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Research Article

Improving Hierarchical Tourism Forecasting through the ARIMA-OC (ARIMA Based on The Optimal Combination) Method

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ABSTRAK

The research explores the ARIMA-OC method (ARIMA based on the Optimal Combination approach) for Hierarchical Forecasting. In this approach, the ARIMA model is used to forecast each individual time series, and the Optimal Combination (OC) technique is applied to merge these initial forecasts into an updated set of predictions. The study compares the ARIMA model with the Exponential Tail Smoothing (ETS) model, with both models being integrated using five different strategies: the Bottom-up approach (BU), the Top-down approach using Forecasted Proportion (TDFP), two Top-down approaches based on Historical Proportions (TDHP1 and TDHP2), and the Optimal Combination approach (OC). To assess how ARIMA-OC performs with small samples, a simulation was carried out, revealing that ARIMA-OC surpasses the other methods according to the MASE metric. Furthermore, non-parametric tests like the Friedman test and the Nemenyi post-hoc test were used to validate the effectiveness of Hierarchical Forecasting.

Keyword: *The ARIMA-OC; The Friedman test the MASE; The Nemenyi-post-hoc test*

Introduction

Over the last forty years, the tourism sector has seen remarkable expansion and has garnered considerable attention from both the business world and academic researchers (Waciko, K.J & Ismail, B, 2019). This growth has led to a heightened focus on modeling and forecasting tourism demand. The most widely used indicator of tourism demand is the count of tourist arrivals at a particular destination. Hierarchical forecasting, an advanced forecasting technique, deals with a set of time series organized in a hierarchical manner. A considerable number of studies have utilized hierarchical forecasting, particularly in analyzing tourism demand. Hyndman et al. (2007) demonstrated that their optimal combination approach performed better than other existing methods for handling hierarchical data. Similarly, Athanasopoulos and Hyndman (2007) demonstrated the value of hierarchical forecasting by generating extended forecasts for domestic tourism demand in Australia.

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and handle credit risk more quickly and accurately. The use of machine learning algorithms enables faster and more precise decision-making. In a study conducted by Kosiorowski et al. (2017) in Poland's Silesia region, a macro model was developed to assess air pollution during both day and night across five subregions. The researchers evaluated the effectiveness of hierarchical time series forecasting in enhancing local community welfare and introduced a new nonparametric, robust method for forecasting hierarchical functional time series.

Athanasopoulos et al. (2017) presented the idea of Temporal Hierarchies for time series forecasting, which involves building a temporal hierarchy using non-overlapping time aggregations and merging forecasts from all levels to produce accurate and consistent results. In another study, Mircetic et al. (2017) proposed a revised top-down approach for hierarchical forecasting within a beverage supply chain.

Athanasopoulos et al. (2009) applied Hierarchical Forecasting to the tourism sector, generating long-term forecasts for domestic tourism demand in Australia. Their results aligned with those of Hyndman et al. (2011), who introduced an optimal combination method that surpassed other hierarchical data techniques. Both studies exclusively used Exponential Tail Smoothing (ETS) with the optimal combination approach (ETS-OC), which proved more effective than alternative methods.

Waciko and Ismail (2020) noted that advanced quantitative models have been widely developed in academic research. Both practitioners and statisticians are interested in designing advanced hybrid models to boost prediction accuracy. However, there remains a need for dedicated research into the application of hierarchical forecasting for tourist arrivals and the development of suitable test statistics to confirm the effectiveness of hierarchical forecasting methods.

Methods

The time series $\{x_t, t \in I\}$ is considered to follow an ARIMA(p,q) process, if it can be expressed as,

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + ... + \phi_p x_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q} \quad (1)$$

With $\phi_p \neq 0, \theta_q \neq 0, \sigma_\varepsilon^2 > 0$, p and q are called AR and MA orders, respectively. If x_t has a nonzero mean μ, set $\alpha = \mu(1 - \phi_1 - ... - \phi_p)$ and the model can be written as,

$$x_t = \alpha + \phi_1 x_{t-1} + \phi_2 x_{t-2} + ... + \phi_p x_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q} \quad (2)$$

where, the noise ε_t is assumed to be Gaussian white noise with mean zero and variance σ_ε^2. the model is called AR(p) when $q = 0$ and the model is called MA(q) when $p = 0$ (Shumway and Stoffer, 2006).

