

Article

A Hybrid Smoothing Model for Historical Reconstruction of Route-Level Airline Passenger Demand

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Featured Application

Airlines, airport authorities, route planners, and transportation analysts can use the proposed Guerrero–Holt–Winters (GHW) hybrid model to reconstruct and interpret historical route-level passenger (pax) demand. The GHW model decomposes pax demand into long-term trend, seasonal variation, and irregular components, offering a practical framework for analyzing historical market behavior, evaluating route performance, and monitoring demand patterns. The proposed model focuses on historical demand reconstruction and interpretation, while future forecasting is outside the scope of this paper.

Abstract

Historical pax demand estimation is important for understanding long-term demand dynamics and supporting airline planning, strategic decision-making, and transportation policy analysis. However, current decomposition approaches either estimate trends without explicitly modeling seasonality or jointly estimate trend and seasonal components without providing user control over trend smoothness. This paper proposes a Guerrero–Holt–Winters (GHW) hybrid smoothing model to estimate and reconstruct historical route-level airline pax demand. The GHW model combines Guerrero’s user-controlled trend estimation with the multiplicative seasonal structure of the Holt–Winters (HW) model to produce an interpretable decomposition of historical demand into trend, seasonal, and irregular components. The model is applied to quarterly pax demand data for ten representative U.S. domestic air routes covering the period 2015–2023. The results show that the proposed GHW model achieves lower in-sample reconstruction errors than the multiplicative HW model at lower degrees of trend smoothness within the evaluated range. Among the evaluated specifications, $\lambda = 1$, corresponding to a Guerrero smoothness index of $S(1; 36) = 58.82\%$, produces the lowest in-sample reconstruction error. The historical reconstruction error, measured by the root mean squared error (RMSE), is reduced by approximately 54.4% relative to the multiplicative HW model. Similar improvements are observed under MAE, MAPE, and sMAPE, indicating that the reduction in reconstruction error at this smoothness level is consistent across the four error measures. An expanded benchmark comparison with HW, ETS state-space exponential smoothing, STL decomposition, and HP1600 further shows that the GHW model produces the lowest in-sample reconstruction errors across all four evaluation error metrics and all ten routes analyzed. A sensitivity analysis further demonstrates that reconstruction accuracy declines as the degree of trend smoothness increases from $S(\lambda; 36) = 58.82\%$ to 88.63%, whereas the estimated seasonal factors remain remarkably stable across the evaluated smoothness range. A COVID-19 robustness analysis further shows that reconstruction errors are substan-



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tially lower in the Pre-COVID period than in the Post-COVID period across all ten routes, indicating that reconstruction accuracy is sensitive to the period analyzed.

Keywords: airline passenger demand; historical demand reconstruction; time-series decomposition; exponential smoothing; Holt–Winters model; trend estimation; seasonal analysis

1. Introduction

Accurate estimation of airline passenger (pax) demand is essential for route planning, capacity allocation, fleet scheduling, airport operations, infrastructure planning, and strategic decision-making. Pax demand directly influences airline scheduling, revenue management, marketing, fleet planning, workforce planning, resource allocation, airport master planning, and public-policy decisions [1]. Recent studies also highlight that pax demand estimation is central to resource planning in the air transport industry and that demand models must account for historical demand patterns and factors affecting route- or flight-trend-level demand [2].

In applied airline and airport management, historical pax demand estimation is valuable even when the objective is not to generate future forecasts. Accurately reconstructing historical demand components can help identify a route's long-term behavior, distinguish recurrent seasonal patterns from irregular deviations, and support retrospective evaluation of operational, market, or external changes. Recent papers on air pax demand highlight that pax flow analysis is relevant for airport management, operational planning, scheduling, and transport-system decision-making [3–6]. Jin et al. [3] describe pax demand dynamics as complex, nonlinear, and non-stationary; Dantas et al. [7] demonstrate that air transportation demand series contain identifiable trend and seasonal components; and Hopfe et al. [5] emphasize that pax flow modeling becomes especially difficult during volatile periods such as the COVID-19 pandemic.

Pax demand is difficult to estimate because it is influenced by multiple interacting factors, including economic conditions, service characteristics, geographic factors, airfares, seasonality, market uncertainty, consumer preferences, and external shocks such as pandemics and geopolitical events [8]. Similarly, Lundaeva et al. [2] indicate that demand estimation models should account for historical demand data, economic indicators, socioeconomic indicators, airfare data, and external factors. Recent pax demand papers also show that model development has increasingly moved toward hybrid, combination, neural-network, and spatiotemporal architectures to address the nonlinear, volatile, and data-dependent behavior of pax demand [3–6]. Hu [4], for example, indicates that no single model is superior in all situations and that mixed methods can reduce the risk of relying on an incorrect forecasting model. Liang et al. [6] also emphasize that hybrid models can integrate preprocessing, decomposition, optimization, and prediction components for complex air pax demand series.

From a time-series perspective, pax demand can be decomposed into components such as level, trend, seasonality, and irregular variation. Estimating these components is important because each provides distinct information about the observed demand process: the trend describes the long-term movement of pax demand, seasonality reflects recurrent intra-year travel patterns, and irregular variation captures short-term deviations caused by operational, economic, or external disturbances. Time-series decomposition and component estimation provide a useful basis for representing these structures by allowing analysts to distinguish long-term movements from recurrent seasonal behavior and irregular devia-

tions [9,10]. The practical interpretation of these components provides valuable information for airline and airport decision-makers. The estimated trend can be used to analyze the long-term evolution of route-level passenger demand, supporting strategic planning, route performance evaluation, network planning, and infrastructure planning [11–13]. The seasonal component identifies recurrent travel patterns that are useful for scheduling, fleet assignment, capacity planning, and resource allocation [11]. The irregular component, or error term, represents deviations from the reconstructed pax demand pattern that the estimated trend and seasonal components cannot explain. These deviations may reflect unexpected events, such as severe weather, economic disruptions, operational disturbances, public health emergencies, and other unforeseen events. Therefore, estimating these components separately provides a more informative representation of historical pax demand and facilitates the interpretation of route-level pax demand dynamics [14].

Several time-series methods have been used to estimate and analyze pax demand, including statistical, econometric, artificial intelligence, deep-learning, and hybrid methodologies [1,8]. Among them, exponential smoothing models are widely used because they provide simple, adaptive mechanisms for representing level, trend, and seasonality [10,15]. In particular, the Holt–Winters (HW) model estimates level, trend, and seasonal components through recursive updating equations, making it suitable for seasonal time series [16,17]. However, because the HW model jointly updates these components, short-term fluctuations and seasonal movements may influence the estimated long-term component, reducing trend interpretability when the series contains strong seasonality or abrupt irregular variation. Therefore, although HW is useful for representing seasonal time series, its recursive joint-updating structure is not designed to isolate the long-term trend from seasonal and irregular movements when the objective is historical component interpretation rather than future forecasting.

The user-controlled smoothing methodology proposed by Guerrero [18] offers an alternative approach to estimating a stable long-term trend. The method allows analysts to specify the desired degree of smoothness, yielding an interpretable representation of long-term behavior that is less sensitive to short-term fluctuations. However, Guerrero's [18] methodology was designed primarily for trend estimation and does not explicitly account for seasonal dynamics or irregular variation. This limits its direct application to route-level airline pax demand, where recurrent seasonal movements are a key feature of the observed series. Consequently, Guerrero's [18] methodology is useful for estimating the long-term component, but it requires an additional structure to support a component-wise representation of strongly seasonal pax demand series.

Therefore, there is a methodological opportunity to extend Guerrero's [18] trend-estimation methodology by integrating it into a framework that also accounts for the seasonal structure of pax demand. Existing hybrid models in pax demand studies have frequently combined statistical, artificial intelligence, grey-system, decomposition, and machine learning techniques to enhance modeling accuracy and empirical performance [4,7,8]. However, many hybrid approaches increase model complexity and reduce interpretability. In contrast, less attention has been given to simple, interpretable hybrid smoothing structures that separate long-term trend estimation from the representation of seasonal and short-term variation. This gap is important because models designed for historical estimation and reconstruction should not only reproduce the observed series but also provide interpretable components that can be analyzed separately.

This paper addresses this gap by proposing a Guerrero–Holt–Winters hybrid model (GHW model) to estimate and reconstruct historical route-level pax demand. The method uses Guerrero's [18] user-controlled smoothing approach to estimate the long-term trend and combines it with the multiplicative HW structure to capture seasonal variation in

demand. The aim is to provide an interpretable, component-wise estimation model that extends the practical applicability of Guerrero's [18] trend-estimation methodology to seasonal pax demand data. Therefore, the proposed model is an estimation and reconstruction method for historical route-level demand rather than a forecasting model designed to predict future pax observations.

The main contribution of this paper is the development of a hybrid estimation model for contexts where the objective is to represent, reconstruct, and interpret historical pax demand rather than generate future forecasts. The model uses Guerrero's [18] user-controlled smoothing methodology to estimate the long-term trend and combines it with the multiplicative seasonal structure of Holt–Winters smoothing to capture seasonal variation. In this way, the proposed approach extends the practical applicability of Guerrero's [18] methodology from trend estimation alone to the component-wise estimation of seasonal pax demand series. Therefore, the contribution is both methodological and applied. Methodologically, the model separates controlled trend estimation from seasonal representation, preserving the interpretability of the long-term component while accounting for recurrent seasonal variation. From an applied perspective, it provides an interpretable framework for analyzing route-level pax demand using observed historical data.

The empirical application uses route-level pax data from the U.S. Bureau of Transportation Statistics. We compare the proposed GHW model with the multiplicative HW model, which serves as the reference seasonal smoothing method, to assess its ability to represent and reconstruct historical pax demand behavior. The empirical evaluation therefore focuses on historical representation and reconstruction accuracy rather than out-of-sample predictive accuracy. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on pax demand estimation and hybrid time-series methods. Section 3 presents the proposed hybrid smoothing methodology. Section 4 reports the empirical results. Section 5 discusses implications for applied pax demand analysis. Finally, Section 6 concludes the paper.

2. Literature Review

2.1. Air Pax Demand Estimation and Applied Aviation Context

Pax demand has been widely studied because it is directly related to planning and managing the air transportation industry. Wang and Gao [1] indicate that pax demand affects airline scheduling, revenue management, marketing, fleet planning, workforce planning, resource allocation, network planning, airport master planning, public-policy decisions, and infrastructure development. Their review of pax demand studies also shows that most empirical studies use time-series data, socio-economic factors, airline operational factors, and time-series-based methods to estimate the relationships among variables that affect pax demand.

Pax demand can be analyzed at multiple levels, including aggregate, airport, route, and origin–destination levels. Carson et al. [19] compare aggregate pax demand models with those based on airport-specific information. Their results show that approaches using disaggregate airport-level information outperformed the aggregate approach. These findings are relevant for route-level pax demand because demand behavior is not necessarily homogeneous across airports, routes, or markets. Boonekamp et al. [20] also analyze demand at the airport-pair level and show that route-level demand is influenced by standard demand factors such as GDP, population, tourism, distance, and service-related factors. Their results also demonstrate significant effects for variables such as low-cost carrier presence, ethnic links, and aviation-dependent employment. Together, these papers show that pax demand is affected not only by historical time series but also by route-specific, economic, social, and service-related characteristics.

