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Decomposition Methods for Tourism Demand Forecasting: A Comparative Study

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Abstract

Decomposition methods are extensively used for processing the complex patterns of tourism demand data. Given tourism demand data's intrinsic complexity, it is critical to theoretically understand how different decomposition methods provide solutions. However, a comprehensive comparison of decomposition methods in tourism demand forecasting is still lacking. Hence, this study systematically investigates the forecasting performance of decomposition methods in tourism demand. Nine popular decomposition methods and six forecasting methods are employed, and their forecasting performance is compared. With Hong Kong visitor arrivals from eight major sources as a sample, three main conclusions are obtained from empirical results. First, all the decomposition methods generally outperform benchmark at all horizons, in both the level and directional forecasting. Second, decomposition methods can be divided into four categories based on forecasting accuracy. Finally, variational mode decomposition method is consistently superior to other eight decomposition methods and can provide the best forecasts in all cases.

Keywords

tourism demand forecasting, decomposition methods, variational mode decomposition, decomposition and ensemble, machine learning

Introduction

Tourism demand forecasting is a hot topic in tourism management, and its prediction accuracy has always been a challenging and important task in the field of tourism research (Silva et al. 2019; Song, Wen, and Liu 2019; Y. Zhang et al. 2020a). The prediction model constructed to improve the accuracy mainly relies on consistent patterns of the historical tourism data (Yang et al. 2015; Huang, Zhang, and Ding 2017). However, the time series of historical tourism data (e.g., visitor arrivals) generally show nonlinear and nonstationary characteristics because it is easily affected by other factors in the tourism market, such as income (Serra, Correia, and Rodrigues 2014), exchange rates (Webber 2001), climate change (Lorde, Li, and Airey 2016), weather conditions (Becken 2013), air quality (Hassan 2000), internet search data (X. Li and Law 2020), online review (Önder, Gunter, and Gindl 2020), and public health events (Lee et al. 2012; Xie, Qian, and Wang 2020). Currently, the scholars and practitioners have developed a variety of prediction methods to deal with the complex tourism time series' data features to obtain better prediction performance, which usually includes time series methods (Song and Li 2008), econometric methods (Pan and Yang 2017), and artificial intelligence (AI) methods (Law et al. 2019).

However, no single model can consistently outperform others in all cases from the perspectives of forecasting accuracy (Song and Li 2008). Therefore, further understanding the underlying characteristics of fluctuations in tourism demand has attracted much attention from academic researchers and business practitioners. Notably, the decomposition method is an impressive means to explore and capture the characteristics of tourism demand data from the perspective of time scales (Song et al. 2011; Xie, Qian, and Wang 2020; Y. Zhang et al. 2020b). Based on the idea of "divide and conquer," the decomposition method decomposes the original tourism demand

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time series into subsequences of different time scales, such as trend pattern, periodic pattern, and noise pattern (Xie, Qian, and Wang 2020). Then, the short-term fluctuations, midterm shocks, and long-term trends caused by various market factors can be analyzed, and on this basis, each subsequence can be predicted separately and added together to obtain more accurate prediction results (Xie, Qian, and Wang 2020; Y. Zhang et al. 2020b).

In particular, the decomposition methods can be roughly divided into three categories according to the different ways of processing: filtering, denoising, and multiscaling (X. Li and Law 2020; Y. Zhang et al. 2020a). As for the filtering methods, they commonly decomposed the observed variable into trend and cycle by filtering, such as Hodrick-Prescott filter and Hamilton filter (Bosupeng 2019). As for the denoising methods, the mainly involved step is to remove the time series noise and then use the reconstructed time series with the forecasting techniques for prediction, such as Singular-Spectrum Analysis (SSA) (Hassani et al. 2015) and wavelet decomposition (Kummong and Supratid 2016). As for the multiscale methods, the idea is to regard time series as the superposition of different frequency components, which usually include seasonal trend decomposition based on Loess (STL) (Y. Zhang et al. 2020a), structural time-series model (Song, Wen, and Liu 2019; J. L. Chen et al. 2019), empirical mode decomposition (EMD) family (X. Li and Law 2020). Therefore, the significance of the decomposition method and perspective for exploring the characteristics of tourism time series is widely known.

Nevertheless, although the decomposition-based methods have enormously enriched the tourism demand forecasting research, a comprehensive comparison study on such promising methods, that is, employing the different decomposition methods with prediction techniques for modeling and forecasting the tourism demand, is still lacking. On the one hand, although prior empirical research indicate that the decomposition-based forecasting model can improve forecast accuracy, the evidence on which it is based remains inconclusive. Moreover, there is no clear evidence that any single decomposition method can always outperform the other decomposition methods in predicting competition. On the other hand, with only a few pieces of literature on decomposition-based forecasts, this promising research field is still not known by scholars, especially potential researchers. Therefore, this article attempts to fill in such a literature gap by presenting a comprehensive comparative study on different types of decomposition-ensemble method in tourism research, providing a systematic analysis on each type from the perspectives of data characteristics and making clear operational guidelines. Relative to the existing studies, the major contributions of this article can be summarized into two aspects:

1. It might be the first attempt to comprehensively compare and evaluate the decomposition-based methods used in tourism demand forecasting, and it may contribute immensely to the ongoing interest in using the decomposition-based methods for improving prediction accuracy.
2. By comparing and summarizing the principles of each decomposition method to improve the accuracy of tourism prediction from the perspective of the tourism time series component characteristic, a series of comprehensive forecasting frameworks based on the decomposition method are formed.

The remaining parts of this article are organized as follows: Literature review is provided in the next section. The third section formulates the proposed methodology. The fourth section conducts the empirical study and discusses the effectiveness of different decomposition-based forecasts. The fifth section concludes the study and outlines the promising directions for future research.

Literature Review

This section reviews relevant literature about tourism forecasting with decomposition methods and tourist arrivals forecasting models in the field of tourism demand forecasting. A list of the literature using decomposition methods is shown in Table 1.

Tourism Forecasting with Decomposition Methods

The principle of "divide and conquer" as the idea of decomposition forecasting method aims to improve prediction accuracy, by capturing data characteristics and reducing the complexity of the time series (X. Li and Law 2020; Y. Zhang et al. 2020b). Correspondingly, the decomposition forecasting method can be grouped into three categories in terms of the processing means, which are filtering, denoising, and multiscaling.

As for filtering decomposition methods, they will produce the trends and cyclical components using the filtering method (Bosupeng 2019). For example, Kožić (2014) used the HP filter as the detrending method for decomposing the annual international tourist arrivals into two components: the trend series and the cycle series. Recently, Bosupeng (2019) employed the Hamilton filter and the HP filter to evaluate the trends of tourist arrivals in Australia and supported the Hamilton filter as an effective tool for improving the accuracy in out-of-sample forecast. Meanwhile, the empirical results show that the Hamilton method is superior to the HP filter when facing the original tourist arrivals time series.

The denoising decomposition methods such as SSA and Wavelet decomposition have also received continuous attention in the field of tourism demand forecasting because these methods effectively deal with the time series noise through decomposition, filtering, and reconstruction of the

Table 1. Available Studies of Tourism Prediction with Decomposition Method.

References	Frequency	Variables	Methods	Decomposition process types: Filtering	Denoising	Multiscaling
Apergis, Mervar, and Payne (2017)	Monthly	Tourist arrivals	Fourier		√	
Beneki, Eeckels, and Leon (2012)	Monthly	Tourism receipts	SSA		√	
Bosupeng (2019)	Quarterly	Tourist arrivals	Hamilton filter; HP	√		
C. F. Chen, Lai, and Yeh (2012)	Monthly	Tourist arrivals	EMD			√
Cho (2001)	Quarterly	Tourist arrivals; Economic indicators	MD			√
Hassani et al. (2015)	Monthly	Tourist arrivals	SSA		√	
Kožić (2014)	Annual	Tourist arrivals	HP	√		
Kummong and Supratid (2016)	Monthly	Tourist arrivals	Wavelet		√	
X. Li and Law (2020)	Monthly	Tourist arrivals; Google Trends	EEMD			√
C. Li et al. (2020)	Monthly	Tourist arrivals;	EEMD			√
S. Lin, Chen, and Liao (2018)	Daily	Tourist arrivals	EMD			√
Smeral (2012)	Annual	Tourism import	HP	√		
G. Zhang et al. (2017)	Daily	Hotel occupancy rate	EEMD			√
M. Zhang et al. (2018)	Weekly	Hotel occupancy rate	EEMD			√
Y. Zhang et al. (2020a)	Monthly	Tourist arrivals	STL			√
Y. Zhang et al. (2020b)	Monthly	Tourist arrivals	STL			√
This study	Monthly	Tourist arrivals	CS; EEMD; Fourier; HP; SSA; STL; STSM; VMD; Wavelet	√	√	√

Notes: CS = compressed sensing; EMD = empirical mode decomposition; EEMD = ensemble empirical mode decomposition; HP = Hodrick-Prescott filter; MD = multiplicative decomposition; SSA = singular spectrum analysis; STL = seasonal trend decomposition; STSM = structural time series model; VMD = variational mode decomposition.

original time series, thus improving the accuracy of tourism demand prediction (Kummong and Supratid 2016; Hassani et al. 2017). In particular, Kummong and Supratid (2016) proposed a hybrid forecasting model with the discrete wavelet decomposition leading to accurate performance, by extracting the hidden features of Thailand's tourism time series at various frequency resolution levels. Hassani et al. (2015) employed SSA for forecasting the monthly US tourist arrivals by filtering the noise and achieved a better prediction accuracy. Moreover, Hassani et al. (2017) also used the SSA for denoising the monthly international tourist arrivals in European countries and obtained similar higher performance.