AR operator is defined to be

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p \quad (3)$$

Is a polynomial in B of order p and MA operator is

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + ... + \theta_q B^q \quad (4)$$

Unlike AR process, MA process is stationary for any values of the parameters $\theta_1, \theta_2, ..., \theta_q$. The ARMA($p,q$) model in (5) can be written using the AR operator (3), and the MA operator (4) in a concise form as,

$$\phi(B) x_t = \theta(B) \varepsilon_t \quad (5)$$

Box and Jenkins (1970) develop ARIMA models. Many time series models such as AR, MA or ARMA cannot be specifically applied because of non-stationary. To make them stationary, one possible way to treat the non-stationary series is to apply *differencing*. The first differences, namely $(x_t - x_{t-1}) = (1 - B)x_t$ To offer second differences, and so on. The d th differences can be written as $(1 - B)^d X_t$.

If the original data series is differenced d times before applying an ARMA (p,q) model, then the resulting model for the undifferenced series is called an ARIMA (*p,d,q)* process where the letter "I" stands for integrated, and d indicates the number of differences performed. Model (5) Model (5) can be extended as follows,

$$\phi(B)(1 - B)^d x_t = \theta(B) \varepsilon_t \quad (6)$$

The combined AR operator is now $\phi(B)(1 - B)^d$. Suppose substitute the operator B with a variable x in this expression, in that case, it can be immediately shown that the function $\phi(x)(1 - x)^d$ has d roots on the unit circle (as $(1 - x) = 0$ when $x = 1$) suggesting that the mechanism is non-stationary, which is why differentiation is required.

In this research, a novel approach for hierarchical time series forecasting called ARIMA-OC (ARIMA based on the Optimal Combination method) was introduced. The ARIMA model (6) is applied to forecast each individual series, while the Optimal Combination technique is used to optimally merge these base forecasts, resulting in a set of updated forecasts.

Suppose $\hat{Z}_{X,n}(h)$ the generated h-step ahead forecasts for each individual series (using the ARIMA model) are represented as follows Z_X (ARIMA model)., $\hat{Z}_{AB,n}(h)$ represents the h-step-ahead base forecast of series AB generated by the ARIMA model, Z_{AB} using the sample data $Z_{AB,1},\ldots,Z_{AB,n}$ at level *i*. All h-step ahead base forecasts are collectively denoted as $\hat{Z}_{i,n}(h)$. These forecasts depend on the sample value for $t = 1,2,\ldots,n$, therefore correspond to predictions for time $n+h$. The core idea of the Optimal Combination (OC) approach is to express these h-step-ahead base forecasts within a hierarchy using a linear regression framework.

$$\hat{Z}_n(h) = M\beta_h + \varepsilon_h \qquad (7)$$

Where $\beta_h = E\left[\hat{Z}_{K,n}(h) \mid Z_1,\ldots,Z_n\right]$ is the unknown mean of the base forecasts at the bottom level is represented K, and ε_h has zero mean and covariance matrix $V[\varepsilon_h] = \Sigma_h$. If Σ_h is known, the Generalized Least Squares (GLS) method can be used to obtain the minimum variance unbiased estimate of β_h. Typically, this matrix is not known, but Hyndman et al. (2017) demonstrated that, under the reasonable assumption that $\varepsilon_h \approx M\varepsilon_{K,h}$ where $\varepsilon_{K,h}$ contains the forecast errors in the bottom level, the best linear unbiased estimator for β_h is $\hat{\beta}_h = (M'M)^{-1}M'\hat{Z}_n(h)$. This leads to the revised forecasts given by $\tilde{Z}_n(h) = M\hat{\beta}_h$ and This results in revised forecasts, which can be generally expressed as shown in equation (8), can written as,

$$\tilde{Z}_n(h) = MP\hat{Z}_n(h) \qquad (8)$$

P varies depending on the hierarchical method used.

$$P = (M'M)^{-1}M' \qquad (9)$$

The MASE is used as measures to compare forecast performance.