Airport-level studies also show that pax demand may exhibit trends, seasonality, shocks, and irregular changes. Tsui et al. [21] analyze Hong Kong International Airport passenger throughput using SARIMA and ARIMAX models. Their analysis shows that passenger traffic can exhibit trends, seasonal patterns, and abrupt changes associated with events such as the SARS outbreak. Kim and Shin [22] argue that traditional time-series models alone may not adequately capture short-term pax demand fluctuations, and they use search-engine query data as additional information to represent short-term changes in pax demand. These studies are important because they show that pax demand is a dynamic process affected by internal time-series behavior and external factors.

Recent papers highlight the complexity of pax demand and the need for methodologies that capture nonlinear, volatile, non-stationary, and seasonal behavior. Xie et al. [23] propose a hybrid approach that combines seasonal decomposition with least-squares support vector regression for short-term pax demand. Their methodology first decomposes the pax demand series into trend-cycle, seasonal, and irregular components, then models each component independently before integrating the results. This paper is relevant to our paper because it underscores the importance of treating the components of pax demand separately when the series is highly volatile and irregular. Jin et al. [3] also describe pax demand as complex, nonlinear, and non-stationary, and they propose a hybrid ensemble model based on variational mode decomposition, ARMA, and kernel extreme learning machine.

Other papers have used model combinations, neural networks, and external information to address the complexity of pax demand. Hu [4] proposes a nonadditive forecast-combination model based on grey theory. The results show that no single model is superior in all situations, so mixing models can reduce the risk of relying on a single model. Hopfe et al. [5] compare neural-network models with ARIMA, SARIMA, and SARIMAX for airport pax flows during volatile periods and show that volatility increases the difficulty of modeling pax flow. Liang et al. [6] propose a hybrid model that incorporates search-engine data, spatial effects, decomposition, optimization, and multi-model fusion, indicating that recent pax demand estimation methods are moving toward hybrid structures.

Although these papers explain the complexity of pax demand and the usefulness of hybrid and decomposition-based methods, most are primarily forecasting-oriented. In contrast, this paper focuses on historical estimation, reconstruction, and interpretation of route-level pax demand components. This distinction matters because analyzing historical pax demand can reveal how the long-term component evolved and how seasonal and irregular movements contributed to the observed series. Therefore, these papers support the applied context of our paper by showing that pax demand is complex and important for airline and airport management. However, our paper contributes differently: it proposes an interpretable, component-wise method to estimate, reconstruct, and analyze historical route-level pax demand, rather than to forecast future demand.

2.2. Historical Demand Reconstruction and Component Estimation

Time-series analysis generally has two complementary objectives: forecasting future observations and reconstructing the historical behavior of the observed process. Forecasting estimates future values, whereas historical demand reconstruction focuses on identifying and estimating the underlying components that explain a time series' historical evolution. These components include the long-term trend, the seasonal pattern, and the irregular component (error term), each providing distinct information about the data's dynamics. Estimating these components separately enables the identification of persistent changes, recurrent seasonal behavior, and random disturbances, thereby improving the interpretation of complex time series. Therefore, historical reconstruction is an important analytical tool for understanding the evolution of transportation demand, where the objective goes

beyond prediction to understanding and explaining the temporal structure of the observed data [9,24].

Historical demand reconstruction is commonly performed through time-series decomposition techniques that separate a time series into its underlying trend, seasonal, and irregular components. One of the most influential methods, the Seasonal-Trend decomposition using Loess (STL) provides a flexible way to estimate these components while accommodating complex seasonal patterns [9]. State-space formulations later extended this idea by representing the level, trend, and seasonal components as latent processes that evolve, allowing recursive estimation through exponential smoothing methods [14]. These methods improve the estimation of the underlying components and make it easier to distinguish systematic changes from random disturbances. Robust component estimation is also important because observed time series often contain structural breaks, outliers, and unexpected events. In these situations, conventional decomposition methods may not perform well. Robust trend and seasonal estimation techniques were developed to address this problem and improve the reliability of the reconstructed components [24].

In the air transportation industry, reconstructing historical pax demand provides insights that extend beyond forecasting future traffic volumes. The estimated trend can be used to analyze the long-term evolution of route-level demand, helping identify long-term market growth or decline and supporting strategic planning. The seasonal component reveals recurring travel patterns that are useful for scheduling, fleet assignment, and capacity planning. Finally, the irregular component captures deviations associated with unexpected events such as economic crises, severe weather, operational disruptions, or public health emergencies. Together, these components provide a more complete understanding of historical pax demand and support retrospective analyses of market behavior [11,12].

2.3. Classical Time-Series, Smoothing, and Decomposition Methods

Classical time-series methods have been widely used in pax demand studies because they provide structured ways to characterize temporal dependence, trend, seasonality, and error term (irregular variations). In these methods, the observed series are analyzed mainly through their past behaviors, making them useful for studying the internal dynamics of pax demand. Tsui et al. [21] apply SARIMA and ARIMAX models to pax demand data from Hong Kong International Airport. Their analysis shows that airport pax series can exhibit different trends, seasonal patterns, and abrupt changes associated with external events such as the SARS outbreak. Their paper also illustrates how classical statistical models can incorporate seasonal structure, explanatory variables, and intervention effects in airport pax demand analysis. Among classical methods, decomposition has been used to separate the observed series into components with different roles. Xie et al. [23] propose two hybrid approaches that combine seasonal decomposition with least-squares support vector regression for short-term pax demand forecasting. In their approach, the pax demand series is decomposed into trend-cycle, seasonal-factor, and irregular components, which are then modeled independently before being combined into an aggregated output. This structure is important because it shows that pax demand can be analyzed by separating the long-term component, recurrent seasonal behavior, and irregular variation. Although their objective is forecasting, the decomposition step is directly related to the component-wise logic used in this paper.

Smoothing methods are another family of classical time-series models. Kim and Shin [18] classify time-series methods for airport pax demand forecasting into smoothing methods, ARIMA methods, and hybrid models. They indicate that smoothing models are methods that remove irregular fluctuations from the time series and use the basic movements of the series to forecast future values. This characteristic makes smoothing

methods relevant when the aim is to obtain a clearer representation of the underlying movement of pax demand. However, Kim and Shin [22] also discussed that traditional time-series models may be limited when short-term fluctuations are affected by factors outside the historical series.

Exponential smoothing methods are especially relevant to our study because they provide simple, recursive structures for representing level, trend, and seasonality. The HW model updates level, trend, and seasonal components through recursive equations, making it suitable for seasonal time series.

Smoothing methods have been used as time-series methods and as benchmarks or components within broader modeling frameworks for pax demand analysis. Jin et al. [3] review previous pax demand forecasting studies and report that time-series methods used in the air transportation industry include smoothing techniques, ARIMA/SARIMA models, grey theory, seasonal adjustment methods, and HW, among others. This supports including smoothing methods in the methodological background for pax demand analysis.

However, classical smoothing and decomposition methods also have limitations. In the HW model, the level, trend, and seasonal components are updated jointly through recursive equations. This mathematical structure is useful for adaptive modeling of seasonal time series. Still, the model does not estimate the long-term trend independently from the seasonal component and the error term. Therefore, when the aim is to isolate and interpret the long-term component separately, this structure may reduce the interpretability of the estimated trend, especially in strongly seasonal pax demand series. This limitation is highly relevant to our paper because the aim is not to forecast future observations, but to estimate, reconstruct, and interpret historical demand components.

Therefore, classical time-series, smoothing, and decomposition methods provide the methodological basis for this paper. Decomposition separates demand into meaningful components, while exponential smoothing provides an adaptive structure for representing seasonal behavior. Nevertheless, standard decomposition and HW do not directly address the specific aim of our paper: estimating a stable long-term trend through controlled smoothing while also representing the seasonal structure of route-level pax demand. This motivates the development of a hybrid smoothing approach that combines controlled trend estimation with multiplicative seasonal representation.

2.4. Hybrid and Decomposition-Based Pax Demand Models

Hybrid and decomposition-based models have been used in pax demand studies because pax demand can exhibit nonlinear, non-stationary, seasonal, volatile, and irregular behavior. These approaches typically combine multiple methodologies to leverage each method's strengths. In pax demand papers, hybrid structures commonly include decomposition methods, statistical models, artificial intelligence models, neural network models, grey prediction, optimization algorithms, or ensemble strategies.

Bao et al. [25] develop a hybrid approach for air pax traffic forecasting based on ensemble empirical mode decomposition, a slope-based method, and support vector machines (SVMs). Their method first decomposes the original air pax traffic series into intrinsic mode functions and a residual component using ensemble empirical mode decomposition with a slope-based method. Then, it models each component using SVMs. The component-level results are integrated through another SVM to obtain the final forecast. Their empirical results, based on monthly air pax traffic series from six airlines in the United States (US) and the United Kingdom (UK), show that the proposed EEMD-Slope-SVMs model outperforms single SVM, HW, and ARIMA benchmarks. This paper is relevant to our paper because it shows how decomposition-based preprocessing can be combined with another

modeling method to reduce the complexity of pax demand series before integrating the component-level results.

Xie et al. [23] also apply a decomposition-based hybrid structure for short-term pax demand forecasting. Their approach decomposes the pax demand series into trend-cycle, seasonal, and irregular components and then models these components independently using least-squares support vector regression. They then combine the component-level results into an aggregated output. Although their aim is forecasting, their methodology supports the idea that pax demand can be treated component by component when the series contains strong seasonal and irregular behavior.

Jin et al. [3] develop a hybrid model for pax demand based on variational mode decomposition, ARMA, and kernel extreme learning machine. Their model applies variational mode decomposition to decompose the original data into several mode functions. It then models stationary components using ARMA and non-stationary components using a kernel extreme learning machine. Their results confirm that decomposition-based hybrid models can be useful when pax demand presents complex nonlinear and non-stationary behavior.

Grey-model and forecast-combination approaches have also been used to address uncertainty and model-selection risk in pax demand papers. Hu [4] develops a nonadditive forecast-combination model based on grey prediction and the Choquet fuzzy integral. Hu [4] indicates that no single model is superior in all situations and that mixing forecasting methods can reduce the risk of relying on an incorrect model. Carmona-Benitez and Nieto [26] also mix SARIMA with a damped-trend grey forecasting model to forecast pax demand, showing another example of hybridization between classical time-series structures and grey-system methods.

Recent papers have extended hybrid pax demand models by incorporating neural networks, external variables, spatial effects, and optimization algorithms. Hopfe et al. [5] compare neural networks with ARIMA, SARIMA, and SARIMAX for pax demand during volatile periods. Their paper shows that model performance may depend on the volatility level in the observed pax demand process. Liang et al. [6] develop a hybrid forecasting model that includes search-engine data, spatial effects, decomposition, optimization, and multi-model fusion. Their model shows the tendency toward more complex hybrid structures for pax demand forecasting.

