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Combined Hierarchical Tourist Arrival Forecasts for Great Zimbabwe National Monuments

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Abstract

Precise tourism estimates for tourism destination sites are crucial for decision-making. The objective of the study is to model and project Great Zimbabwe National Monuments (GZNM) tourist arrivals by combining hierarchical tourism forecasts. The approach improves tourism forecasting accuracy. GZNM monthly tourist arrivals are grouped according to tourism sources. A logarithm transformation is applied to tame the volatile data. Forecasting accuracy of the Simple Average Combination Method (SACM) and three hierarchical forecasting approaches (top-down, bottom-up, and optimal combination) were compared. The SACM under Autoregressive Integrated Moving Average (ARIMA) outperformed the other models, according to Root Mean Square Error (RMSE) measure. SACM is used to combine future tourist arrivals for the following 60 months and show a slow increase in tourist arrivals at GZNM. The data used in modeling are outside the COVID-19 pandemic period. Tourism stakeholders are encouraged to adopt the SACM in future tourism projections as it improves forecasting accuracy. Tourism stakeholders could carefully strategise and plan a recovery and ensure improvement in the tourism sector beyond the COVID-19 pandemic period. The COVID-19 pandemic is significantly affecting the tourism industry, reducing tourist arrivals to zero in some cases. The study revealed a fresh line of inquiry into how combining projections can increase forecasting accuracy.

Keywords: Hierarchical forecasting; combination forecasts; tourist arrivals; tourism destination

Introduction

In the tourism industry accurate tourism demand forecasts are critical, so are the methods that generate the forecasts (Song & Li, 2008). Accurate tourism demand forecasts play a pivotal role in: budgeting, optimal pricing, effective event organisation, investment decisions, revenue collection strategies, marketing and strategic planning, government policy formulation and implementation, resource mobilisation and allocation and infrastructure development for all tourism stakeholders. Under-estimation and over-estimation risks at both country and tourism destination sites can be reduced through the availability of accurate tourist arrivals information. With precise tourism destination forecasts, effective planning and management are feasible. Investment in tourism infrastructure such as hotels, airports, roads and shopping malls can be achieved through accurate tourism demand forecasts. However, the development of tourism infrastructure is expensive and risky; it needs adequate funding and proper long-term planning (Abdullah et al., 2014).

Models for specific tourism destinations are essential for tourism destination management as they provide useful information for tourism destination re-branding. Popular tourism destinations such as the Great Zimbabwe National Monuments (GZNM) and the Victoria Falls rainforest need to re-brand to keep on attracting a significant number of tourist arrivals. Foreign currency earnings from international tourist arrivals who visit these resort places could help in solving the foreign currency challenges being faced by a country. The huge debt that Zimbabwe owes to other countries could be reduced if foreign currency earnings from the tourism industry are well managed.

The tourism destination sites such as the GZNM create employment for local citizens around the monument area, including local traditional dancers and sculptors. Several families in the communities benefit from this national heritage site. Destination management is achieved through the use of accurate tourism forecasts. Accurate tourism forecasts must be available for the destination to have adequate recreational and ablution facilities and enough tour guides among other things. Transport operators, accommodation, food and beverage providers close to the monuments need to be well informed to avoid under (over) budgeting as most tourism products are perishable.

GZNM are unique because of the way they were constructed. They are located in the Masvingo province; approximately 30 km outside Masvingo's Central Business District. The monuments are close to Lake Mutirikwi. They are one of the major tourist attractions in Zimbabwe and are recognized among UNESCO's World Heritage Sites. GZNM are the most extensive ruins in Africa (Matura & Mapira, 2018) and the most popular tourist destination after the Victoria Falls (Macheka, 2016). They are the most visited tourist attraction site in Masvingo province and command a considerable number of tourist arrivals. Hence, this study focuses on these famous ruins in the Masvingo province. Having an accurate number of tourist arrivals, both locals and internationals for the site are crucial for planning, marketing and re-branding purposes.

Tourist arrivals at GZNM are categorised into three groups: Locals (L), Foreigners (F) and Schools (S). By locals, we are referring to Zimbabwe citizens residing in the country. Foreigners are all non-Zimbabwean residents and schools refer to all school children, from primary schools to tertiary institutions. Foreign tourists have expectations and standards when they visit the monuments, hence there is need for accurate foreigner visitor statistics. Schools encompass various age groups with varying needs; thus, accurate forecasts for proper planning to meet needs are needed. When there is grouping of tourist arrivals at GZNM, a hierarchical forecasting approach is applicable. Accurate estimates for independent groups are crucial to meet the needs of every particular group.