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{|e_t|}{\frac{1}{n-1}\sum_{t=2}^{n}|Z_t - Z_{t-1}|}\right) \qquad (10)$$

Where $e_t = Z_t - \hat{Z}_t$ is the forecast error is represented as the difference between the actual value and the forecasted value, Z_t is the actual value, $\hat{Z}_t$ The forecast value and *n* refers to the length of the forecasting horizon or the size of the test set. (Waciko, K.J and Ismail, B, 2018). In this research, suitable statistical tests like the Friedman test and the Nemenyi post-hoc test (applied after the Friedman test) are used to validate the results of Hierarchical Forecasting. Friedman test (Friedman, 1937, 1940) is an alternative to the one-way ANOVA with repeated measures. Data should be at least an ordinal or continuous and samples are do not need to be normally distributed. The Friedman statistic *S* can be represented as,

$$S = \left[\frac{12n}{nk(k+1)}\sum_{j=1}^{k}R_j^2\right] - 3n(k+1) \qquad (11)$$

The procedure for testing the null hypothesis,

$$H_0 : \tau_1 = \ldots = \tau_k$$

versus

$$H_1 : \tau_1,\ldots,\tau_k \text{ not all equal}$$

at the α level of significance,

Reject H_0 if $S \geq s_\alpha$;
otherwise do not reject (12)

Where the constant s'_α is selected to create the type I error probability equal to α. For detail see in Hollander and Wolfe (1999).

The Nemenyi post-hoc test, following the Friedman test, requires a balanced design $(n_1 = n_2 = \ldots. = n_k = n)$ for each group k and α Friedman-type ranking of the data. The inequality applied in this study was derived from Nemenyi (1969), where the critical difference represents the difference between the mean rank sums $(|\bar{R}_i - \bar{R}_j|)$:

$$|\bar{R}_i - \bar{R}_j| > \frac{q_{\infty;k;\alpha}}{\sqrt{2}}\sqrt{\frac{k(k+1)}{6n}} \qquad (13)$$

This inequality results in the same critical differences for the rank sums $(|\bar{R}_i - \bar{R}_j|)$ when it is multiplied with n for $\alpha = 0.05$.

This research examines hierarchical time series methods applied to international tourist arrivals in Indonesia. The data consists of monthly records of tourist arrivals for each series, covering the period from January 2014 to December 2018. The data was obtained from the Ministry of Tourism of the Republic of Indonesia (www.kemenparekraf.go.id). Within a hierarchy, data and forecasts are organized by breaking down the information for various geographical regions and provinces.

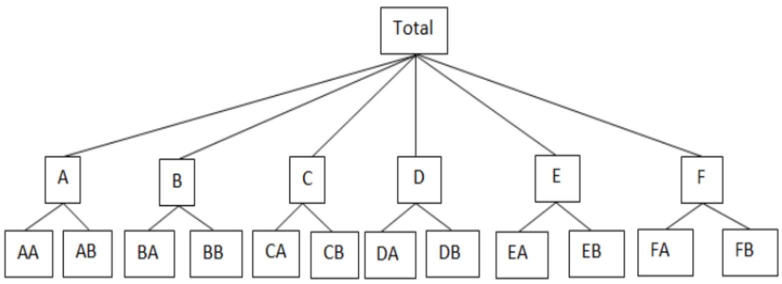

Figure. 1 A Hierarchical Time Series Tourist Arrival in Indonesia

Figure 1 illustrates $K = 2 - \text{level}$ hierarchy structure. At the highest level (level 0) is the "Total," representing the most aggregated data. This total is divided into two series at level 1, and each of these series is further subdivided into two additional series at the lowest level.

Nomenclature for Hierarchical Time Series Tourist Arrival in Indonesia

Total = Disaggregated data of International Tourist arrival to Indonesia.

A= Series A-level 1 (Bali & Nusa Tenggara Region)

B= Series B-level 1 (Sumatra Region).

C= Series C-level 1 (Java Region).

D= Series D-level 1 (Kalimantan Region).

E= Series E-level 1 (Sulawesi Region).

F= Series F-level 1 (Maluku & Papua Region).

AA= Series A-level 2 within series A-level 1 (Province of Bali).

AB= refers to Series B-level 2, which is a subdivision of Series A-level 1 (all province in Bali & Nusa Tenggara Region excluding the province of Bali).