Overall, the reviewed papers show that hybrid and decomposition-based models have been useful for handling complex pax demand behavior in forecasting-oriented applications. However, most of these models are designed primarily to improve forecasting accuracy. They often combine several advanced techniques, such as decomposition algorithms, machine learning models, neural networks, optimization algorithms, or ensemble structures. In contrast, our paper focuses on a simpler and more interpretable hybrid smoothing structure for historical estimation and reconstruction. The aim is to estimate the long-term trend separately while representing the seasonal structure of route-level pax demand within a component-wise model.

2.5. Trend Estimation, Guerrero Methodology, and Research Gap

Sections 2.1–2.3 demonstrate that pax demand papers have used classical time-series models, decomposition methods, hybrid models, grey models, neural networks, and external-information-based architectures to analyze or forecast pax demand. These studies show that pax demand series may present trend, seasonality, irregular variation, volatility, nonlinearity, and non-stationarity. Decomposition-based studies such as [3,6,23,25] show that separating or transforming the original series into components can reduce the series' complexity before applying another modeling method. However, these papers are mainly

forecasting-oriented because they aim to improve future prediction accuracy rather than estimate, reconstruct, and interpret historical pax demand components.

Trend estimation is important in this paper because the trend represents the long-term movement of pax demand. In route-level pax demand, the trend can provide information about a route's underlying evolution. At the same time, the seasonal component represents recurrent intra-year movements, and the irregular component, or error term, represents deviations not explained by the systematic components. For this reason, a method that estimates the trend separately from seasonal and irregular variation (the error term) can provide a more interpretable representation of historical pax demand behavior.

The HW model is a classical smoothing structure for seasonal time series because it updates level, trend, and seasonal components through recursive equations. This mathematical structure is useful for adaptively representing seasonal time series because the estimated components evolve as new observations become available. However, this time-series model updates these components simultaneously and does not estimate the long-term trend independently of the seasonal and irregular components. Therefore, when the aim is to isolate and interpret the long-term component separately, this structure may reduce the interpretability of the estimated trend, especially in strongly seasonal pax demand series. This is an important limitation for this paper because the aim is not to forecast future observations, but to estimate, reconstruct, and interpret historical pax demand components.

Guerrero [18] proposed a user-controlled smoothing methodology for estimating the trend component of a time series. His method allows the analyst to specify the desired degree of smoothness and obtain a trend estimate that reflects the long-term movement of the series while reducing the influence of short-term fluctuations. In this way, his methodology provides an interpretable representation of the underlying behavior of a time series and offers explicit control over the flexibility of the estimated trend. This characteristic makes Guerrero's [18] methodology especially relevant when the aim is descriptive analysis and historical interpretation rather than forecasting.

However, Guerrero's [18] methodology estimates the long-term trend of a series and does not explicitly represent recurrent seasonal patterns or short-term variation around the trend. This limitation matters for route-level pax demand because the observed series typically contain both long-term movements and strong seasonal behavior. Therefore, although Guerrero's [18] methodology is useful for estimating the long-term component of a series, it is insufficient to reconstruct the full historical behavior of pax demand when seasonality is a central feature of the observed data.

This paper addresses this main methodological gap. Existing hybrid and decomposition-based pax demand models show the usefulness of mixing methods. However, most are designed mainly to improve forecasting accuracy and often rely on complex structures such as machine learning models, decomposition algorithms, neural networks, optimization procedures, or ensemble methods. At the same time, the HW model represents seasonal behavior but updates the trend jointly with the other components, while Guerrero's [18] user-controlled smoothing methodology provides interpretable trend estimation without explicitly representing seasonality. Therefore, there is a methodological opportunity to develop simple and interpretable hybrid smoothing frameworks that combine two objectives: estimating the long-term trend separately and representing the seasonal structure of pax demand for historical reconstruction and interpretation.

This paper addresses this gap by combining Guerrero's [18] user-controlled trend estimation methodology with the multiplicative seasonal structure of HW smoothing. The proposed GHW model is designed for historical estimation and reconstruction, not for future forecasting. The objective of the GHW model is to estimate the long-term trend separately while representing the seasonal structure of route-level pax demand

within a component-wise method. In this way, this paper applies Guerrero's [18] trend-estimation methodology with the multiplicative seasonal structure of the HW model to analyze historical pax demand series characterized by seasonality, providing a simple and interpretable alternative to more complex forecasting-oriented hybrid models.

3. Methodology

This section develops the proposed GHW model, which is a hybrid smoothing methodology for estimating, reconstructing, and interpreting historical route-level pax demand. The method addresses two methodological limitations identified in the literature review. First, the multiplicative HW model provides a classical framework for seasonal smoothing, but it updates the level, trend, and seasonal components jointly. Second, Guerrero's [18] methodology provides a controlled trend-smoothing procedure, including applications that do not directly represent recurrent seasonal patterns. The proposed GHW model combines Guerrero's [18] trend-estimation procedure with the multiplicative seasonal structure of HW smoothing. The aim is to estimate a stable long-term trend separately while representing the seasonal structure of pax demand within an interpretable component-wise model. Under this formulation, the observed pax demand series is reconstructed using a controlled long-term trend component and a multiplicative seasonal component. At the same time, the remaining variation is represented through an irregular component. For that reason, the GHW model is formulated as a historical estimation and reconstruction method rather than as a forecasting method.

3.1. Holt–Winters Multiplicative Exponential Smoothing

The multiplicative HW model is a multiplicative seasonal structure method incorporated into the proposed hybrid estimation model. HW smoothing represents a seasonal time series through recursively updated level, trend, and seasonal components.

Let $\{y_t\}_{t=1}^N$ denote a time series observed at equally spaced time intervals, where $y_t > 0$. Let m denote the seasonal period. In the multiplicative HW formulation, l_t denotes the level component at time t , b_t denotes the trend or slope component at time t , and s_t denotes the multiplicative seasonal factor at time t . Under the multiplicative seasonal specification, the seasonal factor rescales the non-seasonal baseline, so that seasonal effects are proportional to the level of the series.

Given smoothing parameters $\alpha, \beta, \gamma \in (0, 1)$, the recursive updates for calculating each component are:

$$l_t = \alpha \left(\frac{y_t}{s_{t-m}} \right) + (1 - \alpha)(l_{t-1} + b_{t-1}), \quad (1)$$

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}, \quad (2)$$

$$s_t = \gamma \left(\frac{y_t}{l_t} \right) + (1 - \gamma)s_{t-m}, \quad (3)$$

where α, β , and γ are the smoothing parameters associated with the level, local trend, and seasonal factors, respectively. Specifically, α controls the updating of the level component, β controls the updating of the local trend component, and γ controls the updating of the multiplicative seasonal factor.

The multiplicative HW recursion is initialized following the procedure described by Chopra and Meindl [27]. The historical demand series is first deseasonalized, and a linear regression of the deseasonalized demand on time is used to obtain the initial level (l_0) and local trend (b_0) from the regression intercept and slope, respectively. The initial seasonal factors (s_0) are obtained from ratios of observed demand to the corresponding fitted deseasonalized values, averaged for each seasonal position. For the quarterly data used in this paper ($m = 4$), we obtain four initial seasonal factors.

Although this paper focuses on historical estimation and reconstruction rather than future forecasting, we report the standard HW forecast equation to identify the multiplicative seasonal structure used as the basis for the proposed GHW model. Let $h \geq 1$ be the forecast horizon and define the seasonal index selector as

$$j(h) = ((h - 1) \bmod m) + 1, \quad (4)$$

Then, the multiplicative HW point forecast is given by

$$\hat{y}_{t+h|t} = (l_t + hb_t)s_{t-m+j(h)}, \quad (5)$$

In this paper, HW is not used as the proposed model for future prediction. Instead, it serves as a reference seasonal smoothing method and provides multiplicative seasonal logic incorporated into the proposed hybrid GHW model.

3.2. Guerrero Trend Estimation with User-Chosen Smoothness

Guerrero [18] develops a method for estimating trends in which the analyst fixes the desired percentage of smoothness at the outset, and the corresponding smoothing parameter is then obtained from a smoothness index associated with the Hodrick–Prescott (HP) filtering framework. The purpose of his method is descriptive trend estimation rather than business-cycle extraction or forecasting. In this setting, the observed series is represented through an unobserved-components formulation,

$$y_t = x_t + \eta_t, \quad t = 1, \dots, N, \quad (6)$$

where x_t is the trend component and η_t is a noise component. The trend is estimated using the HP filter as a penalized least-squares problem.

Let $y = (y_1, \dots, y_N)'$, $x = (x_1, \dots, x_N)'$ and let K_2 be the $(N - 2) \times N$ second-difference operator such that $(K_2x)_t = x_t - 2x_{t+1} + x_{t+2}$, $t = 1, \dots, N - 2$.

Guerrero [18] links the HP objective to the statistical model

$$y = x + \eta, \quad \eta \sim \left(0, \sigma_\eta^2 I_N\right), \quad (7)$$

and

$$K_2x = \varepsilon, \quad \varepsilon \sim \left(0, \sigma_\varepsilon^2 I_{N-2}\right), \quad (8)$$

with mutual independence. Under this setup,

$$\lambda = \frac{\sigma_\eta^2}{\sigma_\varepsilon^2}, \quad (9)$$

Thus, λ controls the balance between fidelity to the observed data and smoothness of the estimated trend. A larger value of λ penalizes variation in the second differences more strongly, producing a smoother trend.

Guerrero [18] formalizes trend smoothness through a smoothness index and provides a method for selecting λ according to a user-chosen smoothness percentage. The smoothness index is defined as:

$$S(\lambda; N) = 1 - \frac{1}{N} \text{tr} \left[(I_N + \lambda K_2' K_2)^{-1} \right], \quad (10)$$

where $\text{tr}(\cdot)$ denotes the matrix trace. The index has the following limiting behavior:

$$S(\lambda; N) \rightarrow 0 \text{ as } \lambda \rightarrow 0, \quad (11)$$

and

$$S(\lambda; N) \rightarrow 1 - 2/N \text{ as } \lambda \rightarrow \infty, \quad (12)$$

Guerrero [18] uses this index to express the degree of trend smoothness in percentage terms. Therefore, instead of choosing λ directly, the analyst specifies a desired smoothness level S^* , and the smoothing parameter is obtained by solving

$$S(\lambda; N) = S^*, \quad (13)$$

In the proposed GHW model, Equation (13) provides an objective criterion for determining λ independently of the GHW model reconstruction error. Accordingly, the desired trend smoothness S^* is specified first, and the corresponding value of λ is obtained from the Guerrero smoothness criterion rather than selected by minimizing the reconstruction RMSE.