Tourism forecasting studies for Zimbabwe exist (see Chikobvu & Makoni, 2019; Karambakuwa et al., 2011; Machipisa, 2001; Muchapondwa & Pimhidzai, 2011; Mutanga et al., 2017) but little has been said about combined forecasts. Makoni et al. (2021) and Makoni and Chikobvu (2018) applied the hierarchical forecasting approaches to Zimbabwe's international tourists (including regional tourists) and the Victoria Falls Rainforest tourist arrivals, respectively. The papers did not combine the forecasts to improve forecasting accuracy as considered in this paper. This study aims to model and project GZNM tourist arrivals by combining hierarchical tourism forecasts. Lei and Wang (2017) and Huang et al. (2017) indicated that accurate tourism models for specific tourism destinations are still underdeveloped. This study will compliment on destination tourism demand forecasting by considering GZNM. The research becomes the first to combine hierarchical forecasts in projecting future tourism demand in Zimbabwe. With hierarchical forecasting, it is now possible to estimate tourism forecasts for independent groups using one model. Valuable information from the study helps GZNM authorities to develop cost-effective marketing strategies. The approach can be applied to various tourism destinations in the country. Statistical forecasting improves forecast performance (Van Sommeren, 2011) and combining forecasts improve forecasting accuracy (Armstrong, 2001; Hibon & Evgeniou, 2005). Furthermore, combining forecasts reduce errors emanating from faulty assumptions as well as mistakes in data being used (Armstrong, 2001). The rest of the paper is organised as follows: Section 1 was the introduction and Section 2 is the literature review. Section 3 presents the methods; the results and discussion are presented in Section 4. Section 5 concludes and gives recommendations.

Literature review

Tourism modeling is essential, and it can be done using several techniques. Econometric and univariate methods are commonly used in tourism modelling. For example, Li et al. (2000) used an econometric approach to model Thailand's inbound tourist arrivals. The Time-Varying Parameter (TVP) model proved to be the best for Thailand's tourism data. In other tourism studies, Goh and Law (2002) found out the superiority of Seasonal Autoregressive Integrated Moving Average (SARIMA) models over Autoregressive Integrated Moving Average ARIMA models, while Cho (2001) concluded the opposite. Smeral and Wüger (2005) fitted a Naïve model that outperformed both the ARIMA and SARIMA models. From these few studies, it can be noted that there is no single model that outclasses the rest, thus, combining forecasts from different models may lead to better results.

According to Li et al. (2019), a combination forecasting method generates forecasts by combining the estimates from several individual models using specific weighting methods. Li et al. (2019) combined interval tourism forecasts in Hong Kong. The authors concluded that combining forecasts is an effective way of improving forecasting accuracy. Wong et al. (2007) noted that forecasting failure risks from a single model could be avoided by combining forecasts. It is crucial to adopt this noble idea of combining forecasts. Comprehensive information is critical for decision-making and can be obtained from the point and interval forecasts, thus, combining forecasts (point/interval) results in superior results.

Song et al. (2009) combined forecasts from four forecasting methods (ARIMA, Autoregressive Distributed Lag Model (ADLM), Vector Autoregressive (VAR) and Error Correction Model (ECM). Hong Kong's tourism data was used. It was concluded that combined forecasts reduce forecasting failure risk and the approach is suitable for practical situations. Song et al. (2009) examined the forecasting performance of different combination techniques in Hong Kong. It was concluded that combined model forecasts are more accurate than single model forecasts in all forecasting horizons. Combining forecasts is useful for long-term forecasting but increasing the number of combined models does not necessarily improve forecasting accuracy (Song et al., 2009). The authors recommended the use of combined model forecasts and indicated that long-term forecasts are essential for practical situations.

Shen et al. (2011) employed two time-series and five econometrics models in modeling and forecasting tourist arrivals in the UK. From the employed models, six combinations were formed and evaluated. Research findings indicated the superiority of combined forecasts than those from individual forecasts. The authors concluded that combining at least three individual model forecasts yields more accurate results. The current study will combine forecasts from the top-down, bottom-up, and optimal combination approaches; hence better results are expected. Armstrong (2001) recommended the use of five or more methods when combining forecasts as a way of improving forecasting accuracy. When combining forecasts, equal weights or different weights can be used, and the approach is more efficient in uncertain situations or when one is not sure about the best method (Armstrong, 2012).