BA= refers to Series A-level 2, which is a subdivision of Series B-level 1 (Province of Kepulauan Riau).

BB= refers to Series B-level 2, which is a subdivision of Series B-level 1 (all province in Sumatra Region excluding the province of Kepulauan Riau).

CA= refers to Series C-level 2, which is a subdivision of Series A-level 1 (Province of East Java).

CB= refers to Series B-level 2, which is a subdivision of Series C-level 1 (all province in Java Region excluding Province of East Java).

DA= refers to Series D-level 2, which is a subdivision of Series D-level 1 (Province of West Kalimantan).

DB= refers to Series B-level 2, which is a subdivision of Series D-level 1 (all Province in Kalimantan Region excluding the province of West Kalimantan).

EA= refers to Series A-level 2, which is a subdivision of Series E-level 1 (Province of North Sulawesi).

EB= refers to Series B-level 2, which is a subdivision of Series E-level 1 (all province in Sulawesi Region excluding province of North Sulawesi).

FA= refers to Series A-level 2, which is a subdivision of Series F-level 1 (Province of Maluku).

FB= refers to Series B-level 2, which is a subdivision of Series F-level 1 (all province in Maluku & Papua Region excluding Province of Maluku)

n = Total number of series in the hierarchy;

Z_t = The t th observation for "Total" series for $t = 1,\ldots,T$;

Z_t = vector of all observations at time t;

$Z_{j,t}$ = The t th observation of the series corresponds to and j represents a specific element within the hierarchical tree. For Instance, $Z_{A,t}$ denotes the t th observation of the series associated with node A at level 1, $Z_{AB,t}$ while denotes the t th observation of the series linked to node AB at level 2, and forth.

At any given time t, the values at the lowest level of the hierarchy add up to the value of the series at the level above. For example, as shown in,

$$Z_t = Z_{AA,t} + Z_{AB,t} + Z_{BA,t} + Z_{BB,t} + Z_{CA,t} + Z_{CB,t} + Z_{DA,t} + Z_{DB,t} + Z_{EA,t} + Z_{EB,t} + Z_{FA,t} + Z_{FB,t}$$

Where,

$$Z_{A,t} = Z_{AA,t} + Z_{AB,t};$$
$$Z_{B,t} = Z_{BA,t} + Z_{BB,t};$$
$$Z_{C,t} = Z_{CA,t} + Z_{CB,t};$$
$$Z_{D,t} = Z_{DA,t} + Z_{DB,t};$$
$$Z_{E,t} = Z_{EA,t} + Z_{EB,t};$$
$$Z_{F,t} = Z_{FA,t} + Z_{FB,t};$$

Thus, it can be written as,

$$Z_t = Z_{A,t} + Z_{B,t} + Z_{C,t} + Z_{D,t} + Z_{E,t} + Z_{F,t}$$

This relationship can be expressed using matrix notation.

$$\begin{bmatrix} Z_t \\ Z_{A,t} \\ Z_{B,t} \\ Z_{C,t} \\ Z_{D,t} \\ Z_{E,t} \\ Z_{F,t} \\ Z_{AA,t} \\ Z_{AB,t} \\ Z_{BA,t} \\ Z_{BB,t} \\ Z_{CA,t} \\ Z_{CB,t} \\ Z_{DA,t} \\ Z_{DB,t} \\ Z_{EA,t} \\ Z_{EB,t} \\ Z_{FA,t} \\ Z_{FB,t} \end{bmatrix} = \begin{bmatrix} 1&1&1&1&1&1&1&1&1&1&1&1 \\ 1&1&0&0&0&0&0&0&0&0&0&0 \\ 0&0&1&1&0&0&0&0&0&0&0&0 \\ 0&0&0&0&1&1&0&0&0&0&0&0 \\ 0&0&0&0&0&0&1&1&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0&1&1 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0&0&0&1 \end{bmatrix} \begin{bmatrix} Z_{AA,t} \\ Z_{AB,t} \\ Z_{BA,t} \\ Z_{BB,t} \\ Z_{CA,t} \\ Z_{CB,t} \\ Z_{DA,t} \\ Z_{DB,t} \\ Z_{EA,t} \\ Z_{EB,t} \\ Z_{FA,t} \\ Z_{FB,t} \end{bmatrix}$$