Once λ has been obtained, the controlled trend estimate is computed as

$$\hat{x}_\lambda = (I_N + \lambda K_2' K_2)^{-1} y, \quad (14)$$

For consistency with the proposed GHW model, the controlled trend estimate is then denoted as

$$\hat{\tau}_t = \hat{x}_{\lambda,t}, \quad t = 1, \dots, N, \quad (15)$$

3.3. Guerrero–Holt–Winters Hybrid Model (GHW)

This section proposes a hybrid smoothing approach that combines Guerrero's [18] user-controlled trend-estimation methodology with the multiplicative seasonal structure of HW smoothing. The proposed GHW model aims to estimate, reconstruct, and interpret historical route-level pax demand, not to generate future forecasts. The proposed method separates the long-term trend from the seasonal component, allowing the trend to be estimated through controlled smoothing while the seasonal structure is represented multiplicatively.

Let $\{y_t\}_{t=1}^N$ denote the observed pax demand series. The proposed hybrid representation is given by

$$y_t = \tau_t s_t e_t, \quad (16)$$

where τ_t is the long-term trend component estimated using the Guerrero [18] methodology, s_t is the multiplicative seasonal factor, and e_t is the irregular or error component. The reconstructed value of pax demand is defined as:

$$\hat{y}_t^{GHW} = \hat{\tau}_t \hat{s}_t^{HW}, \quad (17)$$

Therefore, the estimated irregular component is obtained as

$$\hat{e}_t = \frac{y_t}{\hat{y}_t^{GHW}} = \frac{y_t}{\hat{\tau}_t \hat{s}_t^{HW}}, \quad (18)$$

The first step of the proposed GHW model is to estimate the long-term trend (τ_t) using Guerrero's [18] user-controlled smoothing methodology. Following Guerrero [18], the degree of trend smoothness is expressed through the smoothness index $S(\lambda; N)$ defined in Equation (10). Thus, each evaluated value of λ corresponds to a specific degree of trend smoothness, determined independently of the GHW reconstruction error. In the empirical analysis, several values of λ , and consequently several smoothness levels, are evaluated through a sensitivity analysis to assess the effect of trend smoothness on historical reconstruction accuracy and component interpretability.

The second step is to estimate the multiplicative seasonal component. After estimating Guerrero's [18] trend component $\hat{\tau}_t$, the dynamic seasonal factor $\hat{s}_t^{HW}$ is obtained from the HW seasonal updating equations. In the proposed GHW model, the complete multiplicative HW recursion is used to estimate the level (l_t), local trend (b_t), and seasonal factor ($\hat{s}_t^{HW}$). The HW level (l_t) and local trend (b_t) are auxiliary states required for the recursive estimation of the seasonal factor ($\hat{s}_t^{HW}$); however, they are not used as the long-term trend component ($\hat{\tau}_t$) in the final GHW reconstruction. Instead, the long-term component ($\hat{\tau}_t$) is estimated independently using Guerrero's trend-estimation methodology. Consequently, the final historical reconstruction combines the estimated Guerrero trend ($\hat{\tau}_t$) with the multiplicative seasonal factor obtained from the HW recursion ($\hat{s}_t^{HW}$), as defined in Equation (17).

Accordingly, the HW smoothing parameters α , β , and γ retain their standard roles in the HW recursion. Although the HW level (l_t) and local trend (b_t) are not used as the final long-term component of the GHW reconstruction, their recursive estimation is required to compute the HW seasonal factors used by the proposed model.

For each route and each evaluated value of λ , the HW smoothing parameters α , β , and γ are jointly estimated by minimizing the RMSE between the observed pax demand (y_t) and the final GHW reconstruction ($\hat{y}_t^{GHW}$) subject to the constraints ($0 < \alpha < 1$, $0 < \beta < 1$, and $0 < \gamma < 1$). For a fixed value of λ , the Guerrero trend ($\hat{\tau}_t$) is first estimated. The multiplicative HW recursion is then evaluated for admissible values of α , β , γ , and the resulting HW seasonal factor ($\hat{s}_t^{HW}$) is combined with the Guerrero trend ($\hat{\tau}_t$) to obtain the GHW reconstruction ($\hat{y}_t^{GHW}$). The values of α , β , and γ that minimize the GHW reconstruction RMSE are retained. This optimization is performed independently for each route and each evaluated value of λ . Consequently, the optimized HW smoothing parameters are specific to each route and evaluated value of λ .

$$(\alpha^*, \beta^*, \gamma^*)_\lambda = \underset{0 < \alpha, \beta, \gamma < 1}{\operatorname{argmin}} \sqrt{\frac{1}{N} \sum_{t=1}^N [y_t - \hat{y}_t^{GHW}(\lambda, \alpha, \beta, \gamma)]^2}, \quad (19)$$

where $(\alpha^*, \beta^*, \gamma^*)_\lambda$ denotes the set of HW smoothing parameters that minimizes the GHW reconstruction RMSE for a given value of λ .

The additive reconstruction residual is

$$u_t = y_t - \hat{y}_t^{GHW}, \quad (20)$$

The parameter λ controls the degree of smoothness of the Guerrero trend, whereas the HW smoothing parameters α , β , and γ control the recursive estimation of the HW level (l_t), local trend (b_t), and seasonal factor ($\hat{s}_t^{HW}$), respectively. The data frequency determines the seasonal period m ; for example, $m = 12$ for monthly data with annual seasonality and $m = 4$ for the quarterly data used in this research. Thus, the GHW model distinguishes the parameter controlling the smoothness of the long-term Guerrero trend from those governing the recursive estimation of the HW components.

In this way, the GHW model provides an interpretable component-wise reconstruction of historical pax demand. The method is designed for cases in which the analyst wants to examine the long-term movement and seasonal structure of a route-level pax demand series, rather than produce future forecasts. Its contribution is to extend the practical applicability of Guerrero's [18] trend estimation methodology to a seasonal pax demand context through a multiplicative seasonal reconstruction model.

Algorithm 1 shows the GHW historical reconstruction procedure:

Algorithm 1. GHW historical reconstruction procedure

Input: Historical pax demand y_t , seasonal periodicity m , and evaluated value of λ .

Step 1: Initialize the multiplicative HW level (l_0), local trend (b_0) and seasonal factors as described in Section 3.1.

Step 2: Estimate the Guerrero long-term trend $\hat{\tau}_t(\lambda)$.

Step 3: For admissible values of α , β , and γ recursively estimate l_t , b_t , and $\hat{s}_t^{HW}$ using the multiplicative HW equations.

Step 4: Calculate $\hat{y}_t^{GHW} = \hat{\tau}_t(\lambda)\hat{s}_t^{HW}$.

Step 5: Calculate the RMSE between y_t and $\hat{y}_t^{GHW}$.

Step 6: Optimize α , β , and γ according to Equation (19) and retain $(\alpha^*, \beta^*, \gamma^*)_\lambda$.

Step 7: Using optimized parameters, obtain the final GHW reconstruction, multiplicative irregular component, and additive reconstruction residual.

Step 8: Repeat Steps 2–7 for each evaluated value of λ and independently for each route.

Output: Guerrero trend, HW seasonal factors, GHW reconstructed pax demand, multiplicative irregular component, additive reconstruction residual, RMSE, and optimized HW smoothing parameters for each evaluated λ .

4. Empirical Application

4.1. Case Study and Route Selection

The case study uses quarterly route-level pax demand data from the U.S. Bureau of Transportation Statistics (BTS) T-100 Domestic Market database for ten selected U.S. domestic air routes during 2015–2023 [28]. The aim is to evaluate the proposed GHW hybrid model's ability to estimate, reconstruct, and interpret historical pax demand components at the route level. The analysis focuses on historical reconstruction rather than future forecasting; therefore, the selected data provide a suitable setting for evaluating how the proposed method separates the long-term trend from the seasonal component and the irregular variation, or error term, of pax demand.

The period 2015–2023 was selected because it provides a recent and consistent sample for all routes under study included in the analysis. It also encompasses different demand phases, including pre-pandemic conditions, the COVID-19 disruption, and the post-pandemic recovery period. This makes the sample useful for evaluating an estimation framework designed to represent long-term movement, recurrent seasonal behavior, and irregular deviations in route-level pax demand. Since the data are quarterly, the seasonal period is defined as $m = 4$, corresponding to four observations per year.

The BTS T-100 database contains many U.S. domestic routes. For the empirical analysis, a representative sample of ten routes was selected. Route selection was based on three criteria: (i) complete quarterly pax demand data for the entire study period (2015–2023); (ii) representation of different market characteristics; and (iii) suitability for evaluating the proposed historical reconstruction methodology.

The selected routes are ATL-DFW, ATL-FLL, ATL-MCO, HNL-LAX, LAS-LAX, JFK-LAX, LAX-ORD, LGA-ORD, HNL-OGG, and LAX-SFO (Table 1). They represent different types of U.S. domestic air transportation markets. ATL-DFW and LGA-ORD are business-oriented or high-connectivity routes linking major metropolitan areas and airline hubs. ATL-MCO, ATL-FLL, LAS-LAX, HNL-LAX, and HNL-OGG represent leisure, tourism, coastal, and island markets, where seasonal demand patterns are generally more pronounced. JFK-LAX is a long-haul transcontinental route connecting two major U.S. metropolitan areas, whereas LAX-ORD and LAX-SFO represent major intercity and regional corridors.

Together, these routes provide a diverse set of pax demand characteristics for evaluating the proposed GHW model.

Table 1. U.S. domestic routes analyzed in the case study and their applied market classification.

Route	Route Type	Applied Interpretation
ATL-DFW	Business/hub-to-hub	Major airline hubs and high-connectivity business route
LGA-ORD	Business/metropolitan corridor	Large metropolitan markets with business and network traffic
ATL-MCO	Leisure/tourism	Orlando-oriented leisure and tourism demand
ATL-FLL	Leisure/coastal market	Florida leisure and coastal travel demand
LAS-LAX	Leisure/short-haul corridor	Las Vegas–Los Angeles leisure and regional traffic
HNL-LAX	Long-haul leisure/island-mainland	Hawaii–mainland tourism and long-haul leisure demand
HNL-OGG	Island/regional tourism	Inter-island Hawaiian market with tourism and local mobility
JFK-LAX	Transcontinental metropolitan	Major long-haul route between large metropolitan areas
LAX-ORD	Major intercity/network corridor	Large hub and intercity market
LAX-SFO	West Coast corridor	High-frequency regional air traffic corridor (business and leisure)

For each route, the observed series is defined as quarterly pax demand: y_t = pax demand on a given route during quarter t , where $t = 1, \dots, N$ and $N = 36$ for the 2015–2023 period.

The model is applied separately to each route. This route-by-route implementation is consistent with the objective of obtaining interpretable components for each market, rather than estimating a single aggregate pax demand series. For each route, the GHW model estimates a controlled long-term trend, a multiplicative quarterly seasonal component, and an irregular component. The reconstructed historical pax demand obtained from the proposed model is then compared with the fitted values produced by the multiplicative Holt–Winters method. This comparison is appropriate because Holt–Winters is the classical seasonal smoothing method most directly related to the proposed hybrid structure.

Table 1 summarizes the route categories.

Overall, the selected routes constitute a suitable case-study set because they represent different types of U.S. domestic air passenger markets, including hub-to-hub connections, leisure-oriented markets, transcontinental corridors, major intercity routes, and island-related traffic (Table 1). This variation supports the empirical objective of evaluating the proposed GHW model across route-level pax demand series with different trends and seasonal behavior.