Finally, the multiscale decomposition methods based on the "divide and conquer" principle are usually used to extract and capture the nonlinear and nonstationary data characteristics in the field of tourism by means of steps such as data decomposition, component prediction, and combined prediction (Xie, Qian, and Wang 2020). For example, C. F. Chen, Lai, and Yeh (2012) applied the EMD technique for adaptively decomposing the complicated tourism raw time series into several components, which have different frequency bands from high frequency to low frequency. X. Li and Law (2020) decomposed the search engine data, which is an effective variable for modeling the tourist demand, into different components using the EEMD and demonstrated the decomposition-based method on tourism forecasting considering online search engine data can achieve better forecasting performance. Besides, STL as a common decomposition method has also been employed for decomposing the tourist arrivals. Accordingly, the forecasting method based on STL has achieved better prediction results in Y. Zhang et al. (2020b). Similarly, the structured time series model (STSM) as an extension of the basic structural model is also used for tourism demand forecasting by focusing on trends and seasonal and cyclical components (Kulendran and Witt 2003;

Song, Qiu, and Park 2019). For example, Song et al. (2011) combined the STSM and the time-varying parameter (TVP) regression approach for forecasting quarterly tourist arrivals to Hong Kong and the empirical results show that the TVP-STSM outperforms the benchmarks.

Obviously, it is useful to consider various decomposition methods in tourism demand forecasting. However, all the above studies with the decomposition forecasts in tourism demand have not conducted a comprehensive comparison of different decomposition methods, in terms of capturing tourism data features and improving forecasting accuracy. Based on this research gap, this study systematically proposes a forecasting analysis framework based on the decomposition method, and demonstrates comprehensive empirical evidence, by comparing the accuracy of decomposition forecasts and individual forecasts.

Tourist Arrivals Forecasting Models

The commonly modeling and forecasting models in the field of tourism demand are also generally grouped into three categories: time series, econometric methods, and artificial intelligence (AI) techniques (Song and Li 2008; X. Li et al. 2017).

Considering the historical observations of the tourist arrivals, the time series methods have been extensively employed for tourism demand forecasting (Lim and McAleer 2002; Du Preez and Witt 2003; Song and Li 2008; Athanasopoulos et al. 2011; C. Zhang et al. 2020). In general, the autoregressive integrated moving average (ARIMA) and the variants (e.g., seasonal ARIMA) are the most commonly used prediction models (Gil-Alana, De Gracia, and Cuñado 2004; Chu 2009; Assaf, Barros, and Gil-Alana 2011; Park, Lee, and Song 2017). However, the ARIMA models do not always have a better and more stable prediction performance than other models (Sun et al. 2019). Although some previous studies proved that ARIMA models can obtain better prediction results than other methods, at the same time some studies would get contradicting results (Gunter and Önder 2015). For example, Goh and Law (2002) demonstrated that the seasonal ARIMA (i.e., SARIMA) exceeded the benchmarks, and Smeral and Wüger (2005) obtained that the Naïve model is superior to the SARIMA model.

By effectively exploring the causal relationship between influencing factors and tourist arrivals, or determining the significant degree of the impact of various explanatory variables on tourism demand, econometric models have also been widely used to improve the accuracy of tourism demand forecasting (Song, Qiu, and Park 2019; X. Li et al. 2017). The autoregressive distributed lag model, the error correction model, the vector autoregressive (VAR) generalized autoregressive conditional heteroskedastic (GARCH) models, and mixed-data sampling (MIDAS) are the most commonly used methods for forecasting (Chan, Lim, and McAleer 2005; G. Li et al. 2006; Wong et al. 2007; Page, Song, and Wu 2012; V. S. Lin, Liu, and Song 2015; Bangwayo-skeete and Skeete 2015), and their corresponding extended variants such as vector error correction model (VECM), Bayesian VAR (BVAR), and global VAR (GVAR) are also widely introduced into this field (Wong, Song, and Chon 2006; Bonham, Gangnes, and Zhou 2009; Assaf et al. 2018).

In recent years, the AI-based forecasting models, as a popular and effective tool for processing the nonlinear data without any assumptions such as stationarity or distribution, have already been applied to tourism forecasting (Song, Qiu, and Park 2019; Sun et al. 2019). Generally, the common AI models include support vector regression (SVR), the fuzzy time series, genetic algorithms, back propagation neural network (BPNN), extreme learning machine (ELM), random vector functional link network (RVFL), and long-/short-term memory (LSTM) (S. Li et al. 2018; Sun et al. 2019; Song, Qiu, and Park 2019; Tang et al. 2020). For example, Sun et al. (2019) proposed a forecasting approach with kernel ELM for significantly improving the forecasting performance. Xie, Qian, and Wang (2020) incorporated the BPNN as the benchmark forecasting model into the proposed forecasting framework. Moreover, Law et al. (2019) adopted the LSTM for forecasting, and the empirical results proved that the deep learning approach significantly outperforms SVR and artificial neural network models.

It is worth noting that in terms of prediction accuracy, each forecasting technology has its corresponding advantage and disadvantage, and no one prediction technology is superior to all other methods in all cases (Song and Li 2008; X. Li et al. 2017). Therefore, based on the above three categories of forecasting methods, this article selects six common forecasting techniques to predict the visitor arrivals in eight major inbound markets in Hong Kong, to find the most suitable forecasting technique for the sample of this study.

Methodology

Model Framework

A comprehensive prediction methodology with different decomposition methods is formulated for visitor arrivals forecasting with the three main stages of the data decomposition, data forecasting, and data evaluation, as the general framework illustrated in Figure 1.

Stage 1: Data decomposition. In this stage, the decomposition method D_k ($k = 1, 2, \ldots, n$) is selected one by one from the decomposition method pool to decompose the original visitor arrival observations. In particular, two substeps are involved: (1) data collection, to collect the inbound visitor arrival data from major countries based on market share; (2) decomposition process, to decompose the data into components C_i ($i \geq 2$) according to different principles. For example, the HP filter will transform the original time series into 2

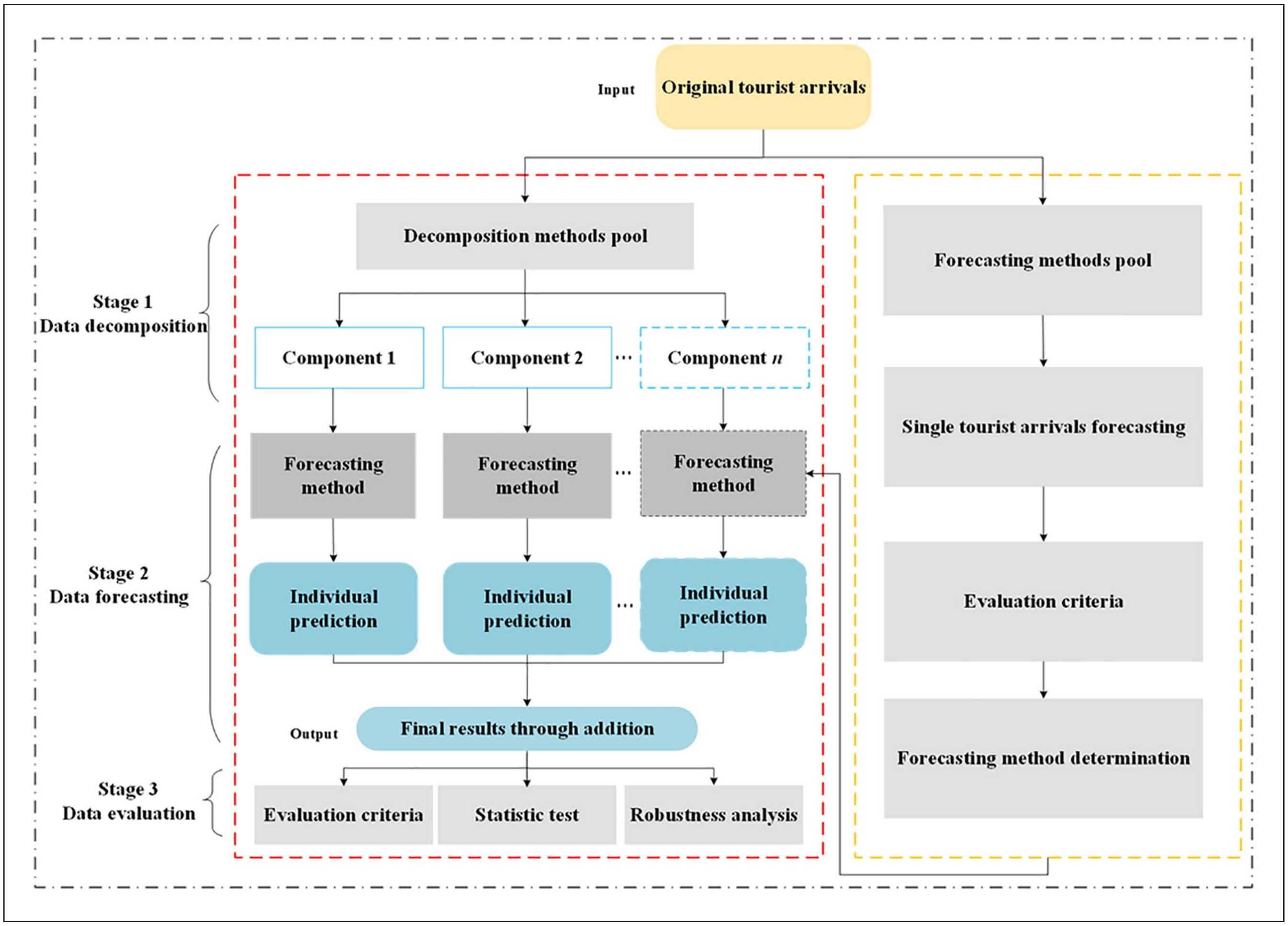

Figure 1. General framework in this study for forecasting tourist arrivals.

components; meanwhile, the STL can obtain 3 components (Bosupeng 2019; Zhang et al. 2020b).