Figure 2 presents the framework of the proposed study, which begins by comparing the ARIMA model with the Exponential Tail Smoothing (ETS) model. Both models are then combined with five different hierarchical forecasting approaches: the Bottom-Up (BU) approach, the Top-Down approach based on Forecasted Proportions (TDFP), the Top-Down approach using Average Historical Proportions or Historical Proportion 1 (TDHP1), the Top-Down approach using Proportions of Historical Averages or Historical Proportion 2 (TDHP2), and the Optimal Combination (OC) approach. The Mean Absolute Scaled Error (MASE) is employed as a metric to evaluate and compare forecasting performance.

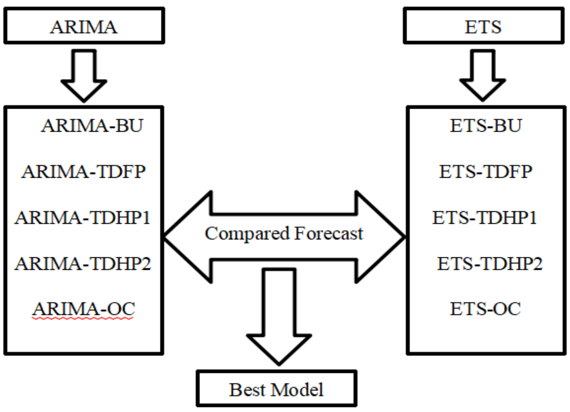

Figure 2. The Framework of the Proposed Study

Results and Discussion

Table 1 displays the outcomes of a simulation study that evaluates the forecast accuracy of different methods. Unlike previous studies conducted by Hyndman et al. (2011) and Athanasopoulos et al. (2009) that emphasized on ETS-OC method, this study focuses on a new approach called ARIMA-OC (ARIMA based on optimal combination approach) and examines its performance using the MASE criterion.

The combination of the ARIMA forecasted method with five different approaches is superior to the combination of the ETS forecasted method with five different approaches. Table 1 shows that the mean MASE for ARIMA-OC is 0.87. To check that not all the mean of MASE for ARIMA combining with five different approaches are equal, see Table 2.

Table 1 Out-of-sample Forecasting performance

MASE	***Forecast Horizon* (h=month)** **Forecast method = ETS**												
Approach	1	2	3	4	5	6	7	8	9	10	11	12	**Average**
BU	0.97	0.97	0.69	0.68	0.90	8.34	0.81	0.81	**1.26**	**0.91**	1.01	1.01	1.53
TDFP	0.96	0.96	**0.66**	**0.66**	0.97	0.94	0.79	0.79	1.51	1.04	1.01	1.01	0.94
TDHP1	1.09	1.10	0.98	0.98	**0.87**	1.11	1.06	0.95	1.87	1.83	2.09	2.09	1.34
TDHP2	1.09	1.10	0.98	0.97	0.88	1.12	1.07	0.95	1.87	1.83	2.08	2.09	1.34
OC	**0.96**	**0.96**	0.67	0.66	0.92	**0.87**	**0.78**	**0.78**	1.43	0.95	**0.99**	**0.99**	**0.91**
MASE	***Forecast Horizon* (h=month)** **Forecast method = ARIMA**												
Approach	1	2	3	4	5	6	7	8	9	10	11	12	**Average**
BU	0.98	0.98	0.69	0.67	**0.77**	**0.98**	0.81	0.8	0.95	**0.92**	0.99	0.99	0.88
TDFP	**0.91**	**0.92**	0.7	0.67	0.95	1.08	0.81	0.8	**0.9**	0.96	0.99	0.99	0.89
TDHP1	0.96	0.97	1	1.02	0.86	1.06	1.07	0.96	1.89	1.85	2.15	2.15	1.33
TDHP2	0.96	0.97	0.98	0.98	0.86	1.05	1.08	0.96	1.89	1.85	2.14	2.14	1.32
OC	0.93	0.93	**0.69**	**0.66**	0.83	1	**0.8**	**0.79**	0.93	0.94	**0.98**	**0.98**	**0.87**

Note: ETS= Exponential Tail Smoothing model/ the state space model; ARIMA= autoregressive integrated moving average; BU= The bottom-up approach; TDFP= Top-down approach based on forecasted proportions.; TDHP1= Top-down approach based on historical proportions 1/ based on the average historical proportions; TDHP2= Top-down approach based on historical proportions 2/based on proportions of historical averages.; OC= The optimal combination approach.