4.2. Component Estimation Using the GHW Model

The proposed GHW model is applied route by route. The GHW model estimates route-specific long-term trends, seasonal factors, and irregular components, rather than imposing a common structure across all routes.

For each route r , the observed quarterly pax demand series is denoted by $y_{r,t}$, where $t = 1, \dots, 36$. The estimation procedures for the trend, seasonal, and irregular components follow the methodology described in Section 3.

This procedure produces three interpretable components for each route: a controlled long-term trend, a multiplicative quarterly seasonal factor, and an irregular component. The trend component represents the smoothed long-term trajectory of route-level pax demand, the seasonal component represents recurrent quarterly variation, and the irregular component captures deviations not represented by the seasonal-trend reconstruction.

4.3. Reconstruction Accuracy and Sensitivity Analysis

In this section, the empirical performance of the proposed GHW model is evaluated, and its reconstruction accuracy is compared with that of the multiplicative HW model. The analysis focuses on historical demand reconstruction rather than forecast performance. First, reconstruction errors obtained from the GHW and Holt–Winters models are compared. Second, the optimized parameter values obtained for the GHW model are presented and discussed for different values of the trend-smoothing parameter λ . Third, a sensitivity analysis examines the effect of the trend-smoothing parameter λ on reconstruction accuracy and seasonal-factor estimation within the GHW model. Finally, the implications of different degrees of trend smoothness are examined to characterize the trade-off between reconstruction accuracy and component interpretability.

4.3.1. Reconstruction Accuracy of the GHW and Holt–Winters Models

Table 2 reports the reconstruction accuracy of the proposed GHW model and the multiplicative HW model for the ten route-level pax demand series. Reconstruction accuracy is evaluated using the root mean squared error (RMSE), which measures the average magnitude of the deviations between the observed and reconstructed demand series. For the GHW specification with $\lambda = 1$, the proposed model achieved lower RMSE values than the HW model for all routes under study. HNL-OGG (59.87%), HNL-LAX (59.28%), JFK-LAX (58.17%), LAS-LAX (57.35%), and LAX-ORD (57.02%) show the largest improvements, whilst LGA-ORD (41.14%) shows the smallest improvements. At this evaluated smoothing level, the reduction in RMSE relative to HW ranged from approximately 41% to 60% across the ten routes. The broader effect of the trend-smoothing parameter λ on reconstruction accuracy is examined separately in the sensitivity analysis in Section 4.3.2.

Table 2. Reconstruction accuracy of the GHW and HW models measured by RMSE.

ROUTE $\lambda = 1$	RMSE GHW [pax]	RMSE HW [pax]	Improvement [%]
ATL-DFW	36,017.52	82,601.99	56.40
ATL-FLL	53,112.25	118,438.97	55.16
ATL-MCO	58,189.16	133,317.22	56.35
HNL-LAX	46,415.98	113,977.79	59.28
LAS-LAX	53,840.48	126,232.72	57.35
JFK-LAX	63,865.77	152,679.88	58.17
LAX-ORD	47,815.79	111,264.06	57.02
LGA-ORD	70,678.94	120,075.40	41.14
HNL-OGG	38,887.46	96,899.27	59.87
LAX-SFO	77,371.21	143,153.63	45.95

Although RMSE is frequently used as a forecasting performance metric, in this paper it is used exclusively as a measure of historical reconstruction accuracy. Specifically, RMSE quantifies the extent to which the reconstructed passenger-demand series reproduces the observed historical series and does not evaluate out-of-sample predictive performance.

Table 2 indicates that the proposed GHW model provides a more accurate reconstruction of historical route-level pax demand than the multiplicative HW model. The results suggest that combining the Guerrero trend-estimation approach with the HW model seasonal structure improves the representation of historical demand patterns while maintaining an interpretable component-wise framework.

Figure 1 shows the percentage reduction in RMSE achieved by the proposed GHW model relative to the multiplicative HW model for each route. The figure shows that the proposed model consistently outperformed the HW model across all routes, with RMSE

reductions ranging from 41.14% for LGA–ORD to 59.87% for HNL–OGG. These results indicate that the proposed GHW model provides consistent improvements across all routes.

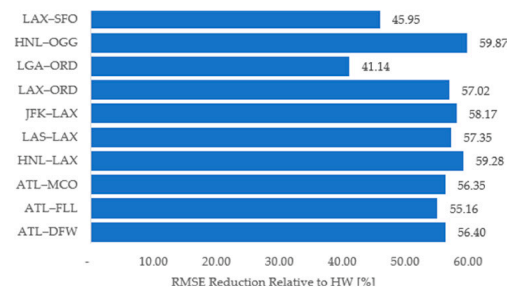


Figure 1. Route-level RMSE reduction in the proposed GHW model relative to the multiplicative HW model for $\lambda = 1$.

Table 3 shows the reconstruction accuracy of the proposed GHW model and the multiplicative HW model measured by the mean absolute error (MAE). As with the RMSE results, the proposed GHW model achieved lower MAE values than the HW model for all routes under study when $\lambda = 1$. LAS-LAX (52.98%), ATL-MCO (52.18%), HNL-OGG (51.35%), HNL-LAX (50.35%), and ATL-DFW (50.16%) show the largest improvements, whereas LGA-ORD (28.92%) and LAX-SFO (34.82%) exhibit the smallest improvements. Overall, the GHW model reduced MAE by approximately 29% to 53% across the analyzed routes, confirming that the proposed methodology consistently improves historical pax demand reconstruction according to an absolute error measure.

Table 3. Reconstruction accuracy of the GHW and HW models measured by MAE.

ROUTE $\lambda = 1$	MAE GHW [pax]	MAE HW [pax]	Improvement [%]
ATL-DFW	25,120.56	50,406.05	50.16
ATL-FLL	33,614.85	66,591.09	49.52
ATL-MCO	38,018.80	79,507.09	52.18
HNL-LAX	31,606.86	63,656.92	50.35
LAS-LAX	35,297.31	75,064.47	52.98
JFK-LAX	43,895.73	87,085.00	49.59
LAX-ORD	35,390.29	69,394.67	49.00
LGA-ORD	53,033.83	74,610.91	28.92
HNL-OGG	27,716.71	56,976.70	51.35
LAX-SFO	58,536.52	89,809.16	34.82

Table 4 shows the reconstruction accuracy of the proposed GHW model and the multiplicative HW model measured by the mean absolute percentage error (MAPE). Consistent with the RMSE and MAE results, the proposed GHW model achieved lower MAPE values than the HW model for all the routes under study when $\lambda = 1$. HNL-LAX (62.35%), JFK-LAX (61.74%), HNL-OGG (61.56%), LAS-LAX (60.16%), and ATL-MCO (59.29%) show the largest improvements, whereas LAX-SFO (55.53%), ATL-DFW (55.56%), and LGA-ORD (55.85%) exhibit the smallest improvements. Overall, the GHW model reduced MAPE by approximately 56% to 62% across the analyzed routes, providing additional evidence that the proposed methodology consistently improves the historical reconstruction of route-level pax demand.

Table 4. Reconstruction accuracy of the GHW and HW models measured by MAPE.

ROUTE $\lambda = 1$	MAPE GHW [%]	MAPE HW [%]	Improvement [%]
ATL-DFW	10.55	23.74	55.56
ATL-FLL	12.01	28.52	57.91
ATL-MCO	12.89	31.67	59.29
HNL-LAX	17.74	47.12	62.35
LAS-LAX	13.40	33.62	60.16
JFK-LAX	16.49	43.11	61.74
LAX-ORD	10.39	24.68	57.90
LGA-ORD	20.73	46.96	55.85
HNL-OGG	12.94	33.65	61.56
LAX-SFO	20.00	44.97	55.53

Table 5 shows the reconstruction accuracy of the proposed GHW model and the multiplicative HW model measured by the symmetric mean absolute percentage error (sMAPE). As with RMSE, MAE, and MAPE, the proposed GHW model achieved lower sMAPE values than the HW model for all routes under study when $\lambda = 1$. LAS-LAX (51.02%), ATL-MCO (49.88%), LAX-ORD (48.30%), HNL-OGG (47.93%), and ATL-DFW (46.77%) show the largest improvements, whereas LGA-ORD (38.24%) and LAX-SFO (38.65%) exhibit the smallest improvements. Overall, the GHW model reduced sMAPE by approximately 38% to 51% across the analyzed routes, providing further evidence that the proposed methodology consistently improves the historical reconstruction of route-level pax demand.

Table 5. Reconstruction accuracy of the GHW and HW models measured by sMAPE.

ROUTE $\lambda = 1$	sMAPE GHW [%]	sMAPE HW [%]	Improvement [%]
ATL-DFW	8.34	15.66	46.77
ATL-FLL	8.50	15.72	45.94
ATL-MCO	8.92	17.79	49.88
HNL-LAX	10.97	19.68	44.26
LAS-LAX	8.78	17.93	51.02
JFK-LAX	10.36	19.49	46.83
LAX-ORD	8.49	16.43	48.30
LGA-ORD	13.16	21.30	38.24
HNL-OGG	9.46	18.17	47.93
LAX-SFO	12.80	20.87	38.65

The error metrics show lower in-sample historical reconstruction errors for the proposed GHW model than for the multiplicative HW model at $\lambda = 1$ across the ten routes analyzed. Both the absolute and percentage-based error measures support this finding.

Figure 2 shows the historical reconstruction obtained with the proposed GHW model for three representative routes using $\lambda = 1$. The upper plots compare the observed demand, estimated Guerrero trend, and reconstructed demand, whereas the lower plots show the corresponding reconstruction residuals. The results demonstrate that the model accurately reconstructs the observed pax demand while preserving the long-term evolution represented by the Guerrero trend. The largest residuals occur during the COVID-19 pandemic, when the abrupt collapse in pax demand deviates markedly from the long-term trend and seasonal pattern captured by the model.

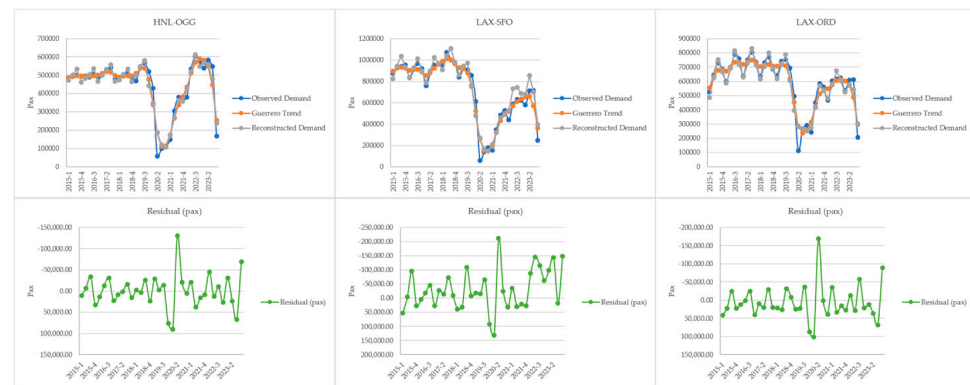


Figure 2. Historical reconstruction of passenger demand for three representative routes using the proposed GHW model ($\lambda = 1$).