Winkler and Makridakis (1983) investigated five approaches of combining forecasts obtained using weighted averages. Two out of the five methods yielded accurate results that surpass the results of individual models. Combining forecasts is then recommended from this study. However, Kascha and Ravazzolo (2012) noted that combination forecasts might not surpass individual forecasts, but they produce better results as they provide insurance against a wrong model selection. Besides the existence of vast combination forecasts literature, no consensus has been reached concerning the best approach that outperforms all methods.

The hierarchical forecasting approach results in coherent forecasts, and it improves forecasting accuracy. Kourentzesa and Athanasopoulos (2018) projected Australia's tourism demand using hierarchical forecasting approach. According to Athanasopoulos et al. (2009) the top-down, bottom-up, and optimal combination are the commonly used hierarchical forecasting approaches. The methods work well with both aggregated and disaggregated data. After noting advantages of the hierarchical forecasting approach, Athanasopoulos et al. (2009) and Taieb et al. (2017) adopted the approach and projected Australia's tourism demand and the UK's electricity demand, respectively. Taieb et al. (2017) disaggregated electricity data according to the geographical area and predicted future electricity demand. Athanasopoulos et al. (2009) grouped tourism data according to regions, states, and zones and projected future tourism demand. Both models (electricity and tourism) gave precise forecasts indicating a possible increase in both electricity and tourism demand.

Several authors have different views on the best performing hierarchical forecasting method. For example, Fliedner (1999) and Jain (1995) concluded that the top-down was the best performing approach. However, Dangerfield and Morris (1992), Kinney (1971), and Wanke and Saliby (2007) are among the authors who concluded that the bottom-up approach was the best. Furthermore, Li et al. (2005) concluded that no single forecasting approach could outperform all other methods in all cases. Jain (1995) noted the top-down approach as the best, while Wanke and Saliby (2007) stated that the bottom-up approach was the best. Combining forecast may be a solution to this debate. According to Wong et al. (2007), it is more certain that combination forecasts outperform individual forecasts.

Averaging independent forecasts are sometimes referred to as combined forecasts (Armstrong, 2001), and this is the approach that is used in this study. The hierarchical forecasting approaches (bottom-up, top-down and optimal combination) are employed, and the forecasts from these methods are averaged to give final forecasts for Zimbabwe's tourism arrivals.

Methods

The hierarchical forecasting methods that are used in this study are briefly explained.

Hierarchical tree diagram

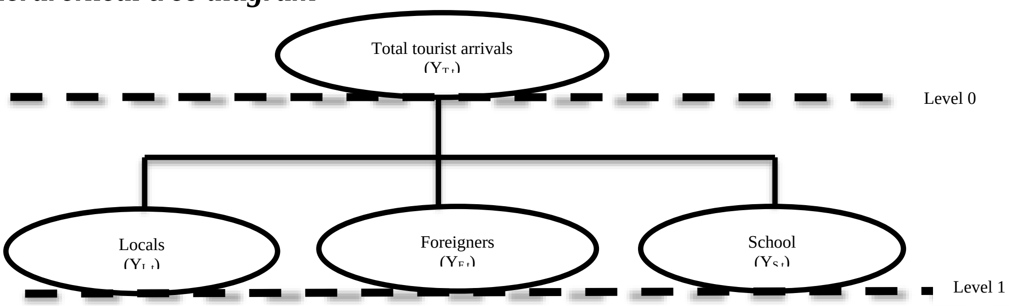

Figure 1: A one-level hierarchical tree diagram for GZNM tourist arrivals

Tourist arrivals at GZNM are into three groups: Locals (L), Foreigners (F) and Schools (S). This grouping results in a one-level hierarchical structure. Figure 1 shows the hierarchical structure of GZNM tourist arrivals.

Considering the hierarchical tree diagram in Figure 1, we can have the following equation:

$$\boldsymbol{Y}_t = [Y_t, Y_{L,t}, Y_{F,t},\ Y_{S,t}]' = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} Y_{L,t} \\ Y_{F,t} \\ Y_{S,t} \end{pmatrix}, \qquad (1)$$

where $Y_{L,t}, Y_{F,t}$ and $Y_{S,t}$ are local, foreign and school tourist arrival observations at time t, and Y_t denotes the total number of tourist arrivals at time t. After having equation (1), the bottom-up, top-down and optimal combination approaches can be applied to generate forecasts.

Hierarchical forecasting approaches

We explain the commonly used hierarchical or grouped forecasting approaches: the bottom-up, top-down and optimal combination. In the bottom-up approach, individual forecasts are generated at the lower level and later aggregated up the hierarchy through a summation matrix ($\boldsymbol{S}$). No information is lost in the bottom-up approach and tourism data dynamics are accounted for by the method (Taieb et al., 2017).