Table 2. Friedman Test (the Mean of MASE for ARIMA combining with five different approaches)

MASE Methods		(1)		(2)		(3)		(4)		(5)	
		ARIMA-BU	RANK	ARIMA-TDFP	RANK	ARIMA-TDHP1	RANK	ARIMA-TDHP2	RANK	**ARIMA-OC**	**RANK**
Forecast Horizon (h=month)	1	0.98	5	0.91	1	0.96	3.5	0.96	3.5	**0.93**	**2**
	2	0.98	5	0.92	1	0.97	3.5	0.97	3.5	**0.93**	**2**
	3	0.69	1	0.7	3	1	5	0.98	4	**0.69**	**1**
	4	0.67	2.5	0.67	2.5	1.02	5	0.98	4	**0.66**	**1**
	5	0.77	1	0.95	5	0.86	3.5	0.86	3.5	**0.83**	**2**
	6	0.98	1	1.08	5	1.06	4	1.05	3	**1**	**2**
	7	0.81	2.5	0.81	2.5	1.07	4	1.08	5	**0.8**	**1**
	8	0.8	2.5	0.8	2.5	0.96	4	0.96	5	**0.79**	**1**
	9	0.95	3	0.9	1	1.89	4.5	1.89	4.5	**0.93**	**2**
	10	0.92	1	0.96	3	1.85	4.5	1.85	4.5	**0.94**	**2**
	11	0.99	2.5	0.99	2.5	2.15	5	2.14	4	**0.98**	**1**
	12	0.99	2.5	0.99	2.5	2.15	5	2.14	4	**0.98**	**1**
	Mean	0.88	2.46 (R2)	0.89	2.63 (R3)	1.33	4.29 (R5)	1.32	4.04 (R4)	**0.87**	**1.5 (R1)**

Note: R1= RANK 1 (ARIMA-OC); R2= RANK 2 (ARIMA-BU); R3=RANK 3 (ARIMA-TDFP); R4=RANK 4 (ARIMA- TDHP2); R5=RANK 5 (ARIMA-TDHP1).

Table 2 employs non-parametric tests, specifically the Friedman Test and the Friedman post-hoc test after Nemenyi, given that the data is continuous, the samples are not normally distributed, and there is no interaction between blocks (rows) and treatment (columns). Figure 3 displays the output, including data and Hierarchy Forecasting results of ARIMA-OC at all levels.

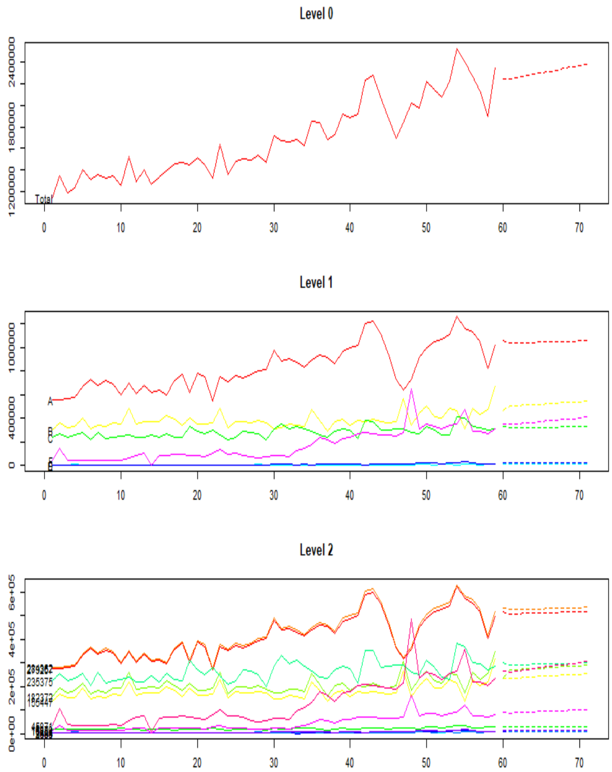

Figure. 3. Hierarchy Forecasting results of ARIMA-OC across all level

The populations have approximately the same shapes since the box-plots are all about the same shape. The five box-plots each have approximately the same shape.