4.3.2. Sensitivity Analysis of the Trend-Smoothing Parameter (λ)

Table 6 presents the sensitivity analysis of the trend-smoothing parameter λ . Following the Guerrero [18] framework described in Section 3.2, each evaluated value of λ corresponds, for the fixed sample size N , to a specific degree of trend smoothness through the index $S(\lambda; N)$. The evaluated values therefore represent progressively increasing degrees of trend smoothness. At the same time, reconstruction error assesses the empirical consequences of these different smoothing levels rather than defining the smoothness criterion itself. Four error measures are used to evaluate reconstruction accuracy: the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (sMAPE). For each value of λ , the average reconstruction error across the ten route-level pax demand series is compared with the corresponding average error obtained from the multiplicative HW model.

Table 6. Sensitivity analysis of the trend-smoothing parameter (λ).

λ	Smoothness Index $S(\lambda; 36)$ [%]	Average RMSE GHW [pax]	RMSE Reduction Relative to HW [%]	Average MAE GHW [pax]	MAE Reduction Relative to HW [%]	Average MAPE GHW [%]	MAPE Reduction Relative to HW [%]	Average sMAPE GHW [%]	sMAPE Reduction Relative to HW [%]
1	58.82	54,619.45	54.43	38,223.14	46.40	14.70	58.91	9.98	45.49
2	65.54	62,045.95	48.24	42,243.52	40.76	17.15	52.11	11.08	39.49
5	72.55	73,257.34	38.88	49,917.31	30.00	21.19	40.83	13.07	28.60
10	76.72	82,414.12	31.24	56,491.68	20.78	24.70	31.02	14.72	19.57
25	81.10	96,430.71	19.55	65,441.87	8.23	29.71	17.03	16.74	8.57
50	83.75	108,287.90	9.66	73,232.57	2.70	33.72	5.83	18.23	0.11
100	85.94	119,464.46	0.33	81,117.11	13.75	37.54	4.85	19.63	7.24
292	88.63	132,974.08	−10.94	91,460.35	28.26	42.41	18.44	21.36	16.69
Average HW [pax]		119,864.09		71,310.21		35.81		18.31	

Note: The smoothness index $S(\lambda; 36)$ is calculated using Equation (10) for the fixed sample size $N = 36$.

Figure 3 compares the average RMSE obtained with the proposed GHW model and the multiplicative HW model across the evaluated values of λ . The corresponding Guerrero smoothness index $S(\lambda; 36)$, reported in Table 6, increases from 58.82% at $\lambda = 1$ to 88.63% at $\lambda = 292$. Over this range, the GHW model's reconstruction error increases as trend smoothness increases. The minimum average RMSE is obtained at $\lambda = 1$, corresponding to $S(1; 36) = 58.82\%$, with an average RMSE of 54,619 pax. At the highest evaluated smoothness level, $\lambda = 292$ and $S(292; 36) = 88.63\%$, the average RMSE increases to 132,974 pax. These results illustrate the empirical trade-off between trend smoothness and in-sample historical reconstruction accuracy within the range examined in this paper.

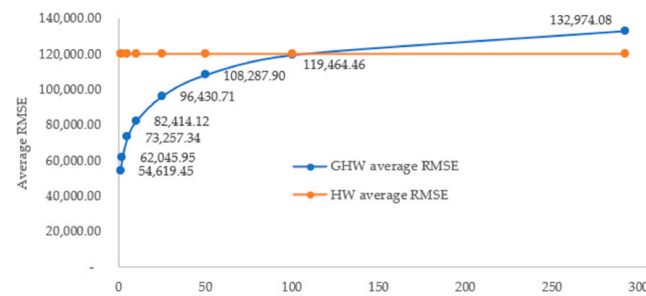


Figure 3. Average RMSE of the proposed GHW model for different values of λ .

A systematic relationship between trend smoothness and reconstruction accuracy is observed across the RMSE, MAE, MAPE, and sMAPE measures. For all four measures, the lowest average reconstruction errors are obtained at $\lambda = 1$, corresponding to a Guerrero smoothness index of $S(1; 36) = 58.82\%$. At this smoothing level, the proposed GHW model reduces the average RMSE, MAE, MAPE, and sMAPE by 54.43%, 46.40%, 58.91%, and 45.49%, respectively, relative to the multiplicative HW model. As λ increases, the smoothness index also increases, reaching $S(292; 36) = 88.63\%$, while the reconstruction errors rise progressively. This pattern indicates that, within the evaluated range, greater trend smoothness is associated with lower in-sample reconstruction fidelity.

The reconstruction advantage of the proposed GHW model relative to the multiplicative HW model decreases as the degree of trend smoothness increases. For λ values between 1 and 25, corresponding to smoothness-index values from $S(1; 36) = 58.82\%$ to $S(25; 36) = 81.10\%$, the proposed model yields lower reconstruction errors than the multiplicative HW model according to all four error measures. At $\lambda = 50$, RMSE, MAPE, and sMAPE remain lower than those of the HW model, whereas MAE is slightly higher. At $\lambda = 100$, corresponding to $S(100; 36) = 85.94\%$, the average RMSE remains slightly lower than that of the HW model, whereas MAE, MAPE, and sMAPE are higher. At $\lambda = 292$, corresponding to $S(292; 36) = 88.63\%$, all four error measures are higher for the GHW model than for the HW model. These results show that increasing the degree of trend smoothness progressively reduces historical reconstruction fidelity within the range evaluated in this paper.

Overall, the sensitivity analysis demonstrates that reconstruction accuracy is highly dependent on the degree of trend smoothness. Within the range of values examined in this paper, $\lambda = 1$ produces the lowest in-sample reconstruction errors. This result should be interpreted as an empirical consequence of the lower degree of trend smoothness associated with this value of λ , rather than as evidence that $\lambda = 1$ represents an optimal smoothness level.

As λ approaches zero, the degree of smoothing decreases and the estimated trend increasingly approaches the observed series. In the limiting case, the trend can reproduce an increasing proportion of the short-term variation in the data, leading to lower in-sample reconstruction error but progressively weakening the distinction between long-term trend and shorter-term variation. Consequently, in this paper, reconstruction error is used only to evaluate the empirical consequences of different smoothing levels and not to select or optimize λ . Minimizing reconstruction error with respect to λ would favor progressively smaller values of λ , because the estimated trend becomes increasingly flexible and approaches the observed series as λ approaches zero. Such a criterion would therefore favor the limiting case of minimal smoothing rather than identify an objectively preferable degree of trend smoothness. Consistent with the Guerrero framework, the degree of trend smoothness is user-controlled through the smoothness criterion independently of reconstruction error. The sensitivity analysis is therefore used to characterize the empirical

trade-off between trend smoothness and historical reconstruction accuracy. Within the range reported in this analysis, $\lambda = 1$, corresponding to $S(1; 36) = 58.82\%$, produces the lowest in-sample reconstruction errors, but it is not interpreted as an objectively optimal or theoretically defined threshold.

4.3.3. Stability of Seasonal Factors Across λ Values

Table 7 reports the quarterly seasonal factors $\hat{s}_t$ estimated by the proposed GHW model for different values of the trend-smoothing parameter λ , corresponding to smoothness-index values $S(\lambda; 36)$ ranging from 58.82% to 88.63%. Table 7 indicates that the estimated seasonal factors remain highly stable across different values of λ . For most routes, the quarterly seasonal indices present little or no variation as λ changes. This suggests that λ mainly affects the flexibility of the estimated trend rather than the seasonal structure of the decomposition. This finding supports the stability of the multiplicative seasonal representation adopted in the proposed GHW model across the evaluated smoothness range.

Table 7. Seasonal factors obtained under different values of the trend-smoothing parameter λ .

Routes	Seasonal Factor	$\lambda = 1$	$\lambda = 2$	$\lambda = 5$	$\lambda = 10$	$\lambda = 25$	$\lambda = 50$	$\lambda = 100$	$\lambda = 292$
ATL-DFW	Q1	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93
	Q2	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02
	Q3	1.07	1.07	1.07	1.07	1.07	1.07	1.07	1.07
	Q4	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
ATL-FLL	Q1	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02
	Q2	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01
	Q3	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	Q4	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
ATL-MCO	Q1	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02
	Q2	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
	Q3	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Q4	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
HNL-LAX	Q1	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93
	Q2	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
	Q3	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
	Q4	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
LAS-LAX	Q1	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
	Q2	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
	Q3	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06
	Q4	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
JFK-LAX	Q1	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
	Q2	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
	Q3	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06
	Q4	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
LAX-ORD	Q1	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
	Q2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	Q3	1.11	1.11	1.11	1.11	1.11	1.11	1.11	1.11
	Q4	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
LGA-ORD	Q1	0.81	0.81	0.81	0.81	0.81	0.83	0.83	0.85
	Q2	1.05	1.05	1.05	1.05	1.10	1.11	1.12	1.12
	Q3	1.14	1.14	1.14	1.14	1.17	1.15	1.16	1.17
	Q4	1.02	1.02	1.02	1.02	1.02	1.03	1.03	1.06

Table 7. Cont.

Routes	Seasonal Factor	$\lambda = 1$	$\lambda = 2$	$\lambda = 5$	$\lambda = 10$	$\lambda = 25$	$\lambda = 50$	$\lambda = 100$	$\lambda = 292$
HNL-OGG	Q1	0.97	0.98	0.97	0.97	0.97	0.97	0.97	0.97
	Q2	1.02	1.03	1.02	1.02	1.02	1.02	1.02	1.02
	Q3	1.09	1.09	1.08	1.08	1.08	1.08	1.08	1.08
	Q4	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93
LAX-SFO	Q1	0.92	0.92	0.92	0.92	0.92	0.92	0.94	0.95
	Q2	1.02	1.02	1.02	1.02	1.02	1.02	1.08	1.09
	Q3	1.11	1.11	1.11	1.11	1.11	1.11	1.12	1.13
	Q4	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.03

For example, the $\hat{s}_t$'s estimated for ATL-DFW remain unchanged across all λ values, with Q1 = 0.93, Q2 = 1.02, Q3 = 1.07, and Q4 = 0.99. Similar behavior is observed for ATL-FLL, ATL-MCO, HNL-LAX, LAS-LAX, JFK-LAX, and LAX-ORD, where the $\hat{s}_t$'s remain constant throughout the entire sensitivity analysis.

Even so, small variations appear for some routes. For example, LGA-ORD shows the largest $\hat{s}_t$'s changes, with Q1 increasing from 0.81 to 0.85, Q2 from 1.05 to 1.12, Q3 from 1.14 to 1.17, and Q4 from 1.02 to 1.06 as λ increases from 1 to 292. Similarly, LAX-SFO shows moderate changes in Q2 and Q3. However, even for these routes, the estimated seasonal factors ($\hat{s}_t$) remain essentially unchanged. The routes continue to exhibit the same seasonal structure, with below-trend demand in some quarters and above-trend demand in others.