Stage 2: Data forecasting. Accordingly, three main substeps are included in this stage, that is, optimal forecasting method selection, individual prediction, and the final prediction. First, the original tourism observations are all predicted one by one using the forecasting method from the forecasting method pool (i.e., p_i [i=1, 2, . . ., m]), and the best forecasting method is selected, where p_i represents the i-th forecasting method in the pool. Second, individual prediction for each component of the C_i by using the best forecasting method, respectively. Third, the final result is generated by a linear combination across all individual prediction results.

Stage 3: Results evaluation. The commonly used evaluation criteria (e.g., mean absolute percentage error [MAPE]) are employed for comparing the forecasting performance; meanwhile, two effective statistic tests (i.e., Wilcoxon signed rank test and superior prediction ability [SPA] test) are used to statistically compare the accuracy of the decomposition models in forecasting tourism demand. Furthermore, the robustness analysis is conducted in terms of multinational inbound visitor arrivals, multistep-ahead prediction (e.g., horizons 1–6), and standard deviation of multiple prediction results.

Decomposition Methods

HP filter. The HP filter method can separate the trend component from the original data (Kožić 2014). The trend component is determined by minimizing the variance of original data y_t around the trend g_t, while considering the second-order differences of the trend. Given time series y_t is composed of two components (i.e., trend [g_t] and cyclical [c_t]), which can be mathematically described as

$$y_t = g_t + c_t, t = 1, \cdots, T \tag{1}$$

$$\min_{\{g_t\}_{t=1}^{T}} \left\{ \sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=1}^{T} \left[\left(g_t - g_{t-1} \right) - \left(g_{t-1} - g_{t-2} \right) \right]^2 \right\} \tag{2}$$

where $c_t = y_t - g_t$, and λ is a positive number that penalizes variability in the trend component series. In this study, λ = 14,400 for the monthly visitor arrivals.

Fourier. Fourier transform as a spectral analysis tool can decompose a time series into a sum of sinusoidal functions, which can achieve noise removal through time-frequency domain conversion (Apergis, Mervar, and Payne 2017). For a smooth seasonal pattern in tourism, the observations can be specified as follows:

$$y(t) = \frac{1}{2}a_0 + \sum_{i=1}^{k}(a_i \sin 2\pi f_i t + b_i \cos 2\pi f_i t) \tag{3}$$

In scientific applications, the signal (e.g., visitor arrivals time series) is usually subject to a certain amount of noise destruction, masking the frequency components of the original sequence. With the Fourier transform, the frequency can be displayed in the frequency domain and the noise can be removed.

STL. Given a data series (e.g., visitor arrivals in this study), and y_t can accordingly be decomposed into trend component (T_t), seasonal component (S_t), and remainder component (R_t) (Y. Zhang et al. 2020b). STL is an iterative method, which includes two recursive procedures (i.e., inner and outer loops). Specifically, six substeps are involved for calculating the S_t and T_t in the inner loop: (1) detrending, $y_t^{\text{detrend}} = y_t - T_t^{(k)}$—where $T_t^{(k)}$ is the estimated trend component at (k+1)-th iteration; (2) seasonal smoothing—a preliminary seasonal component (i.e., $\tilde{S}t^{(k+1)}$) can be extracted from the y_t^{detrend} by using the Loess smoother; (3) low-pass filtering of the smoothed seasonality—a low-pass is applied to $\tilde{S}t^{(k+1)}$, followed by a Loess smoother, to get the remaining trend $\tilde{T}t^{(k+1)}$; (4) detrending of the smoothed seasonality—calculation of the preliminary seasonal component (i.e., $S_t^{(k+1)} = \tilde{S}t^{(k+1)} - \tilde{T}t^{(k+1)}$); (5) deseasonalizing—the seasonally adjusted series: $y_t^{\text{deseason}} = y_t - S_t^{(k+1)}$; and (6) trend smoothing—y_t^{deseason} is smoothed by a Loess smoother to obtain the trend component $T_t^{(k+1)}$.

As for the outer loop, the remaining component $R_t^{(k+1)}$ is computed based on the trend and seasonal components in the inner loop, as follows:

$$R_t^{(k+1)} = y_t - T_t^{(k+1)} - S_t^{(k+1)} \tag{4}$$

where any large values in R_t are treated as outliers and the weight is computed. As for the next iteration of the inner loop, the weight is used to down-weight the effect of outliers identified in the previous iteration of the outer loop.

STSM. The STSM can decompose the original sequence y_t into the trend, seasonal, cycle, and irregular components, which can be given respectively as follows (Kulendran and Witt 2003; Song et al. 2011):

$$y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t \tag{5}$$

where μ_t is the trend component, γ_t is the seasonal component, ψ_t is the cycle component, and ε_t is the Gaussian white noise with zero mean and variance σ_ε^2.

The trend components and seasonal components can be expressed as

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{6}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{7}$$

$$\gamma_t = -\sum_{j=1}^{m-1}\gamma_{t-j} + w_t \tag{8}$$

where $\eta_t : NID(0, \sigma_\eta^2)$, $\zeta_t : NID(0, \sigma_\zeta^2)$, and $\eta_t : NID(0, \sigma_\eta^2)$.

SSA. SSA is based on singular value decomposition (SVD), including two complementary stages of decomposition and reconstruction, in which the decomposition stage includes two steps of embedding and singular value decomposition (SVD), and the reconstruction stage includes two steps of grouping and reconstruction (Hassani et al. 2017).

Embedding. Select an appropriate embedding dimension L, and map the one-dimensional time series $[y_1, y_2,\ldots, y_N]^{\mathrm{T}}$ onto the multidimensional series $[y_i, y_{i+1},\ldots, y_{i+L-1}]^{\mathrm{T}}$, $i = 1, 2,\ldots K$, where $K = N - L + 1$. The embedding whilst the vectors $\boldsymbol{X}_i$ are called L-lagged vectors and obtain trajectory matrix X,

$$X = \begin{bmatrix} y_1 & y_2 & \cdots & y_k \\ y_2 & y_3 & \cdots & y_{k+1} \\ \vdots & \vdots & \cdots & \vdots \\ y_L & y_{L+1} & \cdots & y_N \end{bmatrix} \tag{9}$$

where $\boldsymbol{X}$ is also a Hankel matrix.

SVD. Calculation of the XX^{T} and the corresponding SVD is carried out. Thus, L eigenvalues $\lambda_1, \lambda_2,\ldots, \lambda_L$ and corresponding eigenvectors $U_1, U_2, \ldots, U_L$ are obtained, and then:

$$X = S_1 + S_2 + \cdots + S_d \tag{10}$$

where d = rank(X), $S_i = (\lambda_i)^{0.5} U_i V_i^{\mathrm{T}}$ denotes the i-th SVD component. $\boldsymbol{U}_i$ and $\boldsymbol{V}_i$ represent the left and right eigenvectors of the trajectory matrix. $\left\{\sqrt{\lambda_i}\right\}$ is the spectrum of the matrix $\boldsymbol{X}$. The maximum eigenvalue corresponds to the maximum eigenvector, and the eigenvector corresponding to the smaller eigenvalue is generally considered to be noise.

Grouping. Split the elementary matrices $\boldsymbol{X}_i$ into m disjoint subsets, that is, $I_1, I_2, \ldots, I_m$; denote $I = \{i_1, \ldots, i_p\}$ as a group of indices $i_1, \ldots, i_p$. Then the matrix $\boldsymbol{X}_I$ corresponding to group I can be defined as $\boldsymbol{X}_I = \boldsymbol{X}_{i1} + \ldots + \boldsymbol{X}_{ip}$.

$$X = X_{I_1} + \cdots + X_{I_m} \tag{11}$$

Diagonal averaging. Transform each matrix of the grouped decomposition into a system of new (reconstructed) series of length N. Suppose z_{ij} denotes an element of a matrix $\boldsymbol{Z}$, then the k-th term of the resulting series is obtained by averaging z_{ij} over all i, j such that $i+j=k+2$. Accordingly, the Hankel matrix $\boldsymbol{HZ}$, which is the trajectory matrix corresponding to the series obtained as a result of the diagonal averaging, is obtained from the Hankelization of a matrix $\boldsymbol{Z}$, In its turn, the Hankel matrix $\boldsymbol{HZ}$ defines the series uniquely by relating the values in the diagonals to the values in the series. So, equation (11) can be represented as

$$X = \tilde{X}_{I_1} + \cdots + \tilde{X}_{I_m} \tag{12}$$

where $\tilde{X}_{I_1} = \boldsymbol{HX}$. Hence, the original series is decomposed into the sum of m series, that is,

$$y_n = \sum_{k=1}^{m} \tilde{y}_n^{(k)} \tag{13}$$

Wavelet. The discrete wavelet transform (DWT) can divide a set of time series $y(t)$ into time domain, which is subdivided into frequency "bands" or "scales." It can provide effective support to analyze a set of time series at various frequency fluctuation levels.

The wavelet base can be given as, respectively,

$$\begin{aligned} \varphi_{j,k}(t) &= 2^{j/2}\varphi(2^j t - k), \\ \psi_{j,k}(t) &= 2^{j/2}\psi(2^j t - k) \end{aligned} \tag{14}$$

where $\int \varphi_t dt = 1$ and $\int \psi_t dt = 0$ are two types of the basic wavelets; j is the parameter of dilation of the waves' functions, and k indexes the translation.