In the top-down approach, combined forecasts are generated at the upper level and later disaggregated to the lower levels using forecasted proportions, proportions of historical averages and average historical proportions (Hyndman & Athanasopoulos, 2014). The approach is easy to apply and generates unbiased forecasts (Hyndman et al., 2011). For example, given that the number of lower-level series is m_k, the mean value of the total combined series is $\mathrm{Y_t}$ and the lower-level series are denoted by $\mathrm{Y_{(i,t)}}$; the expression for proportions of the historical averages can be expressed as:

$$\mathrm{p_i} = \left(\sum_{\mathrm{t=1}}^{\mathrm{N}} \frac{\mathrm{Y_{i,t}}}{\mathrm{N}}\right) \left(\sum_{\mathrm{t=1}}^{\mathrm{N}} \frac{\mathrm{Y_t}}{\mathrm{N}}\right). \qquad (2)$$

Hyndman et al. (2011) introduced the optimal combination approach which uses a regression model to optimally combine and reconcile forecasts. The method accounts for relationships between tourism series at each hierarchical level. The regression equation responsible for generating future tourism forecasts can be expressed as:

$$\widehat{\boldsymbol{Y}}_n(h) = \boldsymbol{S}\boldsymbol{\beta}_h + \boldsymbol{\varepsilon}_h \qquad (3)$$

where $\widehat{\boldsymbol{Y}}_n(h)$ are future forecasts (h-step-ahead base forecasts), $\boldsymbol{S}$ is the summing matrix, $\boldsymbol{\varepsilon}_h$ is a white noise with mean zero and covariance matrix given by $\sum_h$. A vector of unknown means of lower-level forecasts is denoted by $\boldsymbol{\beta}_h$.

Forecasting performance evaluation method

Exponential Smoothing (ES) and ARIMA models work well with the hierarchical forecasting approach; hence they are adopted in this study. The ES and ARIMA models are well known for their ability to generate accurate forecasts. Forecasts from these models are evaluated using the Root Mean Square Error (RMSE). A lower RMSE value means a better model. The formula that gives the RMSE is:

$$\mathrm{RMSE} = \sqrt{\frac{(\hat{Y}_t - Y_t)^2}{n}}, \qquad (4)$$

where Y_t and $\hat{Y}_t$ represents the original series and projected series, respectively. The number of observations is denoted by n.

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Forecast combination method

According to Shen et al. (2011), forecasts can be combined using the Simple Average Combination Method (SACM). With this approach, the mean of individual forecasts is calculated to produce combined forecasts. The procedure is robust and useful in business forecasting (Clemen, 1989). According to Stock and Watson (2004) and Timmermann (2006), SACM is a reliable method that is very difficult to beat. The SACM approach is adopted in this study and can be expressed as:

$$CF = \frac{1}{n}\sum_{i=1}^{n} f_{it}, \qquad (5)$$

where the total number of forecasts to be combined is n, f_{it} are individual forecasts at time t and CF are the combined forecasts.

Results and discussion

Exploratory data analysis

Explanatory data analysis of the original disaggregated series was done using R, and the results are shown in Table 1.

Table 1: Descriptive statistics

Category	Mean	SD	Median	Min	Max	Skew	Kurtosis
Locals	1725.05	1230.57	1347.5	9	6635	1.82	3.05
Foreigners	1382.95	1563.25	751.5	4	7963	1.90	3.35
Schools	647.28	637.74	484.5	12	3811	2.58	7.38

Results in Table 1 are summaries that show the distribution of tourist arrivals. Foreign tourist arrivals have the highest maximum numbers (7963), while schools have the smallest maximum numbers (3811). The data are positively skewed, as suggested by positive skewness values. Furthermore, the distribution of the data is leptokurtic, as suggested by kurtosis values.
A boxplot is also constructed to summarise the data and is shown in Figure 2.