The results shown in Table 7 contrast with the substantial changes in reconstruction accuracy reported in Table 6. While the average RMSE increases from 54,619 pax for $\lambda = 1$ to 132,974 pax for $\lambda = 292$, the estimated seasonal factors ($\hat{s}_t$'s) remain mainly unchanged, suggesting that the deterioration in reconstruction performance is primarily associated with changes in the estimated long-term trend rather than with the seasonal component.

The results suggest that the effect of λ is concentrated mainly on estimating the long-term trend component. Consequently, the reduction in reconstruction accuracy observed for larger λ values is principally associated with excessive trend smoothing rather than with changes in the estimated seasonal structure. Hence, these results indicate that the seasonal components of the proposed GHW model are robust to different degrees of trend smoothness. In contrast, the estimated trend component is highly sensitive to the value of λ .

In general, these results demonstrate that the proposed GHW model successfully maintains the seasonal structure of the historical pax demand series across different degrees of trend smoothness. Although the value of λ strongly affects the estimated long-term trend and the resulting reconstruction accuracy, the estimated seasonal factors ($\hat{s}_t$) remain largely unaffected. This finding indicates that the multiplicative seasonal component is robust across the range of trend smoothness values examined in this research.

4.4. Benchmark Comparison

The proposed GHW model is compared with the multiplicative HW, ETS state-space exponential smoothing, STL decomposition, and HP1600 methods to expand the empirical benchmarking. These methods are selected because they represent established smoothing and decomposition approaches for estimating trend and seasonal behavior and are therefore appropriate for comparison with the proposed GHW model's historical reconstruction objective. The proposed GHW reconstruction is first compared with the multiplicative HW model, which provides the classical exponential-smoothing reference for series with trend and proportional seasonality [16,17]. The analysis then expands the benchmarking set to include ETS(M,A,M) state-space exponential smoothing, which provides a likelihood-based

state-space formulation of exponential smoothing with multiplicative errors and multiplicative seasonality [14]; STL log-multiplicative decomposition, which applies seasonal-trend decomposition using LOESS to the logarithm of the series to represent multiplicative seasonality in an additive log scale [9]; and an HP1600 multiplicative decomposition, which uses the Hodrick–Prescott filter with the conventional quarterly smoothing parameter to extract a smooth trend before estimating multiplicative seasonal factors [29]. The trend-smoothing parameter in the GHW framework is further examined using Guerrero’s percentage-of-smoothness criterion, so that the selection of λ is not based exclusively on minimum in-sample reconstruction error [18].

The fitting of all benchmark models was conducted independently for each route, employing the same set of 36 quarterly observations spanning from 2015Q1 to 2023Q4 and the identical seasonal period, $m = 4$. The comparison was designed as an in-sample historical-reconstruction exercise rather than an out-of-sample forecasting evaluation. For the proposed GHW model, the Guerrero trend was estimated for each evaluated value of λ . The multiplicative seasonal reconstruction was obtained route by route. For each route and λ , the smoothing parameters α , β , and γ were selected by minimizing the in-sample root mean square error (RMSE) between the observed passenger-demand series and the GHW reconstructed series. This was done subject to the constraints $0 < \alpha < 1$, $0 < \beta < 1$, and $0 < \gamma < 1$.

The multiplicative Holt–Winters benchmark was fitted using the same quarterly seasonal period, $m = 4$, and a multiplicative seasonal structure. The level, trend, and seasonal smoothing parameters were estimated on a route-by-route basis. This estimation was achieved by minimizing the in-sample reconstruction RMSE, using the initialization procedure described in Section 3.1. The ETS benchmark was specified as ETS(M, A, M), denoting multiplicative error, additive trend, and multiplicative seasonality, and was fitted using its likelihood-based state-space exponential-smoothing estimation procedure. The STL benchmark was implemented as a log-multiplicative decomposition by applying STL to the logarithm of each positive passenger-demand series with quarterly seasonality. The historical reconstruction was obtained by exponentiating the estimated trend-plus-seasonal component. The HP1600 benchmark employed the Hodrick–Prescott filter with $\lambda = 1600$, which is the conventional smoothing value for quarterly data. Multiplicative seasonal factors were subsequently estimated from the trend-adjusted ratios and combined with the HP trend to obtain the historical reconstruction.

The present study introduced no additional route-specific tuning for ETS, STL, or HP1600 beyond their standard specifications. Therefore, all methods were applied to the same observations on a route-by-route basis. The resulting in-sample historical reconstructions were evaluated using the same definitions of root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute percentage error (MAAPE), and standard mean absolute percentage error (sMAPE).

The benchmark comparison does not assess out-of-sample forecasting performance; instead, it evaluates how accurately each method reconstructs the observed quarterly passenger-demand series. Reconstruction performance is evaluated using RMSE, MAE, MAPE, and sMAPE.

Table 8 compares the reconstruction performance of the proposed GHW model with the HW, ETS, STL, and HP1600 benchmark methods across the ten representative routes. The results show that the GHW model produces the lowest RMSE, MAE, MAPE, and sMAPE values for every route analyzed. The results indicate that the lower reconstruction errors of the GHW model are consistent across the four evaluation metrics. Among the alternative benchmarks, STL generally provides competitive reconstruction errors, whereas ETS and HP1600 produce higher errors. Overall, these results show that the proposed

GHW model provides the lowest in-sample historical reconstruction errors among the five methods evaluated in this section.

Table 8. Reconstruction performance of the GHW model and benchmark methods.

Route	Model	RMSE [pax]	MAE [pax]	MAPE [%]	sMAPE [%]	Route	Model	RMSE [pax]	MAE [pax]	MAPE [%]	sMAPE [%]
ATL-DFW	GHW	36,017.52	25,120.56	10.55	8.34	JFK-LAX	GHW	63,865.77	43,895.73	16.49	10.36
	HW	82,601.99	50,406.05	23.74	15.66		HW	152,679.88	87,085.00	43.11	19.49
	ETS	85,755.92	47,779.12	23.99	14.35		ETS	210,774.33	120,225.61	67.75	23.68
	STL	87,556.96	36,764.01	20.55	11.34		STL	111,812.56	46,962.61	26.37	12.30
	HP1600	85,862.72	56,398.63	25.35	16.57		HP1600	195,818.61	136,858.22	59.43	26.46
ATL-FLL	GHW	53,112.25	33,614.85	12.01	8.50	LAX-ORD	GHW	47,815.79	35,390.29	10.39	8.49
	HW	118,438.97	66,591.09	28.52	15.72		HW	111,264.06	69,394.67	24.68	16.43
	ETS	124,404.69	60,009.54	28.92	13.41		ETS	121,118.01	66,470.07	25.47	13.86
	STL	127,629.07	49,188.42	27.87	11.59		STL	100,866.71	41,850.12	18.72	10.47
	HP1600	124,161.09	81,347.16	30.16	17.42		HP1600	134,695.73	97,831.38	31.41	20.65
ATL-MCO	GHW	58,189.16	38,018.80	12.89	8.92	LGA-ORD	GHW	70,678.94	53,033.83	20.73	13.16
	HW	133,317.22	79,507.09	31.67	17.79		HW	120,075.40	74,610.91	46.96	21.30
	ETS	140,504.96	67,495.45	31.66	13.91		ETS	133,979.10	84,371.27	51.83	18.82
	STL	128,302.06	54,759.45	28.73	12.52		STL	131,300.16	72,959.42	29.82	19.91
	HP1600	146,897.25	99,699.30	35.43	19.62		HP1600	181,099.95	136,455.80	76.40	32.30
HNL-LAX	GHW	46,415.98	31,606.86	17.74	10.97	HNL-OGG	GHW	38,887.46	27,716.71	12.94	9.46
	HW	113,977.79	63,656.92	47.12	19.68		HW	96,899.27	56,976.70	33.65	18.17
	ETS	157,960.32	90,034.57	77.26	23.45		ETS	106,972.25	61,166.32	37.34	17.39
	STL	101,456.05	48,027.93	38.12	15.55		STL	78,047.64	40,881.99	23.99	14.10
	HP1600	142,688.69	97,339.48	67.34	25.54		HP1600	128,272.20	92,994.48	50.54	26.83
LAS-LAX	GHW	53,840.48	35,297.31	13.40	8.78	LAX-SFO	GHW	77,371.21	58,536.52	20.00	12.80
	HW	126,232.72	75,064.47	33.62	17.93		HW	143,153.63	89,809.16	44.97	20.87
	ETS	137,418.48	74,007.41	36.57	15.08		ETS	164,540.89	93,922.24	49.77	17.38
	STL	99,656.31	50,107.40	24.80	12.22		STL	121,094.47	57,900.88	30.30	14.41
	HP1600	155,349.19	112,313.54	41.06	22.84		HP1600	196,182.55	145,622.75	62.96	28.55

4.5. COVID-19 Robustness Analysis

A COVID-19 analysis has been performed to analyze the effect of the COVID-19 disruption on reconstruction performance. The analysis considers four sample scenarios: Full sample (2015–2023), COVID-excluded (2015–2019 and 2022–2023), Pre-COVID (2015–2019), and Post-COVID (2022–2023). The GHW model is applied separately to each scenario and route to reconstruct historical pax demand. We evaluate GHW reconstruction performance using MAE, RMSE, MAPE, and sMAPE. Table 9 summarizes the results for the ten representative routes.

The results in Table 9 show clear differences in reconstruction performance across the four scenarios. The Pre-COVID scenario produces the lowest MAE, RMSE, MAPE, and sMAPE for all ten routes, with MAPE ranging from 1.15% to 2.89%. In contrast, the Post-COVID scenario presents substantially higher reconstruction errors, with MAPE ranging from 8.00% to 9.99%. Excluding the 2020–2021 observations generally reduces MAPE and sMAPE relative to the Full-sample scenario, whereas the effects on MAE and RMSE are mixed across routes. These results indicate that the reconstruction performance of the GHW model is sensitive to the period analyzed and show substantial differences between the pre- and post-COVID pax demand patterns.

Table 9. COVID-19 robustness analysis of the GHW model.