Then a set of time series $y(t)$ can be expanded as a linear combination over the wavelet basis, and the wavelet series approximation can be expressed as follows:

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t) \tag{15}$$

where $S_J(t)$, which is also defined as the low-frequency components, is the approximation that captures the long-term properties, and $D_J(t)$, which is also defined as the high-frequency components, can capture local variations over the whole period of $y(t)$ at each scale.

EEMD. EEMD is an extended version for improving the forecasting performance of EMD by adding the white noise to original data and can produce the individual intrinsic mode functions (IMFs) and residuals (X. Li and Law 2020; M. Zhang et al. 2018). First, reconstruct the original data y_t with the white noise repeatedly, that is, $y^i_t = y_t + w^i_t$, where i is the times of repetition; second, decompose each "new" data into IMFs, that is,

$$y_t^i = \sum_{j=1}^{n} IMF^{ij} + R_t^{nj} \tag{16}$$

where IMF^{ij} denotes the j-th components at the i-th decomposition process. Next, the corresponding average of all the IMFs and R_t are calculated.

Compressed sensing. In the theory of signal acquisition and processing, any signal is compressible and can be compressed and sampled effectively if proper sparse representation space is found. Then any signal has only a few nonzero elements in the transform domain, and it can be called the sparse signal. The short representation of sparse signals is as follows (Yu, Zhao, and Tang 2014):

There is an orthonormal basis $\Psi = [\psi_1, \psi_2 \cdots \psi_n]$, and any signal $X \in R^n$ can be expanded as

$$X = \sum_{i=1}^{n} \theta_i \psi_i, \; or \quad X = \Psi\Theta \tag{17}$$

where $\theta_i = \langle X, \psi_i \rangle$ is the projection coefficient, and Ψ is an $n \times n$ matrix with ψ_i as columns. The compressed sensing system works as follows (Yu, Zhao, and Tang 2014):

(1) The transform coefficients $\Theta = \Psi^T X$ can be calculated if the signal X is sparse on the orthonormal basis Ψ.
(2) We design a data matrix Φ that is $M \times N$ dimensional and Φ is stable and irrelevant to the orthonormal basis Ψ. Then use Φ to measure X and acquire a data vector $Y = \Phi\Theta = \Phi\Psi^T X$, where $\Phi\Psi^T$ is defined as an information operator.
(3) After the signal Y is obtained by the receiver, we can recover X as follows:

$$\min \left\| \Psi^T X \right\|_0, \quad s.t. \quad Y = \Phi\Psi^T X \tag{18}$$

VMD. The goal of the variational mode decomposition (VMD) algorithm is to decompose the original signal into a specified number of intrinsic mode functions (IMFs) by constructing and solving the variational problem (H. Li et al. 2020). In particular, the VMD decomposes data sets into several different band-limited modes u_k and adaptively determine the relevant bands w_k, to make the error between the modes balance.

First, each IMF ($r_k(t)$) is redefined as an amplitude-modulated, frequency-modulated signal (AM-FM) in the VMD algorithm and expressed as

$$r_k(t) = m_k(t)\cos(\phi_k(t)) \tag{19}$$

where t denotes the time script, $m_k(t)$ is marked as the instantaneous amplitude of $r_k(t)$, and $\phi_k(t)$ represents a nondecreasing function.

Second, estimating a center frequency for each analytical signal and the spectrum of each mode signal obtained is tuned to the corresponding "baseband":

$$[(\delta(t) + \frac{j}{\pi t}) * r_k(t)]e^{-j\omega_k t} \tag{20}$$

where δ denotes the Dirac distribution and $*$ represents the convolution operator.

Third, estimating the bandwidth of each IMF through the H^{-1} Gaussian smoothness of the demodulated signal, so the constrained variational problem can be converted to solving the following optimization problem:

$$\begin{aligned} & min_{\{r_k,\omega_k\}} = \{\sum_k \left\| \partial_t [(\delta(t) + \frac{j}{\pi t}) * r_k(t)]e^{-j\omega_k t} \right\|_2^2 \} \\ & s.t. \sum_k r_k = y_t, \end{aligned} \tag{21}$$

To solve this constraint variation problem, quadratic penalty terms and Lagrangian multipliers λ are used to transform the above problem into the following unconstrained problem:

$$\begin{aligned} & L(\{u_k\},\{\omega_k\},\lambda) = \\ & \alpha \sum_k \left\| \partial_t [(\delta(t) + \frac{j}{\pi t}) * r_k(t)]e^{-j\omega_k t} \right\|_2^2 + \\ & \left\| y_t - \sum_k r_k(t) \right\|_2^2 + \left\langle \lambda(t), y(t) - \sum_k r_k(t) \right\rangle, \end{aligned} \tag{22}$$

where α is quadratic penalty factor, $\lambda(t)$ denotes the Lagrange multiplier, u_k represents band-limited modes, w_k is the adaptively determined relevant bands.

At last, the alternating direction multiplier method will be introduced to get the saddle point of the above unconstrained problem. The modes u_k, the center frequencies w_k, and Lagrangian multipliers λ can be updated, and finally, the adaptive decomposition of the signal is realized.

Prediction Model

RVFL. RVFL is an extended version of single-hidden layer feed-forward neural networks, without tuning the weights and biases iteratively (Tang et al. 2020). The RVFL network structure connects the input layer to the hidden layer, and also directly connects the input layer to the output layer, which can be represented as

$$\sum_{i=1}^{M} \beta_i g(w_i X + b_i) + \sum_{i=M+1}^{M+N} \beta_i x_i = y_j, (j = 1,2,...,N) \tag{23}$$

where ω_i is the weight value from the input layer to the hidden layer, β_i is the weight vector from the output nodes to the ith hidden node, and b_i is the bias. g represents activation function. And there are ($M+N$) inputs in the output layer. Moreover, equation (23) can be expressed as $H\beta = Y$, where H denotes the output matrix of the hidden layer, β is the matrix of weights, and Y is the matrix of targets. In RVFL, the parameters (i.e., w_i and b_i) are randomly generated without an iterative training, and the output weight vector β can be calculated by the relation $\hat{\beta} = H^{\dagger}Y$, where $H^{\dagger}$ is the Moore-Penrose generalized inverse of the matrix H.

Besides, for comparison purposes, the other five popular forecasting techniques in time series, econometrics methods, and AI techniques are also employed as the forecasting method, such as the Naïve model, seasonal ARIMA model, LSSVR, BPNN, and ELM (Sun et al. 2019; G. Li et al. 2019; Tang et al. 2020).

Empirical Design

Data descriptions. Hong Kong is a globally famous tourist destination, and the visitor arrivals to Hong Kong from eight major countries are considered to be the study samples, which includes both short-haul and long-haul markets (G. Li et al. 2019). In particular, the monthly visitor arrivals were collected from the Wind Database (http://www.wind.com.cn/), as shown in Figure 2. As for a single source market, 228 visitor arrival volumes are included in the sample data covering the period from January 2001 to December 2019. Correspondingly, the model's training data sets include 182 visitor arrivals data in each major country (covering the first 80% of the sample period, i.e., the period from January 2001 to February 2016), while the testing data sets are the latter 20%. Moreover, multistep-ahead predictions at the horizons of 1 to 6 month(s) are performed to verify the robustness of results of the different decomposition-based methods.

Comparison design. Using the proposed framework (refer to Figure 1), the forecasting method selection and the decomposition method comparison are correspondingly shown in Table 2. In Panel A, the best forecasting method with high stability and better prediction performance in all markets is selected, by comparing the commonly used 6 forecasting models. Meanwhile, eight popular decomposition models with the selected optimal forecasting method, that is, VMD, SSA, Wavelet, EEMD, STL, Fourier, HP, and CS, are applied to form eight novel decomposition-based forecasting

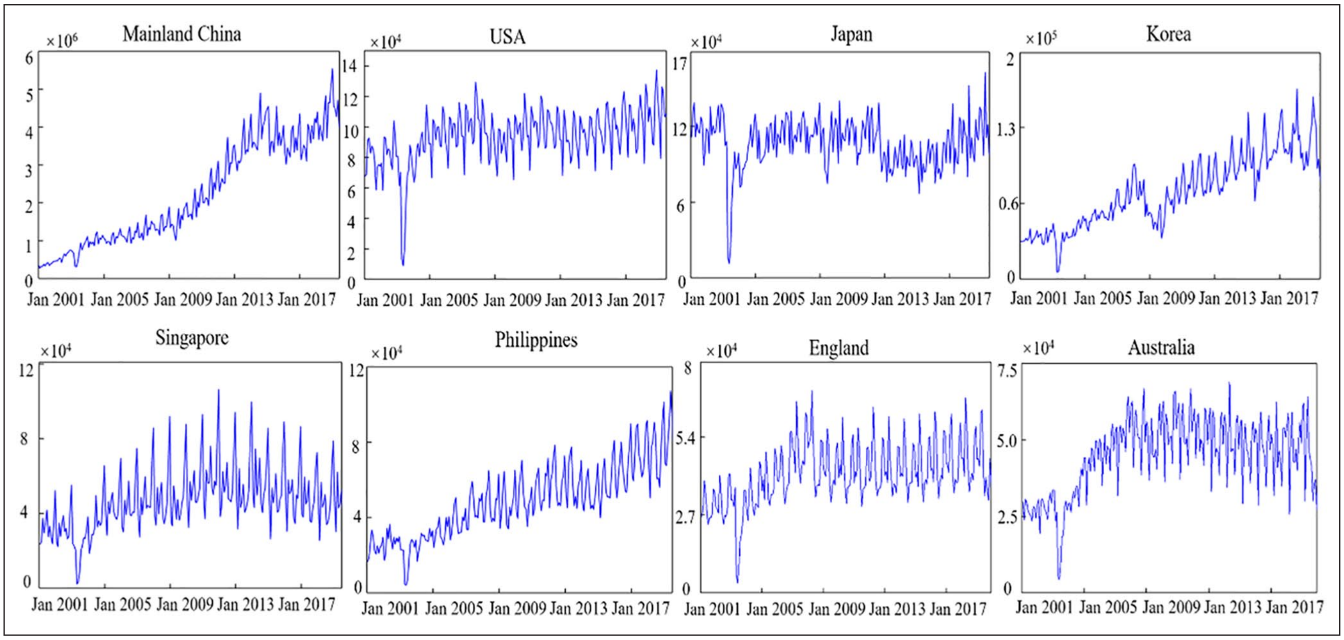

Figure 2. Tourist arrivals to Hong Kong from eight major markets.

