, and residual components. Due to differences between airport datasets, STL model parameters are set according to data characteristics.

Step 2: Forecasting Module. Based on the characteristics of each component, appropriate forecasting models are selected to improve model selection rationality. SVR, capable of predicting nonlinear features, and SARIMA, effective for periodic features, are chosen as the combined model. The training sets of the decomposed trend and seasonal components are used as inputs to train the SVR and SARIMA models separately.

Step 3: Bootstrap Module. After conducting an LB test on the residual component to verify it as a white noise sequence, Bootstrap processing is applied. The Bootstrap resampling mechanism randomly shuffles the residual component to simulate future random variations by continuing past random influences. The processed residual component data are added to the sum of the forecasted trend and seasonal components to generate similar prediction matrices.

Step 4: Interval Construction Module. Quantile processing is applied to the similar prediction values to construct intervals. The model using this approach is named STL-SVR-SARIMA-BT, with its framework illustrated in [Figure 1: see original paper].

3 Experiments

3.1 Dataset and Performance Metrics

This study selects monthly cargo volumes from two major international airports in China—Beijing Airport (S1) and Shanghai Airport (S2)—as research subjects, using air cargo data from January 2006 to May 2020 as the research sample. The data were obtained from the National Bureau of Statistics database (www.stats.gov.cn) and Wind database (www.wind.com.cn). For the forecasting phase, data were processed using min-max normalization, with the normalization formula as follows. [Figure 2: see original paper] and [Figure 3: see original paper] display the normalized monthly cargo volume series line charts for the two airports.

Descriptive statistics () reveal that monthly cargo volume data exhibit unstable fluctuation characteristics. The absolute skewness values for both airports exceed 0, indicating obvious asymmetry. Additionally, the kurtosis values are less than 0, suggesting flatter distributions than normal distributions.

To quantitatively evaluate model prediction performance, this paper selects three statistical metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE); and four interval evaluation metrics: Prediction Interval Coverage Probability (PICP), Prediction Interval Normalized Average Width (PINAW), Average Coverage Error index (ACE), and Coverage Width Criterion (CWC) to describe model performance. Specifically, for statistical metrics, MAE intuitively evaluates model prediction accuracy, MAPE describes the deviation of predicted values from actual values, and RMSE is sensitive to prediction outliers and effectively reflects prediction precision. For interval evaluation metrics, PICP measures the proportion of true values falling within prediction interval bounds, PINAW describes the narrowness of prediction intervals, ACE reflects the deviation of prediction intervals from the nominal confidence level (PINC), and CWC comprehensively evaluates coverage probability and average width. Definitions are provided in .

For component prediction measurement, y_t and $\hat{y}_t$ represent actual and predicted values at time t, respectively, where $t = 1, 2, ..., N$ and N is the sample size. For prediction performance indicators, L_t and U_t are the lower and upper bounds of the prediction interval. R is the range of target values. η and μ are two hyperparameters determining PI performance. γ amplifies PICP differences and penalizes invalid PIs. μ is a control parameter, and PINC is the interval confidence level. Notably, PIs are considered valid when PICP exceeds the nominal confidence level; thus, the obtained interval's PICP should be greater than or equal to the predetermined nominal confidence level.

The data sample was divided into training and test sets using common ratios of 70%:30%, 75%:25%, and 80%:20%. The final division standard was determined based on the principle of minimizing prediction errors. Error results are shown in , indicating that the 75%:25% division yields the smallest training errors. Therefore, the data sample was divided accordingly, resulting in 130 training samples and 43 test samples.

3.2 STL Decomposition of Raw Data

The STL decomposition stage aims to extract the noise sequence from raw data. Noise reduces prediction accuracy and increases difficulty, while removing noise before prediction can address these issues. A trial-and-error method was used to determine model parameters, with Beijing Airport cargo data parameters $(N_s, N_o, N_i, N_t, N_l, N_{iter})$ set as (12,1,5,13,21,17) and Shanghai Airport data parameters as (12,2,0,13,21,17). The decomposed components for both airports are shown in [Figure 4: see original paper] and [Figure 5: see original paper], revealing clear trend and seasonal components.

The decomposed trend, seasonal, and residual components were subjected to Augmented Dickey-Fuller (ADF) tests, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) analyses to examine stationarity and autocorrelation. Due to space limitations, only results are discussed. Comprehensive analysis shows that both trend and residual components are stationary sequences, while trend and seasonal components exhibit autocorrelation. The ACF and PACF of residual components preliminarily indicate no autocorrelation.

Subsequently, an LB test was conducted on the residual component to further verify its lack of autocorrelation. The LB test results for the two white noise sequences are shown in [Figure 6: see original paper] and [Figure 7: see original paper]. The figures indicate that for both airports, the LB test values for lags 1-12 exceed the significance level of 0.05, accepting the null hypothesis of white noise, meaning no autocorrelation exists. This provides a reasonable premise for excluding the residual component from the prediction process and for shuffling it with Bootstrap.

3.3 SVR-SARIMA Prediction

The prediction phase focuses only on non-noise sequences, i.e., the trend component (T_t) and seasonal component (S_t). Since the residual component has been proven to be white noise, it does not participate in the prediction process but is processed separately. The SARIMA model parameters are set to SARIMA(0,1,1)(1,2,0)[12], determined through multiple model experiments minimizing the Akaike Information Criterion (AIC) [28] and Bayesian Information Criterion (BIC) [29]. SVR model parameters are set as: penalty factor $C = 10$, empirical error $\varepsilon = 0.01$, using a polynomial kernel function. The SVR-SARIMA prediction results for Beijing and Shanghai airports are shown in [Figure 8: see original paper] and [Figure 9: see original paper]. compares the prediction effects of single models versus the combined model on trend and seasonal components, showing that the S-S model (SVR-SARIMA combined model) performs optimally for both airports, with errors smaller than those of individual SVR and SARIMA models.