Error Metric	Scenario	ATL-DFW	ATL-FLL	ATL-MCO	HNL-LAX	LAS-LAX	JFK-LAX	LAX-ORD	LGA-ORD	HNL-OGG	LAX-SFO
MAE [pax]	Full Sample	25,120.56	33,614.85	38,018.80	31,606.86	35,297.31	43,895.73	35,390.29	53,033.83	27,716.71	58,536.52
	COVID-excluded	19,345.00	28,781.21	39,453.56	38,334.06	38,183.53	53,541.46	42,272.64	53,336.04	30,165.20	62,753.18
	Pre-COVID	8641.83	8753.16	8167.40	11,435.37	9949.23	13,920.18	17,751.96	20,999.88	8157.61	18,052.34
	Post-COVID	38,451.53	48,502.59	50,325.61	46,443.17	53,885.41	56,696.91	51,674.82	48,910.13	48,609.22	51,176.41
RMSE [pax]	Full Sample	36,017.52	53,112.25	58,189.16	46,415.98	53,840.48	63,865.77	47,815.79	70,678.94	38,887.46	77,371.21
	COVID-excluded	26,329.97	42,131.72	54,217.47	50,028.54	56,216.28	76,691.01	52,815.51	70,815.06	43,105.58	85,199.56
	Pre-COVID	10,107.28	10,878.62	9890.10	12,892.31	12,526.69	17,060.70	21,497.98	26,010.47	9953.21	22,549.09
	Post-COVID	56,134.92	77,436.29	79,251.42	72,845.72	76,315.64	85,043.34	73,295.12	65,525.99	70,174.54	73,438.99
MAPE [%]	Full Sample	10.55	12.01	12.89	17.74	13.40	16.49	10.39	20.73	12.94	20.00
	COVID-excluded	7.44	5.85	7.05	9.38	7.69	11.23	8.93	16.41	9.36	13.73
	Pre-COVID	1.88	1.40	1.15	2.04	1.42	1.63	2.69	2.89	1.64	1.96
	Post-COVID	9.78	8.50	8.00	8.53	8.71	8.56	9.64	9.89	9.99	9.41
sMAPE [%]	Full Sample	8.34	8.50	8.92	10.97	8.78	10.36	8.49	13.16	9.46	12.80
	COVID-excluded	7.05	5.69	6.82	8.69	7.30	9.59	8.49	12.75	8.28	11.13
	Pre-COVID	1.87	1.39	1.15	2.04	1.42	1.62	2.73	2.92	1.64	1.98
	Post-COVID	10.39	9.31	8.71	9.29	9.44	9.27	10.34	10.67	10.83	10.05

Overall, the analysis shows that the GHW model maintains its ability to reconstruct historical pax demand across the different sample scenarios, although its accuracy varies considerably across scenarios. The substantially lower errors in the Pre-COVID scenario indicate stronger reconstruction performance under more stable pax demand conditions. In contrast, the higher errors in the Post-COVID scenario reflect the greater difficulty of reconstructing the pax demand patterns observed after the pandemic. Therefore, the Full-sample scenario should be interpreted considering the structural disruption associated with the COVID-19 period and the differences between pre- and post-COVID pax demand behavior.

5. Discussion

The results demonstrate that the proposed GHW model achieves lower in-sample historical reconstruction errors for route-level pax demand than the evaluated benchmark methods. The GHW model consistently achieves lower reconstruction errors than the HW model when lower degrees of trend smoothness are adopted within the evaluated range. These improvements are observed for RMSE, MAE, MAPE, and sMAPE, indicating that the reconstruction-error reductions observed at lower smoothness levels are consistent across different error measures. These findings suggest that estimating the long-term trend separately from the seasonal component is associated with lower reconstruction errors in the empirical analysis. Whereas the HW model updates the level, trend, and seasonal components simultaneously, the proposed GHW model estimates the long-term trend independently through the Guerrero [18] smoothing procedure before incorporating the multiplicative seasonal component. From a practical perspective, the lower reconstruction errors indicate that the proposed GHW model provides a more accurate representation of the historical evolution of pax demand, thereby offering a useful basis for analyzing long-term market behavior, seasonal travel patterns, and irregular demand disruptions.

Reconstruction accuracy should not be interpreted as direct evidence that the estimated components recover their true latent values because the true underlying trend and seasonal components are unobserved in the empirical pax demand data. Rather, the results evaluate the ability of the GHW model to reconstruct the observed historical pax demand series and generate an interpretable decomposition of its estimated components.

The expanded benchmark comparison further supports the proposed GHW model's historical reconstruction performance. Across the ten representative routes, the GHW model produces the lowest RMSE, MAE, MAPE, and sMAPE values compared with the HW, ETS, STL, and HP1600 methods. Therefore, the lower reconstruction errors observed for the GHW model are not limited to the original comparison with multiplicative HW but are also observed relative to other established smoothing and decomposition methods evaluated in this paper. Among the alternative benchmark methods, STL generally provides the most competitive reconstruction performance.

The sensitivity analysis demonstrates that reconstruction performance depends strongly on the degree of trend smoothness. Across the evaluated values of λ , the Guerrero smoothness index $S(\lambda; 36)$ ranges from 58.82% to 88.63%. As λ increases, the estimated trend becomes progressively smoother and less responsive to variations in the observed demand series, resulting in larger reconstruction errors. These results characterize an empirical trade-off between trend smoothness and in-sample reconstruction fidelity. Importantly, the minimum reconstruction error at $\lambda = 1$, corresponding to $S(1; 36) = 58.82\%$, should not be interpreted as establishing an objectively optimal degree of smoothness, since the smoothness level is defined independently through the Guerrero smoothness index.

The seasonal component behaves differently. The estimated quarterly seasonal factors remain highly stable across the evaluated smoothness range $S(\lambda; 36) = 58.82\%$ to 88.63%, indicating that the seasonal structure of route-level pax demand is largely independent

of the degree of trend smoothing. These findings suggest that the deterioration in reconstruction accuracy observed for larger values of λ is primarily associated with changes in the estimated long-term trend. Consequently, the multiplicative seasonal representation adopted in the proposed GHW model appears to be stable across the evaluated range of trend smoothness.

These findings are consistent with the aim of Guerrero [18], whose methodology was developed to estimate interpretable trends through a user-controlled degree of smoothness. The proposed GHW model extends this idea by combining Guerrero's trend-estimation methodology with the multiplicative seasonal structure of the HW model. The resulting hybrid model provides an interpretable decomposition framework that simultaneously represents the long-term trend, recurring seasonal variation, and irregular fluctuations in historical route-level pax demand.

The COVID-19 robustness analysis shows that reconstruction performance differs considerably across scenarios. The consistently lower reconstruction errors observed in the Pre-COVID scenario across all ten routes indicate stronger GHW reconstruction performance under more stable pax demand conditions. In contrast, the higher errors observed in the Post-COVID scenario indicate greater difficulty in reconstructing pax demand patterns after the pandemic. Moreover, excluding the 2020–2021 observations generally reduces MAPE and sMAPE relative to the Full-sample scenario, whereas the effects on MAE and RMSE are mixed across routes. These findings highlight the importance of considering the COVID-19 disruption and differences between pre- and post-COVID pax demand behavior when interpreting historical reconstruction performance.

The proposed GHW model complements previous studies on airline pax demand analysis by providing an interpretable approach to historical pax demand reconstruction. The proposed model estimates the long-term trend, seasonal pattern, and irregular component separately, resulting in an interpretable decomposition of historical pax demand. This decomposition facilitates retrospective analyses of route performance and supports planning activities that require an understanding of the historical evolution of pax demand. Therefore, the proposed GHW model contributes to the literature on historical pax demand reconstruction by combining controlled trend estimation with multiplicative seasonal decomposition in a single interpretable model.

Overall, the results indicate that combining controlled trend estimation with a multiplicative seasonal representation yields an effective and interpretable approach for analyzing historical route-level pax demand. The proposed GHW model produces accurate historical reconstructions while preserving an interpretable decomposition of the demand series, making it suitable for retrospective analyses in which understanding the long-term trend and seasonal behavior is as important as minimizing reconstruction error.

6. Conclusions

This paper proposed a GHW hybrid smoothing model to estimate and reconstruct historical route-level airline pax demand. The proposed model integrates the user-controlled trend-estimation methodology of Guerrero [18] with the multiplicative seasonal structure of the HW model. The GHW model aims to provide an interpretable decomposition of historical pax demand by separately estimating the long-term trend and seasonal components.

The empirical analysis was conducted using quarterly pax demand data from a larger set of U.S. domestic routes available in the BTS T-100 database. This paper reports the results for ten representative routes covering different market characteristics over the 2015–2023 period. The results show that the proposed GHW model achieves lower reconstruction errors than the multiplicative HW model when $\lambda = 1$, corresponding to a Guerrero smoothness index of $S(1; 36) = 58.82\%$. On average, the GHW model reduced

the RMSE by approximately 54.4%. Similar improvements were also observed for the MAE, MAPE, and sMAPE measures, showing that the reduction in in-sample historical reconstruction error at this evaluated smoothness level is consistent across the four error measures. The expanded benchmark comparison further showed that the proposed GHW model produced the lowest RMSE, MAE, MAPE, and sMAPE values across all ten routes compared with the HW, ETS, STL, and HP1600 methods evaluated in this paper.

The sensitivity analysis demonstrated that reconstruction accuracy was strongly influenced by the degree of trend smoothness. Across the evaluated values of λ , the Guerrero smoothness index $S(\lambda; 36)$ ranged from 58.82% to 88.63%. As λ increased, reconstruction accuracy declined systematically, indicating that greater trend smoothness was associated with lower in-sample reconstruction fidelity within the evaluated range. In contrast, the estimated seasonal factors remained highly stable as λ varied, suggesting that λ primarily affected the trend component rather than the seasonal structure. Among the tested values, $\lambda = 1$, corresponding to $S(1; 36) = 58.82\%$, produced the lowest in-sample reconstruction errors; however, this result is not interpreted as evidence that $\lambda = 1$ represents an objectively optimal smoothness level. The COVID-19 robustness analysis indicates that GHW reconstruction performance depends on the characteristics of the pax demand data analyzed, with substantially lower errors before the pandemic than after.

The main contribution of this paper is the development of an interpretable hybrid smoothing framework that extends Guerrero's [18] trend-estimation methodology to strongly seasonal passenger-demand series. By combining controlled trend estimation with a multiplicative seasonal representation, the proposed model provides an alternative for historical demand reconstruction and component analysis.

The proposed GHW model assumes a single smoothness parameter for the entire sample period. Therefore, the empirical findings should be interpreted within the scope of this research, which considers U.S. domestic markets, quarterly pax demand data, and the 2015–2023 period. Although the analysis used a larger BTS T-100 database, this paper presents results for ten representative routes. The sample includes the COVID-19 pandemic period, which introduced substantial disruptions to pax demand patterns. The proposed GHW model was evaluated against multiplicative HW, ETS, STL, and HP1600 benchmark methods, and its performance was assessed using in-sample historical reconstruction errors. Therefore, future research should validate the proposed GHW model using international markets, different data frequencies, and alternative sample periods; evaluate its performance relative to additional decomposition and smoothing approaches; and explore segment-specific smoothness parameters to account for structural disruptions and changes in pax demand behavior.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16178871/s1>, Supplementary File S1: Ten selected U.S. domestic air routes during 2015–2023.

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Abbreviations

The following abbreviations are used in this manuscript:

BTS	Bureau of Transportation Statistics
COVID-19	Coronavirus Disease 2019
GHW	Guerrero–Holt–Winters
HW	Holt–Winters
O&D	Origin and Destination
Pax	Passenger(s)
RMSE	Root Mean Squared Error
T-100	T-100 Domestic Segment Database
U.S.	United States
Q1	First Quarter
Q2	Second Quarter
Q3	Third Quarter
Q4	Fourth Quarter

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