Table 2. Comparison Design of the Predictors and Decomposition-Based Methods.

Panel A: Single predictor

	Method	Decomposition	Predictor
Predictor pool	Naïve	–	√
	SARIMA	–	√
	LSSVR	–	√
	BPNN	–	√
	ELM	–	√
	RVFL	–	√

Panel B: Decomposition-based method

	Method	Decomposition + Optimal predictor
Decomposition methods pool	VMD-based	√
	SSA-based	√
	Wavelet-based	√
	EEMD-based	√
	STL-based	√
	STSM-based	√
	Fourier-based	√
	HP-based	√
	CS-based	√

methods; moreover, a comprehensive comparison among the eight decomposition-based forecasting methods are conducted for exploring the effectiveness of each decomposition method in improving the accuracy.

Evaluation criteria. To ensure consistency with evaluation measures of the previous tourism forecasting studies, the mean absolute percentage error (MAPE), root mean square error (RMSE), the improvement ratio (IR), and the directional accuracy (DA) are used to evaluate the performance, in which MAPE and RMSE are the level predictions criteria and the DA is the directional prediction criteria (Hassani et al. 2015; Sun et al. 2019; X. Li and Law 2020):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{24}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\hat{y}_t - y_t\right)^2} \tag{25}$$

$$DA = \frac{1}{N}\sum_{t=1}^{N} a_t \times 100\% \tag{26}$$

$$IR = \frac{MAPE_{decomposition} - MAPE_{benchmark}}{MAPE_{benchmark}} \times 100\% \tag{27}$$

where N is the total number of forecasting data, and $\hat{y}_t$ and y_t are the predicted values and the actual values at time t, respectively. IR reveals the improvement of the decomposition-based method compared with the single forecasting method in terms of MAPE. Meanwhile, in DA, $a_t = 1$ if $(\hat{x}_{t+1} - x_t)(x_{t+1} - x_t) \geq 0$, or $a_t = 0$ otherwise.

From a statistical perspective, Wilcoxon signed-rank (i.e., WSR) test and the superior predictive ability (i.e., SPA) test are performed. For the WSR test, the loss differential series $d(t)=g(E_A(t))-g(E_B(t))$ with zero medians is set as the null hypothesis, where $g(\bullet)$ denotes loss function (e.g., mean square error), and $E_A(t)$ and $E_B(t)$ represent the prediction error value of benchmark model A and target model B, respectively. For the SPA test, which is a popular tool to test and compare the effectiveness of different models, the null hypothesis of the SPA test is that the predictive power of benchmark model A is no better than that of target model B.

Model specification. As for prediction models, the optimal form of SARIMA models was estimated by minimizing the Schwarz criterion (SC) and Akaike information criterion (AIC). In LSSVR, the Gaussian RBF kernel function is employed; the regularization and kernel parameters are determined via the grid search method. In BPNN, the hidden nodes are set to 7. In the ELM and RVFL, the number of hidden nodes is similarly determined via the grid searching method, the sigmoidal function $g(x) = 1/(1+e^{-x})$ is selected as the activation function; and the number of iterations is 1,000 (Tang et al. 2020). Owing to the uncertainty attributable to the initial settings and random parameters in AI techniques, the robustness of the model is measured in terms of the standard variances for 10 runs (see the error bars in Figure 3). As for the decomposition methods, wavelet decomposition level 3 and db6 are the used parameters in the Wavelet decomposition method (Kummong and Supratid 2016). The decomposed components of VMD are set to 12 by the grid searching method; meanwhile, the EEMD is also set to 12 to compare with the VMD method.

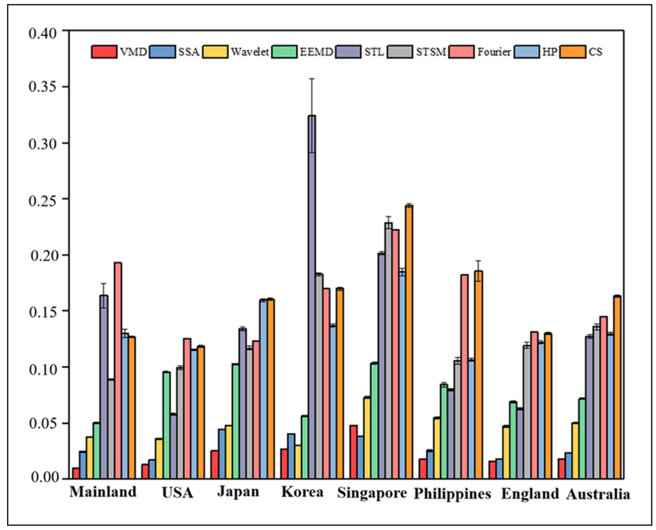

Figure 3. Performance comparison of different methods in terms of MAPE at horizon one.

Empirical Results

Performance of the Single Forecasting Method

To verify different forecasting methods' superiority, a comprehensive comparison among the six forecasting techniques is conducted. Specifically, the single forecasts including six popular forecasting methods (i.e., Naïve, SARIMA, LSSVR, BPNN, ELM, and RVFL) are produced for the eight major countries. Meanwhile, six forecasting horizons from 1-step to 6-step ahead are carried separately, and MAPE, RMSE, and DA are selected as the performance measures. Owing to space constraints and high consistency of the three measures, this section only shows the comparison of average MAPEs at all horizons of each forecasting method, as shown in Figure 4, and the detail of forecast accuracy and ranking of the different forecasting methods are demonstrated in Supplemental Table S1.

Ranking the forecasting performance (i.e., MAPEs value on average) of 6 forecasting methods in 8 countries, respectively, three conclusions can be obtained. First, the machine learning forecasting methods, that is, RVFL and ELM, have a better forecasting performance than the other models in forecasting Hong Kong inbound visitor arrivals in the eight major markets. Overall, RVFL and ELM rank first and second when compared to other forecasting methods, respectively. Remarkably, RVFL consistently achieved the best forecasting performance in four countries (i.e., Mainland China, Japan, South Korea, and Singapore) (see the pink triangle symbol in Figure 4). Second, the forecasting performance of the time series model (i.e., Naïve) closely follows that of the machine learning forecasting methods according to the overall forecasts criteria across countries, which performs best in the United States, England, and Australia. In comparison, the forecast performance in the other four countries is unstable and fluctuates greatly. Third, the other three

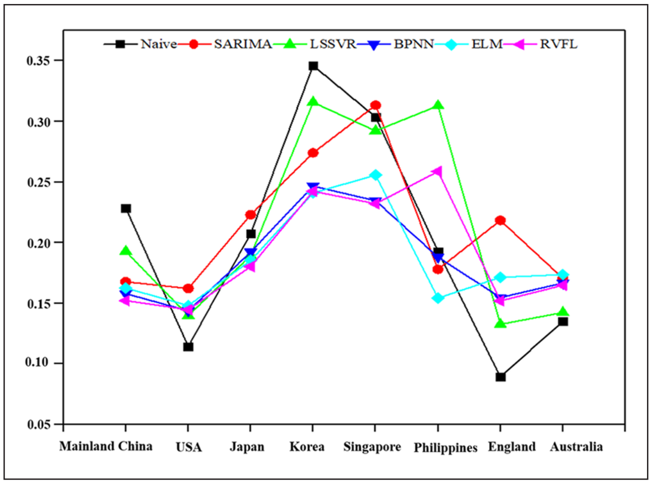

Figure 4. Performance comparison of different predictors in terms of MAPE on average.

models, that is, SARIMA, LSSVR, and BPNN, are unable to achieve the best forecasting performance for any of the countries.

Accordingly, although no single forecasting method can surpass all other forecasting methods under any circumstances, RVFL ranked in the top three in 75% of countries, achieving relative stability and the best forecasting accuracy. Also, compared with other artificial intelligence methods, RVFL is characterized by fast iteration speed and high precision in structure. Furthermore, RVFL, as a machine learning method, can effectively capture and model the nonlinear and nonstationary time series characteristics of the decomposed components in the comprehensive comparison among the decomposition prediction methods (Tang et al. 2020). Therefore, the RVFL is employed in the decomposition-based forecasting framework as the prediction technique for forecasting Hong Kong inbound visitor arrivals.

Performance of Decomposition Forecasts

To evaluate the forecasting performance of different decomposition methods, a systematic comparison among nine decomposition-based forecasting models using RVFL is conducted (i.e., VMD-RVFL, SSA-RVFL, Wavelet-RVFL, EEMD-RVFL, STL-RVFL, STSM-RVFL, Fourier-RVFL, HP-RVFL, and CS-RVFL), and the corresponding forecasting performance evaluating via the MAPE, RMSE, DA, and IR for the eight countries at all horizons (from one-step- to six-step-ahead) are reported, respectively. From these prediction evaluation criteria, one important and obvious conclusion can be obtained that the nine decomposition methods used in this study overall performed better than the benchmark model (i.e., single forecasting method, RVFL). Besides, all decomposition-based methods can be divided into four categories based on prediction accuracy.

