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Design of a Framework for Demand Forecasting Using Time Series Decomposition-Based Approach

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ABSTRACT

In recent years, artificial intelligence (AI) has made highly accurate demand forecasting possible. However, improving forecast accuracy does not necessarily mean reducing inventory costs or improving service levels in supply chain and inventory management, which are closely related to demand forecasting. Workers require not only high accuracy but also a basis for making decisions a based on forecasts. Autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) are demand forecasting methods with high accuracy and interpretability. However, these methods cannot provide evidence for demand fluctuations such as trends and seasonality, although they exhibit an autoregressive time-series structure. In this study, a framework for demand forecasting with high accuracy and interpretability was designed using time series decomposition and ARIMA to support decision makers in demand forecasting. The Seasonal-trend decomposition using locally estimated scatterplot smoothing (STL) is used to decompose a time series into three components trend, seasonality, and residual to provide decision makers with an easily understandable basis for demand changes. In addition, the ARIMA model is used for trends and residuals to achieve highly accurate forecasts. Comparing the prediction accuracies of the proposed STL-ARIMA and SARIMA models shows that STL-ARIMA has higher interpretability than the SARIMA model and the same accuracy.

1. INTRODUCTION

Demand forecasting is used for decision making in various fields, and it is important to achieve high accuracy (Böse, Flunkert, Gasthaus, Januschowski, Lange, Salinas, Schelter, Seeger, & Wang, 2017). AI-based demand forecasting is gaining attention as a highly accurate demand forecasting method (Calster, Baesens & Lemahieu, 2017). However, workers are concerned about the practicality of these methods, paying attention to the tradeoffs between, for example, inventory costs and the level of service achieved (Babai, Ali, Boylan & Syntetos, 2013). In inventory management and supply chain decisions that are closely related to demand forecasting, decision makers must be satisfied with the results and be able to judge their validity. It is difficult for decision makers to use forecast results in their decision making if they do not understand why the forecast results were obtained (Nezu & Motohashi, 2016). The higher the degree of interpretability, (that is, the degree to which humans can understand the basis of judgments made by machines), the easier it is for decision makers to understand the basis for specific predictions, and more proactive decision making becomes possible. Thus, for demand forecasting in a business environment, it is important to achieve highly interpretable forecasts in addition to accuracy (Wu, Wang, Tao & Zeng, 2023; Hirose, 2021).

The decomposition process is fundamental to studying and exploring time series data (Kamath & Li, 2021). After decomposing time series data into trend, seasonality, and residuals, some researchers have performed forecasting using deep-learning models and other highly accurate methods and then recombined the three components for forecasting (Xiong, Li & Bao, 2018; Li, Bao, Gong, Shu & Zhang, 2020). It is possible to decompose a time series into its individual components, as in these studies, to learn the characteristics of the three components and deepen the understanding of time series data. Therefore, the interpretability of the time series can be improved by making each component of the time series easier to understand (Rajapaksha, Bergmeir & Hyndman, 2021). However, highly accurate methods, such as deep learning models, are essentially "black boxes" in terms of changes in time series data because models cannot be represented in relational formulas (Caruana, Lou, Gehrke, Koch, Sturm & Elhadad, 2015; Moraffah, Karami, Guo, Raglin & Liu, 2020). In contrast, the ARIMA and SARIMA models are classical time series forecasting models that have been used for many years in demand forecasting in business environments (Xu, Chan, & Zhang, 2019; Lorente-Leyva. Alemany, Peluffo-Ordóñez & Herrera- Granda, 2020). These models are represented by relational expressions, that reflect the time-series structure and clarify the basis of the forecasts. However, the effects of trend, seasonality, and residuals on the forecast cannot be determined from the relational equation. In this study, interpretability was evaluated from the following two perspectives.

1. The model is expressed in terms of a relational equation.

2. The effect of each of the three components (trend, seasonality, and residuals) on the forecast results is known.

In addition, an attempt was made to design a framework for demand forecasting that is both accurate and interpretable from these perspectives. This makes it possible to make predictions acceptable to workers in terms of inventory management and supply chain. For example, in supply chain information sharing, orders from downstream to upstream that follow the demand process of ARIMA (0,1,1) may arise from information at various downstream stages, including the demand process ARIMA (0,1,1) (Babai et al. 2013). The downstream demand process ARIMA (0, 1, 1) and other downstream information can be used as a reference when making upstream demand forecasts. Thus, the calculation of relational expressions by ARIMA plays an important role in information sharing in the supply chain.