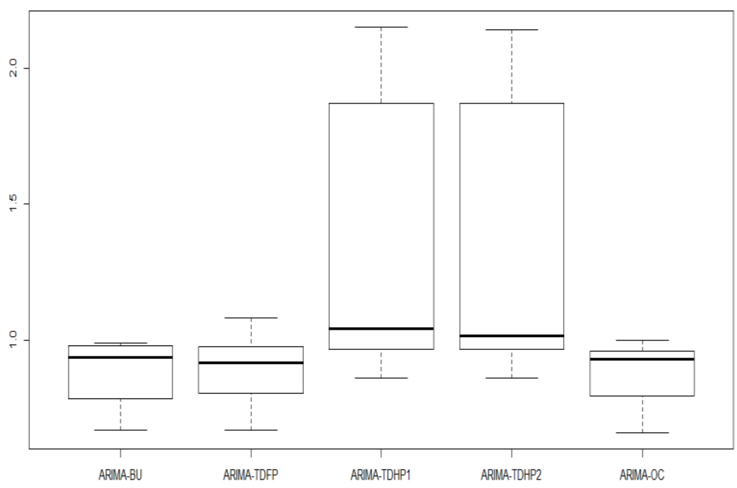

Figure 4. The box-plots Mean MASE of ARIMA combines with five different approaches

Differences of "the Mean MASE probably explaining any differences in variation/spread", show that: The mean MASE of ARIMA-BU = 0.88; The mean MASE of ARIMA-TDFP = 0.89; The mean MASE of ARIMA-TDHP1 = 1.33; The mean MASE of ARIMA-TDHP2 = 1.32 and The mean MASE of ARIMA-OC = 0.87. A box-plot is also useful for assessing differences.
The procedure for testing the Null Hypothesis
$H_0 = \mu_{ARIMA-BU} = \mu_{ARIMA-TDFP} = \mu_{ARIMA-TDHP1} = \mu_{ARIMA-TDHP2} = \mu_{ARIMA-OC}$

versus

H_1 = Not all the mean MASE of ARIMA, combining with five different approaches are equal. At 5 % level of significance, the test statistics for Friedman Test is 26.754. Since ρ - value = $2.229 \times 10^{-5} < 0.05 = \alpha$ (reject H_0), The results of the Friedman test indicate that the ARIMA model, when combined with five different approaches, produces significantly different mean MASE values for the one-year (12-month) ahead forecast.

According to the Nemenyi post-hoc test for multiple joint samples, see the output of Nemenyi post-hoc test in table 4,

Table 4. The output of Nemenyi post-hoc test

METHODS	ARIMA-BU	ARIMA-TDFP	ARIMA-TDFP1	ARIMA-TDHP2
ARIMA-TDFP	0.99969	-	-	-
ARIMA-TDFP1	**0.03644**	0.06225	-	-
ARIMA-TDHP2	0.13728	0.20720	0.98576	-
ARIMA-OC	0.57250	0.44743	**0.00015**	**0.00132**

The treatment ARIMA-OC based on the mean MASE differs highly significant (p < 0.05) to ARIMA-TDHP1 and ARIMA-TDHP2, and the treatment ARIMA-TDHP1 based on the mean MASE differs highly significant (p < 0.05) to ARIMA-BU. Other contrasts are not significant (p > 0.05) for 1 year (12 months) ahead forecast.

Conclusions

This study introduces a Hierarchical Forecasting technique for predicting tourist arrivals, specifically discussing a novel approach called the ARIMA-OC (the ARIMA based on Optimal Combination approach). Results from a simulation study indicate that this method outperforms other techniques. The validity of Hierarchical Forecasting is confirmed through non-parametric tests, such as the Friedman Test and the Nemenyi post-hoc test. Suggestions for future research include incorporating pandemic-related factors such as Covid-19 as a dummy variable in tourism demand studies using panel models, incorporating volatility in developing tourism demand forecasting models, and exploring the use of temporal Hierarchical Forecasting models for predicting tourism demand.

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