As for MAPEs of the nine decomposition methods (see Table 3), we can see that the corresponding prediction errors with MAPEs are lower than the benchmark in most cases, in which the bold font displays the model with the lowest MAPE at each horizon. First, the VMD-RVFL model consistently provides the best forecasting performance, with an average MAPE of less than 4% across all horizons for all countries, which is the best option among the decomposition methods. The main reason can be referred to the effectiveness of VMD in processing nonstationary and nonlinear data. Second, the SSA-RVFL and Wavelet-RVFL models ranked as the second and third best models respectively in predicting performance in all countries, and the average MAPEs of these two models are around 9% and 8%, respectively. Third, the average value of MAPEs in all countries for EEMD-RVFL and STL-RVFL are close behind, and their corresponding values are around 10% and 15%. Fourth, the MAPE values of the remaining four models HP-RVFL, Fourier-RVFL, STSM-RVFL, and CS-RVFL are approximately 16%, 17%, 18%, and 19%. Obviously, we can deduce that the decomposition method is an effective way to model the visitor arrivals and improve the prediction accuracy when comparing with the benchmark's MAPE values.

Furthermore, using the one-step-ahead case as an example as shown in Figure 3, in all the countries' cases, all the decomposition methods are generally consistent and can roughly be divided into four categories in terms of MAPE. In detail, the MAPE value of VMD-RVFL model has always been the smallest in most countries except Singapore and can be considered in the first category (see the red bars). At the same time, the SSA-RVFL and Wavelet-RVFL fall into the second category, ranking second and third in China, the United States, Japan, Singapore, Philippines, England, and Australia, respectively, while in South Korea the situation is reversed. The main reason in this group is that a data-denoising process can reconstruct nonlinear features. Besides, EEMD-RVFL and STL-RVFL can be roughly grouped into the third category. For example, the EEMD-RVFL ranks fourth in Mainland China, Japan, Korea, Singapore, and Australia, and fifth in the United States, Philippines, and England. Moreover, EEMD exists the end-point divergence, which may be the main reason for its inferiority to the VMD method. Meanwhile, STL-RVFL has a similar performance, ranking the fourth in the United States, Philippines, and England, and fifth in Australia. Furthermore, the HP-RVFL, Fourier-RVFL, STSM-RVFL, and CS-RVFL belong to the last category, in which the HP method performs the most stable, Fourier method's forecast accuracy fluctuates greatly, and CS method performs the worst. The main reason for this situation in the last category shows that, because the visitor time series is affected by various factors in the complex tourism system, simple filtering or denoising cannot effectively deal with the nonstationary characteristics of tourism data.

The robustness of the nine decomposition methods with RVFL is assessed to verify their effectiveness and stability in

Table 3. Performance Comparison of Different Decomposition-Based Methods in Terms of MAPE.

Country	*h*	VMD	SSA	Wavelet	EEMD	STL	STSM	Fourier	HP	CS	Benchmark
Mainland (China)	1	**0.0099**	0.0248	0.0381	0.0504	0.1639	0.0891	0.1932	0.1301	0.1272	0.1180
	2	**0.0185**	0.0444	0.0691	0.0709	0.1073	0.1116	0.1935	0.1667	0.1579	0.1513
	3	**0.0421**	0.0657	0.0641	0.0733	0.1213	0.1218	0.1961	0.1358	0.1638	0.1539
	4	**0.0659**	0.0739	0.0707	0.0820	0.1571	0.1342	0.2013	0.1456	0.1655	0.1652
	5	**0.0861**	0.0908	0.0875	0.0950	0.1498	0.1457	0.2075	0.1418	0.1568	0.1629
	6	0.1094	0.1131	**0.0817**	0.0918	0.1446	0.1361	0.2118	0.1570	0.1476	0.1613
	Ave	**0.0553**	0.0688	0.0685	0.0772	0.1407	0.1231	0.2006	0.1462	0.1531	0.1521
USA	1	**0.0133**	0.0175	0.0364	0.0958	0.0581	0.0994	0.1256	0.1157	0.1186	0.1177
	2	**0.0117**	0.0274	0.0617	0.1075	0.0859	0.1125	0.1272	0.1420	0.1587	0.1565
	3	**0.0135**	0.0441	0.0641	0.1109	0.0998	0.1154	0.1292	0.1292	0.1398	0.1376
	4	**0.0176**	0.0491	0.0860	0.1108	0.0922	0.1202	0.1303	0.1294	0.1430	0.1467
	5	**0.0223**	0.0606	0.0868	0.1218	0.0962	0.1401	0.1327	0.1340	0.1526	0.1595
	6	**0.0233**	0.0921	0.0902	0.1226	0.0971	0.1468	0.1371	0.1293	0.1499	0.1496
	Ave	**0.0169**	0.0485	0.0709	0.1116	0.0882	0.1224	0.1303	0.1299	0.1438	0.1446
Japan	1	**0.0256**	0.0444	0.0480	0.1027	0.1343	0.1170	0.1238	0.1600	0.1608	0.1541
	2	**0.0256**	0.0658	0.0860	0.1104	0.1625	0.1514	0.1221	0.1610	0.1706	0.1689
	3	**0.0288**	0.0832	0.0865	0.1156	0.1794	0.1690	0.1210	0.1607	0.1816	0.1843
	4	**0.0326**	0.0864	0.1025	0.1157	0.2008	0.1765	0.1270	0.1699	0.1888	0.1941
	5	**0.0406**	0.1065	0.1217	0.1243	0.2035	0.1789	0.1390	0.1563	0.1946	0.1933
	6	**0.0409**	0.1530	0.1162	0.1275	0.2019	0.1875	0.1503	0.1471	0.1880	0.1863
	Ave	**0.0323**	0.0899	0.0935	0.1160	0.1804	0.1634	0.1305	0.1592	0.1808	0.1802
Korea	1	**0.0268**	0.0403	0.0301	0.0566	0.3246	0.1829	0.1700	0.1373	0.1700	0.1477
	2	**0.0232**	0.0764	0.0760	0.0956	0.2514	0.2542	0.1720	0.1698	0.1720	0.2195
	3	**0.0328**	0.1208	0.0965	0.1378	0.1430	0.2691	0.1867	0.1953	0.1867	0.2436
	4	**0.0327**	0.1429	0.1066	0.1290	0.1807	0.2876	0.2217	0.2137	0.2217	0.2961
	5	**0.0376**	0.1919	0.1165	0.1180	0.1039	0.3153	0.2704	0.1998	0.2704	0.2786
	6	**0.0468**	0.2621	0.1292	0.1297	0.1194	0.3114	0.3147	0.2058	0.3147	0.2691
	Ave	**0.0333**	0.1391	0.0925	0.1111	0.1872	0.2701	0.2226	0.1869	0.2226	0.2424
Singapore	1	0.0483	**0.0383**	0.0730	0.1037	0.2017	0.2289	0.2226	0.1849	0.2442	0.1946
	2	**0.0447**	0.0610	0.1182	0.1118	0.2365	0.3457	0.2245	0.2438	0.2989	0.2189
	3	**0.0554**	0.1048	0.1437	0.1428	0.2452	0.3071	0.2329	0.2277	0.3112	0.2288
	4	**0.0633**	0.1223	0.1810	0.1676	0.2569	0.2880	0.2486	0.2360	0.3201	0.2479
	5	**0.0666**	0.1666	0.1817	0.1803	0.2635	0.2899	0.2721	0.2253	0.3157	0.2515
	6	**0.0685**	0.2611	0.1755	0.1691	0.2675	0.3216	0.2982	0.2067	0.3145	0.2511
	Ave	**0.0578**	0.1257	0.1455	0.1459	0.2452	0.2969	0.2498	0.2207	0.3008	0.2321
Philippines	1	**0.0179**	0.0257	0.0546	0.0844	0.0797	0.1058	0.1823	0.1066	0.1858	0.2027
	2	**0.0267**	0.0617	0.0567	0.1053	0.0929	0.1677	0.1842	0.1178	0.2510	0.3009
	3	**0.0457**	0.0894	0.0586	0.1166	0.1183	0.2293	0.1862	0.1219	0.2933	0.3371
	4	**0.0736**	0.1463	0.0864	0.1307	0.1487	0.2575	0.1909	0.1344	0.2239	0.2442
	5	0.1130	0.2028	**0.1086**	0.1529	0.2315	0.2672	0.1965	0.1437	0.2016	0.2171
	6	0.1767	0.2350	**0.1116**	0.1483	0.2983	0.2545	0.2188	0.1207	0.2496	0.2501
	Ave	**0.0756**	0.1268	0.0794	0.1230	0.1616	0.2137	0.1931	0.1242	0.2342	0.2587
England	1	**0.0159**	0.0183	0.0474	0.0690	0.0628	0.1195	0.1316	0.1223	0.1300	0.1292
	2	**0.0157**	0.0300	0.0751	0.0850	0.0730	0.1197	0.1318	0.1123	0.1364	0.1387
	3	**0.0188**	0.0693	0.0518	0.1175	0.0753	0.1316	0.1321	0.1350	0.1423	0.1451
	4	**0.0187**	0.0597	0.0620	0.1221	0.0790	0.1483	0.1340	0.1401	0.1602	0.1653
	5	**0.0235**	0.0680	0.0764	0.1325	0.0698	0.1430	0.1363	0.1346	0.1562	0.1625
	6	**0.0192**	0.0920	0.0777	0.1195	0.0761	0.1317	0.1364	0.1424	0.1679	0.1703
	Ave	**0.0186**	0.0562	0.0651	0.1076	0.0727	0.1323	0.1337	0.1311	0.1488	0.1519
Australia	1	**0.0182**	0.0239	0.0503	0.0721	0.1274	0.1362	0.1453	0.1296	0.1636	0.1600
	2	**0.0194**	0.0569	0.0915	0.0804	0.1396	0.1414	0.1462	0.1393	0.1839	0.1822
	3	**0.0200**	0.0705	0.0914	0.0822	0.1389	0.1525	0.1495	0.1273	0.1453	0.1452
	4	**0.0210**	0.0761	0.1005	0.0993	0.1460	0.1533	0.1555	0.1228	0.1554	0.1549
	5	**0.0253**	0.0921	0.1019	0.1003	0.1429	0.1596	0.1662	0.1249	0.1662	0.1654
	6	**0.0296**	0.1432	0.0998	0.0887	0.1475	0.1651	0.1752	0.1287	0.1752	0.1809
	Ave	**0.0223**	0.0771	0.0892	0.0871	0.1404	0.1513	0.1563	0.1288	0.1650	0.1648