3.4 Bootstrap Processing of White Noise and Interval Construction

Considering processing efficiency and effectiveness, the number of Bootstrap replications B is set to 1000 in this study. The residual component (white noise portion) is randomly truncated to test set length and shuffled 1000 times using the Bootstrap method, yielding a 1000$×$43 matrix for each airport. Data in each column are sorted from smallest to largest, and selected quantiles (0.80, 0.85, 0.90, 0.95) are extracted to obtain interval bound values, generating upper and lower bound sequences. [Figure 10: see original paper] and [Figure 11: see original paper] display the interval prediction results for Beijing and Shanghai international airports at a 95% PINC.

3.5 Comparative Model Performance Analysis

To further validate the proposed model's effectiveness, a series of comparison models were established, categorized by type: models targeting the prediction component, noise processing component, and interval construction component. The construction of each comparison model is described below:

First, for the prediction component of trend and seasonal components, single Linear Regression (LR), SARIMA, and SVR models were designed (Models 1, 2, 3). Second, for noise processing, the Bootstrap method in the proposed framework was replaced with Moving Block Bootstrap (MBB), creating the STL-SVR-SARIMA-MBB model (Model 4). Finally, for the interval construction component, Wang et al.'s [17] method based on prediction error distribution combined with point prediction results was applied to this research object, establishing the STL-SVR-SARIMA-GLS model (Model 5). The proposed STL-SVR-SARIMA-BT model is designated as Model 6. Model codes and abbreviations are shown in . To visually demonstrate model prediction performance, detailed comparisons of evaluation metrics such as prediction interval coverage probability are provided in and .

As shown in and : (a) The decomposition-integrated combination forecasting concept plays an irreplaceable role in data prediction. Freight volume data contains multiple characteristic components, while single models can only capture partial features. Among models employing decomposition strategies, the proposed decomposition-integrated combination forecasting method achieves higher PICP values, narrower PINAW values, and smaller CWC values compared to other single prediction models. Taking Beijing Airport cargo data results at 95% confidence level as an example, the proposed model's CWC value decreases by over 99% compared to Models 1, 2, and 3, far surpassing comparison models. This indicates that CWC values from single model prediction intervals remain high due to the absence of a "divide and conquer" strategy, indirectly confirming the necessity of combined forecasting.

(b) Intervals constructed by randomly shuffling white noise residual components with Bootstrap are more reasonable. Using Shanghai Airport cargo data at 80% confidence level as an example, Model 6's CWC value is 94.04% smaller than Model 4's. The reason lies in Model 4's MBB method for resampling white noise, which divides the residual component into overlapping blocks according to temporal order and then draws blocks with replacement to form new samples—suitable for time series with autocorrelation. Given that white noise sequences lack autocorrelation, using Bootstrap to shuffle white noise sequences better describes data uncertainty and more reasonably simulates future random components.

(c) Compared with the latest interval construction methods, the proposed method achieves PICP closer to the corresponding PINC, with narrower PINAW and smaller CWC. While wider PINAW can generally achieve desirable PICP, this study aims to minimize PINAW while achieving a balance through CWC. Evaluation metrics show that Model 6's CWC values are optimal or second-optimal across all confidence levels. Thus, compared to Model 5's approach of expanding deterministic predictions into intervals based on point prediction errors, the proposed interval construction method yields prediction intervals containing more observations with smaller widths.

(d) Overall, the proposed model's PICP exceeds the corresponding PINC, satisfying prediction interval probability requirements. Additionally, the model's PINAW is relatively small, and CWC values are minimal or near-minimal across confidence levels, demonstrating that the STL-SVR-SARIMA-BT model outperforms other methods in constructing short-term freight demand prediction intervals.

4 Conclusion

Addressing uncertainty in air cargo demand forecasting, this paper establishes a decomposition-integrated combined forecasting model for airport cargo demand prediction, introduces multiple benchmark models for comparative analysis, and provides an interval construction method. The core concept involves extracting white noise from data, forecasting only the remaining information-containing components, randomly shuffling the extracted white noise sequence with Bootstrap, reconstructing it with prediction results, and constructing interval predictions using quantiles.

Experiments on cargo volumes from two Chinese airports reveal: (1) Appropriate forecasting models should be selected based on data characteristics. For air cargo demand forecasting, SARIMA achieves better results than SVR for seasonal component prediction, while SVR performs well on relatively simple time series data. (2) Compared to using single models for each component, employing multiple models to predict corresponding components and fully leveraging different models' advantages yields superior results. The SVR-SARIMA model effectively overcomes the insufficient fitting capability of single models for complex data, predicting data more accurately than individual SVR or SARIMA models and proving more effective than traditional machine learning support vector machines. (3) Extracting white noise components from raw data significantly reduces prediction difficulty and improves accuracy. Most raw data contains unpredictable white noise (random components); removing it yields components with effective information, enabling prediction free from random interference.

In summary, the established model demonstrates good accuracy, robustness, and operational simplicity, offering new insights for interval prediction. Given its advantages in prediction precision and stability, the proposed model holds broad application prospects for periodic data forecasting and related directions.

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Note: Figure translations are in progress. See original paper for figures.