2. LITERATURE REVIEW

Classical time series forecasting models have long been used in demand forecasting in the business environment (Calster et al. 2017). In particular, the ARIMA model is highly accurate and can reflect the time series structure by expressing the model as a relational equation. Hence, decision makers can convincingly use the results of this model, which is often employed in business environments (Lorente-Leyva et al. 2020). The SARIMA model adds seasonality to the ARIMA model (Xu et al. 2019). The accuracy of this model is improved by accommodating seasonality (Hamzaçebi, 2008). These classical models satisfy Perspective 1 (the model can be expressed in a relational form) but not Perspective 2 (the effects of each component on the predicted results can be known).

Time series decomposition is usually performed to satisfy Perspective 2 (Rajapaksha et al. 2021). Time series decomposition is often performed to learn about component characteristics and gain a better understanding of time series data, but it can also be used to improve forecast accuracy (Hyndman & Athanasopoulos, 2018). Decomposition methods include classical (Pickering, Hossain, French, & Abramson, 2018), X11(Shiskin, Young, & Musgrave, 1967), seasonal extraction in ARIMA time series (SEATS), and STL (Cleveland, Cleveland, McRae & Terpenning, 1990). In particular, STL decomposition has several important advantages over other methods (Li et al. 2020; Patidar, Jenkins, Peacock & McCallum, 2019). For example, it is highly tolerant of time series outliers and can yield robust subsequences. It can also accommodate all types of seasonality. Xiong et al. (2018) used STL decomposition to decompose a time series. They then used a naïve forecasting method for seasonality, using predictions made 12 periods in advance, and a neural network called extreme learning machine (ELM) for trends and residuals. Here, the time series is divided into three components trend, seasonality, and residuals, and the effect of each component on the forecast results can be seen. However, because neural networks are used to predict trends and residuals, the model is not expressed as a relational equation and is interpreted for changes in elements.

In this study, time series decomposition was performed using STL decomposition to observe the effects of trend, seasonality, and residuals. Furthermore, a forecasting method, STL-ARIMA, is proposed that has sufficient accuracy and interpretability as a demand forecasting method for business environments by expressing the change in each component in terms of the relational equation of the ARIMA model.

3. METHODOLOGY

In this study, STL-ARIMA, which satisfies Perspectives 1 and 2, was designed. STL-ARIMA can represent the model equation by elements, which improves not only accuracy but also interpretability. The STL-ARIMA procedure is as follows.

Step 1: The time series data are decomposed into trend, seasonality, and residuals using STL decomposition.
Step 2: Seasonality is predicted with a naive forecasting method, and trend and residuals with an ARIMA model.
Step 3: The three components (trend, seasonality, and residuals) are merged.

3.1. Step 1: Time Series Decomposition

STL decomposition is a filtering method that decomposes a time series into additive components (Li et al. 2020). Time series data X_t can be decomposed into trend T_t, seasonality S_t, and residual R_t.

$$X_t = T_t + S_t + R_t \tag{1}$$

This is an iterative method consisting of an inner and an outer loop. In the inner loop, seasonal smoothing is used to update the seasonal component, and trend smoothing is used to update the trend component. If it is assumed that $S_t^{(k)}$ and $T_t^{(k)}$ are the seasonal and trend components, respectively, at the end of the kth pass, then the update for the (k + 1)th step is computed as follows.

1. Detrending. The detrended series is obtained by subtracting the original series from the estimated trend series $T_t^{(k)}$: $X_t^{(trend)} = X_t - T_t^{(k)}$.
2. Seasonal smoothing. Each subcycle series of the detrended series is smoothed with a locally estimated scatterplot smoothing (LOESS) smoother to obtain the preliminary seasonal component $C_t^{(k+1)}$.
3. Low-pass filtering of the smoothed seasonal components. The $C_t^{(k+1)}$ obtained in Step 2 is low-pass filtered and further LOESS-smoothed to identify the remaining trend $L_t^{(k+1)}$.
4. Smoothed seasonal detrending. The seasonal component $S_t^{(k+1)}$ from the (k + 1)th step is obtained by subtracting the preliminary seasonal series from the low-pass value: $S_t^{(k+1)} = C_t^{(k+1)} - L_t^{(k+1)}$
5. Deseasonalizing. The seasonal component $S_t^{(k+1)}$ is subtracted from the original series X_t to obtain the seasonally adjusted series $X_t^{deseason}$: $X_t^{deseason} = X_t - S_t^{(k+1)}$.
6. Trend smoothing. The non-seasonal series $X_t^{deseason}$ obtained in Step 5 is smoothed by a LOESS smoother to obtain the trend component $T_t^{(k+1)}$.