the field of visitor arrivals forecasting. We ran all the decomposition-ensemble models 10 times and evaluated the corresponding robustness with the standard deviation of MAPE, as shown by the error bars in Figure 3. The error bars of each bar show that all the decomposition-ensemble methods are stable. For example, in the Philippines, the value of the error bar of VMD-RVFL is close to 0. At the same time, although the error bar of the STL method is the largest, it is only 3.3% (see the blue bar in Korea in Figure 3).

Similarly, it is evident from Supplemental Table S2 that in terms of the RMSE criterion at all horizons, the RMSE values among the decomposition-based models can be grouped into four categories and correspondingly have a relatively stable forecasting performance (Supplemental Table S2). Taking Mainland China as an example, the following five conclusions can be drawn. First, all the decomposition-based methods significantly exceed the benchmark except the Fourier and CS in some cases. The decomposition-based models, that is, VMD-RVFL, SSA-RVFL, Wavelet-RVFL, EEMD-RVFL, STL-RVFL, HP-RVFL, and STSM-RVFL, can reduce the average RMSE by approximately 59.3%, 52.6%, 52.9%, 49.9%, 0.5%, 8.6%, 13.7%, and 5.5%, respectively. Second, VMD-RVFL is obviously better than the other eight decomposition methods and is the most stable decomposition method with the best prediction performance. Third, although the following three methods (i.e., SSA, Wavelet, EEMD) all reduce more than 40%, EEMD-RVFL is unstable in other countries (such as only 23% lower than the benchmark in the United States), so SSA-RVFL and Wavelet-RVFL are still considered to be in the second level. Fourth, the STL method is close to the EEMD method in prediction accuracy, and the principle of these two methods is to decompose the visitor time series data into several components (i.e., multiscaling; see Table 1) and can be classified as the third level. Fifth, the last four decomposition methods have similar prediction accuracy, with the worst CS-RVFL.

With one-step-ahead forecast as an example, Figure 5 shows the normalized RMSE of each decomposition method in each country case. Remarkably, VMD-RVFL is still the best-predicted model among countries, with the lowest error. At the same time, the most suitable country for the SSA method is Singapore, the predicted performance in other countries is also very close. Furthermore, the Wavelet, EEMD, Fourier, and CS methods respectively have the best performance in South Korea among all countries. Meanwhile, the STL obtains a better performance in Philippines, and Mainland China has the best prediction performance with STSM method among all the countries. However, since the CS method only smoothed and denoised the original data, it is difficult to extract the information of different time scales effectively and improve the prediction accuracy. Interestingly, the decomposition-based methods that can effectively capture and model the trend terms, periodicity, seasonality, and noise terms of visitor arrival data can significantly improve the prediction accuracy consistently in all countries, such as VMD-RVFL, SSA-RVFL, Wavelet-RVFL, EEMD-RVFL, and STL-RVFL. Meanwhile, the simple smoothing denoising or filtering function of the decomposition method is difficult to improve the prediction accuracy steadily, such as Fourier, HP, and CS. Particularly, the VMD-RVFL outperforms the other eight decomposition ensemble methods at all horizons in all countries (see the bold text in Supplemental Table S2).

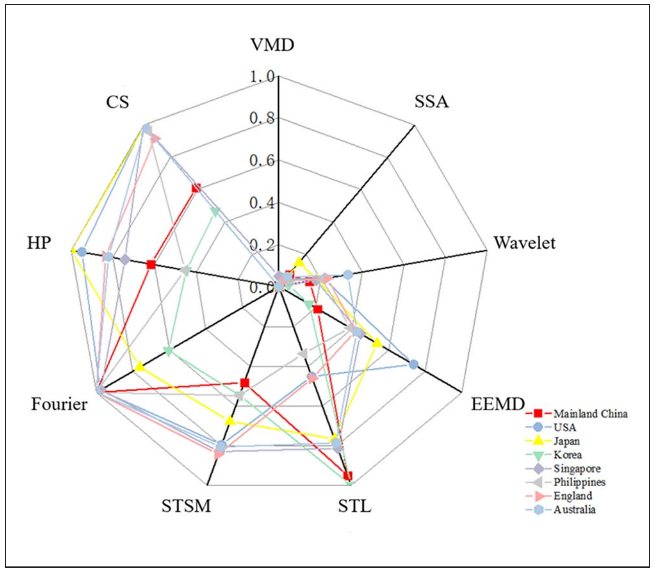

Figure 5. Performance comparison of decomposition methods in terms of normalized root mean square error (RMSE) at horizon 1.

As for directional prediction accuracy, Table 4 demonstrates the comparison results of all the decomposition-based models and the benchmark in terms of DA on average (the bold values indicate the optimal result), and two important conclusions can be found (detailed comparison results of DA are presented in Supplemental Table S3). First, overall, it can be obviously seen that most decomposition-based models can generate much higher directional prediction accuracy in most countries such as VMD, SSA, Wavelet, EEMD, STL, STSM, and HP; meanwhile, some methods such as Fourier and CS only obtain higher DA value in some countries. The hidden reason may be referred to the effectiveness of the concept of "decomposition and ensemble" in modeling nonlinear and complex data, especially the visitor arrivals data. Second, the VMD-RVFL is superior to all of the other models in forecasting Hong Kong inbound visitor arrivals in eight countries, while the Fourier, HP, STSM, and CS model rank the last, and the other four methods (i.e., SSA, Wavelet, EEMD, and STL) rank in the middle. From Figure 6, similar findings can be obtained that all the nine types of decomposition have a better forecasting performance than the benchmark, among which the VMD-RVFL is the optimal decomposition method in all cases (see the red bar).

Table 4. Compare the Performance of Different Methods and Corresponding Ranking by Average DA.

	VMD	SSA	Wavelet	EEMD	STL	STSM	Fourier	HP	CS	Benchmark
China	**0.91 (1)**	0.82 (2)	0.77 (4)	0.78 (3)	0.77 (4)	0.72 (6)	0.52 (9)	0.67 (7)	0.66 (8)	0.67
USA	**0.97 (1)**	0.92 (2)	0.86 (3)	0.78 (6)	0.86 (3)	0.81 (5)	0.70 (9)	0.77 (8)	0.78 (6)	0.76
Japan	**0.93 (1)**	0.85 (2)	0.84 (3)	0.81 (4)	0.77 (7)	0.76 (8)	0.81 (4)	0.78 (6)	0.74 (9)	0.74
Korea	**0.96 (1)**	0.73 (4)	0.79 (2)	0.74 (3)	0.71 (5)	0.54 (7)	0.50 (9)	0.58 (6)	0.53 (8)	0.49
Singapore	**0.95 (1)**	0.92 (2)	0.86 (4)	0.83 (5)	0.89 (3)	0.81 (6)	0.62 (9)	0.78 (7)	0.77 (8)	0.92
Philippines	0.83 (2)	0.75 (3)	**0.87 (1)**	0.71 (4)	0.71 (4)	0.61 (7)	0.49 (9)	0.71 (4)	0.51 (8)	0.50
England	**0.94 (1)**	0.83 (3)	0.84 (2)	0.73 (6)	0.78 (4)	0.70 (7)	0.77 (5)	0.67 (8)	0.67 (8)	0.67
Australia	**0.96 (1)**	0.88 (2)	0.86 (3)	0.86 (3)	0.81 (5)	0.79 (6)	0.67 (9)	0.78 (7)	0.75 (8)	0.74

Note: The bold values indicate the optimal result.

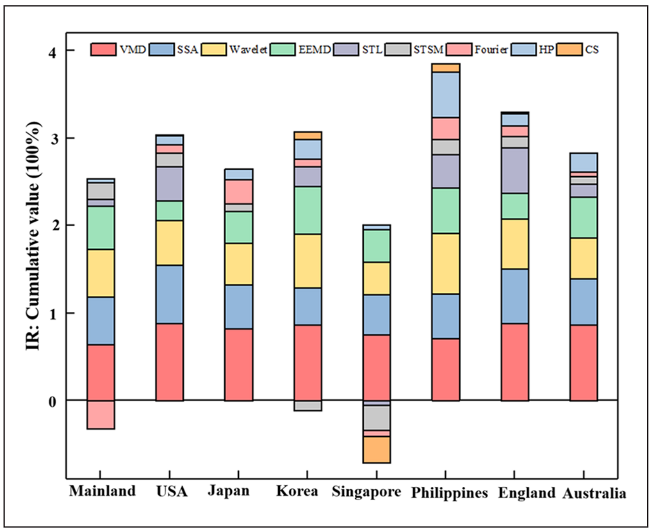

Figure 6. Improvement ratios of decomposition methods on average of all horizons.

To statistically test the differences among the nine decomposition methods in prediction capability, the Wilcoxon signed rank test and SPA test are employed. Taking Mainland China as a sample, the results are all reported in Table 5, with the p values. For example, in panel A, the p value in row 3, column 7, is 0.000, which means that the test rejects the null hypothesis (i.e., there exist significant differences between the forecasts of SSA-RVFL and STSM-RVFL) under the confidence level of 99%. Meanwhile, in panel B, the p value in row 2, column 3, is 1.000; thus, the test accepts the null hypothesis (i.e., the VMD-RVFL is better than that of SSA-RVFL) under the confidence level of 99%.

These analyses have revealed some interesting findings: (1) when VMD-RVFL model is considered as the test target model in panel A (and panel B), all p values are 0.000 (and 1.000) in most cases, suggesting that the VMD-RVFL model is significantly superior to all other decomposition models under a 99% confidence level; (2) among the SSA, Wavelet, EEMD, and STL, SSA statistically exceeds the EEMD and STL methods in panels A and B, followed by Wavelet and EEMD; (3) the Fourier, HP, STSM, and CS model also have similarly lower forecasting performance; however, the STSM statistically outperformed the HP, Fourier, and CS. These findings repeatedly prove the effectiveness of decomposition methods in improving the prediction accuracy for visitor arrivals, and the decomposition methods are roughly divided into four categories according to the accuracy. Furthermore, VMD is verified to be the optimal method among all the nine decomposition methods.

Robustness Analysis

In this section, the standard deviation of evaluation criteria (i.e., MAPE), the different decomposition forecasts with different forecasting methods, and a new study destination (i.e., Singapore monthly visitor arrivals) are conducted to verify the robustness of the proposed comparative decomposition framework. First, as for the standard deviation, because of the different initial settings of RVFL, we ran all the nine decomposition forecasts 10 times and calculated the standard deviation of MAPE, which turned out to 0 for all cases, as shown in Supplemental Table S4. Second, in terms of the different prediction models, the SARIMA and ELM are also used as the forecasting model in the proposed decomposition-ensemble approach, by verifying the robustness of the proposed decomposition forecasts in eight countries (see Supplemental Tables S5 and S6). Finally, we have added Singapore as a new study destination, and the proposed 9 decomposition ensemble methods are used to forecast tourism demand data respectively to address the generalizability of the results, the corresponding MAPE values show that the proposed decomposition methods have the potential to forecast tourism demand in other countries as shown in Supplemental Table S7.

These results are provided in Supplemental Tables S4-S7, and provide evidence that (1) the robustness of the proposed nine decomposition forecasts' prediction results are verified; (2) the different forecasting methods (e.g., SARIMA and ELM) and different study destinations do not affect the consistency of the prediction results of the proposed decomposition forecasts; that is, all the decomposition methods can

Table 5. Two Statistical Test Results of Decomposition-Based Methods in China.

Panel A: The Wilcoxon signed rank test

Model	VMD	SSA	Wavelet	EEMD	STL	STSM	Fourier	HP	CS	RVFL
VMD		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SSA			0.233	0.020	0.000	0.000	0.000	0.000	0.000	0.000
Wavelet				0.254	0.000	0.000	0.000	0.000	0.000	0.000
EEMD					0.000	0.000	0.000	0.000	0.000	0.000
STL						0.051	0.000	0.000	0.000	0.000
STSM							0.000	0.000	0.000	0.000
Fourier								0.000	0.000	0.000
HP									0.211	0.157
CS										0.755

Panel B: The SPA test

Model	VMD	SSA	Wavelet	EEMD	STL	STSM	Fourier	HP	CS	RVFL
VMD		1.000	1.000	1.000	0.987	1.000	1.000	1.000	1.000	1.000
SSA	0.000		0.428	0.503	0.976	1.000	1.000	1.000	1.000	1.000
Wavelet	0.000	0.000		1.000	0.976	1.000	1.000	1.000	1.000	1.000
EEMD	0.000	0.000	0.000		0.954	0.996	1.000	1.000	1.000	1.000
STL	0.007	0.018	0.030	0.062		0.171	0.923	0.402	0.449	0.375
STSM	0.000	0.000	0.000	0.005	0.847		0.997	1.000	0.998	0.999
Fourier	0.000	0.000	0.000	0.000	0.084	0.000		0.001	0.002	0.000
HP	0.000	0.000	0.000	0.000	0.620	0.005	0.999		0.696	0.342
CS	0.000	0.000	0.000	0.000	0.552	0.000	0.999	0.353		0.045
RVFL	0.000	0.000	0.000	0.000	0.552	0.001	1.000	0.633	0.943	

roughly be divided into four categories and the VMD-RVFL model consistently provides the best forecasting performance among all nine decomposition methods.

Summary

Six major conclusions can be obtained from the empirical results.

1. Overall, all the decomposition methods significantly outperform the benchmark in the level and the directional prediction at all horizons, which can be used as an efficient tool for analyzing and forecasting visitor arrivals.
2. Nine decomposition methods can be roughly divided into four groups in terms of forecasting accuracy. Specifically, VMD is the optimal method for visitor arrivals, SSA and Wavelet are close behind, EEMD and STL belong to the third level, the other four methods fall into the fourth level.
3. The effectiveness of VMD in improving prediction could be observed repeatedly, in that VMD significantly outperforms other decomposition methods in terms of both forecasting accuracy and robustness.
4. The effective denoising methods (i.e., SSA and Wavelet) can also significantly achieve a better forecasting performance in all countries from one-step-ahead to six-step-ahead, by filtering the noise and reconstructing a new series with less noise.
5. The multiscale types (i.e., EEMD and STL), which extract components with different time-scale (e.g., cyclical or seasonal pattern), can effectively capture the intrinsic complexity of the data of visitor arrivals and obviously improve the prediction accuracy.
6. According to the decomposition principle, the filtering method (i.e., HP), the simple multiscale method (i.e., STSM), and simple denoising methods (i.e., Fourier and CS) are difficult to achieve stable and better prediction performance, because of the intrinsic complexity of visitor arrival data.

Conclusions and Discussions

The main purpose of this study is to explore how decomposition methods can model nonlinear and nonstationary visitor arrival data and whether different decomposition predictions can consistently improve prediction accuracy. Therefore, a comprehensive comparison of the decomposition methods commonly used in the field of prediction is conducted, that is, VMD, SSA, Wavelet, EEMD, STL, STSM, Fourier, HP, and CS. To verify the robustness of the decomposition method, this study forecasts the Hong Kong inbound tourism demand of its eight major source markets: mainland China, United States, Japan, Korea, Singapore, the Philippines, England, and Australia. Moreover, the best forecasting method, which is selected from the single forecasting methods (i.e., Naïve model, Seasonal ARIMA model, LSSVR, BPNN, ELM, and RVFL), is incorporated into the nine decomposition-ensemble models.

This study proves that the decomposition methods can effectively capture the inherent complexity of tourism demand data to achieve accurate forecasts for visitor arrivals. In particular, most of the decomposition methods in the eight major countries have achieved better prediction accuracy than the benchmark, such as VMD, SSA, Wavelet, EEMD, STL, STSM, and HP. In addition, although some decomposition methods cannot always be better than the best single forecasting method, they only failed to have good prediction performance in some countries, such as Fourier and CS. Consequently, the proposed decomposition-ensemble method is a promising approach toward resolving difficulties in forecasting visitor arrivals volume.

Because of the perishable nature of the tourism product, accurate tourism demand forecasting will be crucial to the optimal allocation of tourism resources. Therefore, the comprehensive comparison framework of decomposition methods in this study will provide the following two management implications. First, the decomposition method can be used as an effective forecasting tool to enable tourism practitioners to accurately predict the scale of future tourist flows and then choose a more reasonable tourism management strategy. Second, analyzing the data patterns of the decomposed subsequences, such as trend items, seasonal items, period items, and noise items, can help practitioners to effectively deal with the impact of various market factors. Thus, we maintain that our findings are of great significance for operational management in the tourism industry, such as strategic planning, resource allocation, investment, pricing, advertising, and crisis management.

Although the proposed framework has obtained a superior standard of forecasting performance, they still have some limitations. First, this study is mainly to compare and analyze the effectiveness of different decomposition methods to improve the accuracy, so the unified forecasting method is selected for different components, that is, RVFL. However, different components have different time scales, and the applicable models are also different. For example, the low-frequency component (e.g., trend component) is more suitable for the time series model, while the high-frequency component (e.g., noise component) may be more suitable for the ANN method. Thus, different forecasting methods can be selected for ensemble according to the time scale characteristics of different components to improve prediction accuracy. Second, other commonly used prediction techniques can also be employed as the forecasting method for further capturing the complex pattern of tourist arrival data, such as the econometrics methods, machine learning methods, and deep learning methods. Third, because it is quite well acknowledged that no forecasting method is universally good for all markets (Song and Li 2008; Song, Qiu, and Park 2019), in the future, we can try to build different decomposition-ensemble methods based on the best forecasting method in different markets. Fourth, as many countries and regions as possible need to be considered to demonstrate the robustness of the proposed approach. Fifth, the impact of COVID-19 on tourism demand can be quantitatively studied based on the decomposition methods, such as VMD and EEMD (X. Zhang, Lai, and Wang 2008).

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Supplemental Material

Supplemental material for this article is available online.

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