In the outer loop, the remaining component R_t is calculated using the trend and seasonal components obtained in the inner loop: $R_t^{(k+1)} = X_t - T_t^{(k+1)} - S_t^{(k+1)}$

Time series decomposition enables one to measure the strength of trends and seasonality in time series data (Wang & Hyndman, 2006). The trend and seasonality strengths F_T and F_S are defined as

$$F_T = \max\left[0{,}1 - \frac{Var(R_t)}{Var(T_t + R_t)}\right] \tag{2}$$

$$F_S = \max\left[0{,}1 - \frac{Var(R_t)}{Var(S_t + R_t)}\right] \tag{3}$$

The strengths of the trend and seasonality can be expressed between 0 and 1 the higher the number, the stronger they are.

3.2. Step 2: Prediction of Each Component

The trends, seasonality, and residuals are forecast. Trends and residuals represent changes in time series data in a relational equation by forecasting using the ARIMA model. This satisfies Perspective 1 and facilitates interpretation. The Akaike information criterion is used to select the order and coefficients of the ARIMA model. For seasonality, a naïve forecasting method is used that takes the forecast value as it was 12 periods ago. This is because STL decomposition repeats the values for the number of years in the training period without changing the values for the 12 periods.

The ARIMA model combines autoregressive, integrated, and moving average models (Sharma & Mishra, 2023). If the observations at discrete times 1, 2, ···, n are $y_1, y_2, \cdots, y_n$, B is the lag operator, $\varphi_p(B)$ is an autoregressive operator, and $\theta_q(B)$ is a moving average operator, then a_t is Gaussian white noise with zero mean and constant variance. The ARIMA(p, d, q) model is as

$$\varphi_p(B)(1-B)^d y_t = \theta_q(B) a_t \tag{4}$$

$$B y_t = y_{t-1} \tag{5}$$

$$\varphi_p(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p \tag{6}$$

$$\theta_q(B) = 1 - \theta_1 B - \cdots - \theta_q B^q \tag{7}$$

3.3. Step 3: Merge the Components

The predicted values of trends, seasonality, and residuals are added together to form the predicted values of the time series data.

4. Results and Discussion

4.1. Data Description

The data used were open data obtained from the Global Economic Data, Indicators, Charts & Forecasts. Twenty Japanese monthly datasets for automobiles, inflation, energy, electronics, business/economy, investment, etc. were used. The data period covers eight years, or 96 months, from April 2012 to March 2019. Table 1 summarizes the data.

Table 1: Data items.

	Data
A	Motor Vehicle Production
B	OECD Business Climate Index Survey Manufacturing
C	Building Construction Started
D	Population
E	Production Volume Digital Still Camera
F	Production Coke
G	JP Index Share Price
H	JP Exports fob
I	Treasury Acc Balance Private Sector General Acc GA
J	Consumer Price Index
K	JP Official Rate End of Period National Currency per SDR
L	Portfolio Investment Assets PIA Total
M	Iron Steel Inventory Rate JISF Ordinary Steel
N	JP Other Depository Corporations MFSM 2000 Foreign Assets Net
O	Retail Price Tokyo Food Tune Fish
P	Industrial Production Index IPI Mining Manufacturing
Q	Production Shipment Index PSI Mining Manufacturing
R	Billing Semiconductor Manufacturing Equipment 3 Month Average
S	Visitor Arrivals Total
T	Vehicle registrations OECD countries

4.2. Results and Verification

Predictions were made for three test periods: three, six, and twelve months. Table 2 shows the results for the three month test period. STL-ARIMA was validated by comparing these results with the prediction results from the SARIMA model. SARIMA is a highly accurate model that maps seasonality to ARIMA (Hamzaçebi, 2008). The root mean square error (RMSE) values were compared and evaluated. When y_i is the measured value, $\hat{y_t}$ is the predicted value, and n is the total number of data points, the RMSE is expressed as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{8}$$

When the test period was three months, STL-ARIMA outperformed the SARIMA model for 10 data points (see Table 2). The STL-ARIMA model was more accurate than the SARIMA model for eight data sets when six months were used and for seven data sets when twelve months were used. Specifically, STL-ARIMA is as accurate as SARIMA when data from a variety of fields are used for forecasting. In addition, it is better suited to short-term forecasts than to long-term forecasts. Regarding interpretability, Perspective 1 is achieved because both methods enable the model to be represented by a relational equation. The SARIMA model does not achieve Perspective 2. The STL-ARIMA model achieves Perspective 2 because it uses time series decomposition to indicate the strength of the trend and seasonality, and forecasts are made for each of the components. STL-ARIMA satisfies these two interpretability aspects and is more interpretable than SARIMA.

Table 2. RMSEs of STL-ARIMA and SARIMA.

	STL-ARIMA	SARIMA		STL-ARIMA	SARIMA
A	**2.68.E+04**	3.74.E+04	K	3.00.E+00	**1.76.E+00**
B	1.59.E-01	**2.51.E-02**	L	3.61.E+03	**2.98.E+03**
C	**3.32.E+02**	5.69.E+02	M	**2.39.E+00**	3.01.E+00
D	2.11.E+01	**1.66.E+01**	N	**1.09.E+06**	1.43.E+06
E	**5.50.E+01**	1.49.E+02	O	1.54.E+01	**4.66.E+00**
F	3.91.E+01	**1.55.E+01**	P	**1.79.E+00**	2.29.E+00
G	5.48.E+00	**1.61.E+00**	Q	**2.24.E+00**	4.43.E+00
H	2.90.E+03	**1.71.E+03**	R	**5.57.E+03**	1.76.E+04
I	**4.83.E+02**	5.28.E+02	S	3.34.E+04	**2.95.E+04**
J	6.20.E-01	**6.23.E-02**	T	**7.54.E+03**	7.93.E+03

4.3. Considerations

STL-ARIMA and SARIMA were compared, and which features make them suitable for which types of data was investigated. The strengths of trend FT and seasonality FS for each dataset were divided into five intervals, each with a range of 0.2. Figure 1 shows the strength of the trend in the time series and the number of superior predictions for STL-ARIMA and SARIMA. Figure 2 shows a similar result for seasonality. The vertical axes in Figures 1 and 2 show the number of data for the method with the smallest error comparing STL-ARIMA and SARIMA for each of the data in Table 2. For example, Figure 1 shows that STL-ARIMA has better accuracy than SARIMA and that there are three data sets with a trend of 0.2-0.4. Figure 3 shows the relationship between the trend and the strength of seasonality for each dataset. This shows that STL-ARIMA is better suited for data with weak trends and strong seasonality than the SARIMA model. However, SARIMA performed better for data with a strong trend.

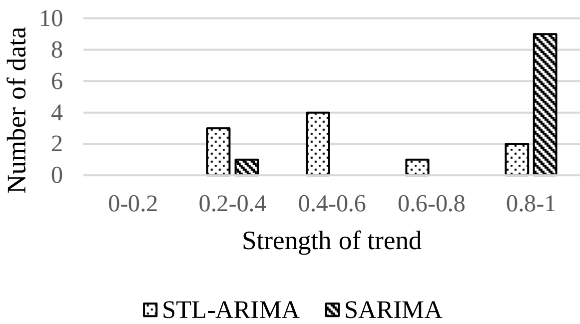

Figure 1. Trend strength and suitable methods.

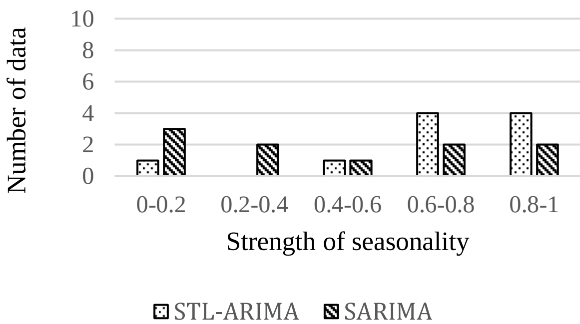

Figure 2. Seasonality strength and suitable methods.

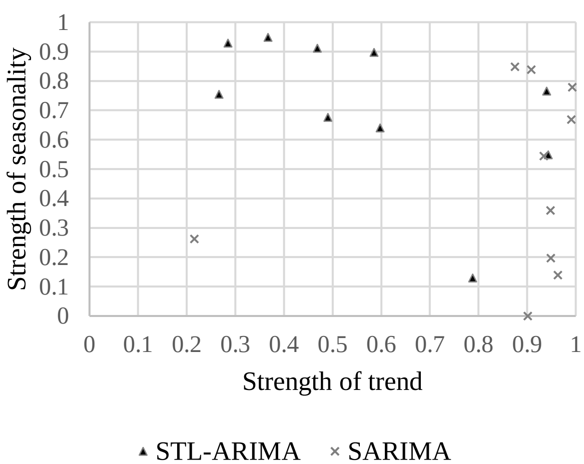

Figure 3. Relationship between trend and seasonality strength

5. CONCLUSION

A framework for demand forecasting was designed that is both accurate and interpretable enough to be used as a demand forecast for business environments. First, time series decomposition was performed using STL decomposition to read the effects of trend, seasonality, and residuals in the time series. STL-ARIMA, a forecasting method with accuracy and interpretability, was developed by expressing the changes in the components in terms of the ARIMA model relationship. STL-ARIMA satisfied the two interpretability perspectives and, thus, had better interpretability than SARIMA, but with comparable accuracy. The data for which STL-ARIMA was suitable were those with strong seasonality. In contrast, it was not suitable for data with a strong trend. Planned future work includes testing the accuracy of the time series decomposition method and the component-by-component prediction method when they are replaced by other highly interpretable methods.

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