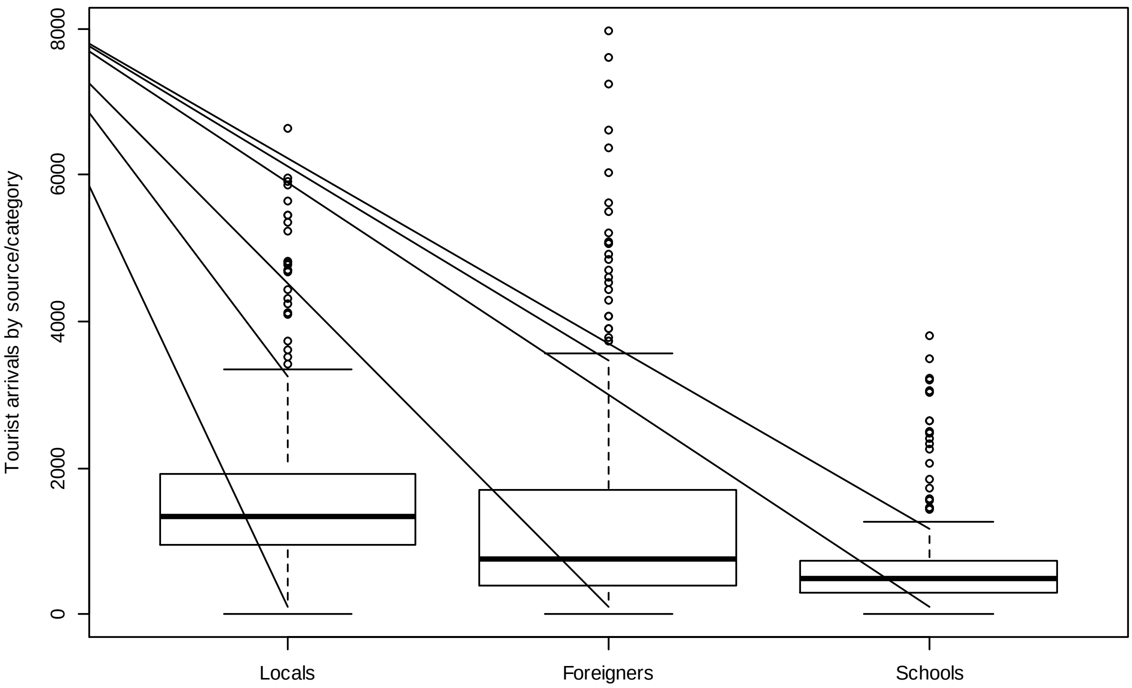

Figure 2: BGZNM box-plot

According to Figure 2, local tourists constitute a significant percentage of GZNM tourists, followed by foreign tourists and lastly, by school tourists.

Time-series plots

The behaviour of tourism data at GZNM are examined through the use of a time-series plot.

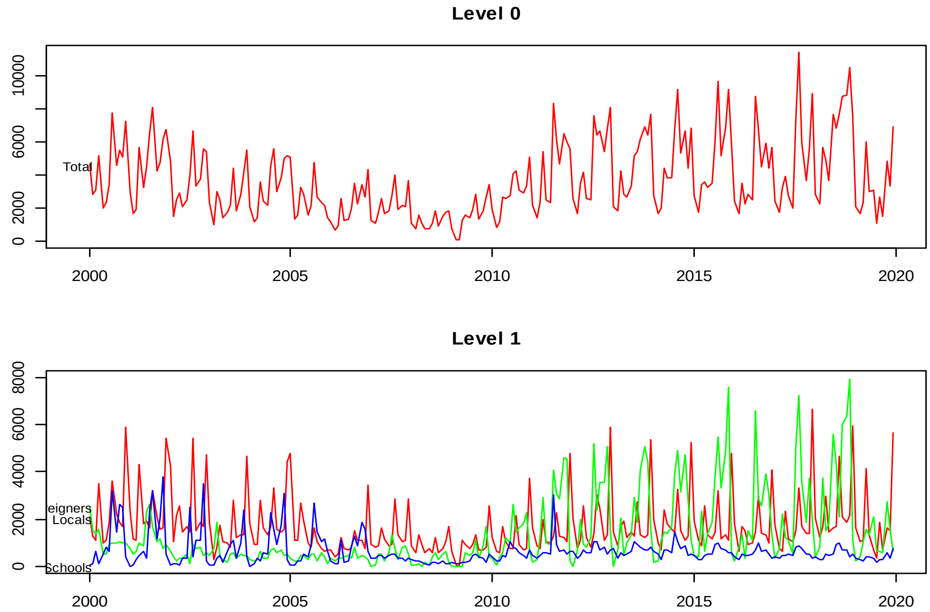

Figure 3: Time series plot of the original series

Figure 3 shows that school tourist arrivals for the study period are lower. Between the years 2000-2008, school tourist arrival numbers were high. This could be due to the nature of the curriculum that was in place at the time. The curriculum emphasised more on traditions and cultures (history). The change of curriculum saw the number of school tourists decreasing.

From the year 2000 to the year 2007, foreign tourist arrivals who wanted to know the type of architecture used to build the monuments grew. The number of local and international tourist arrivals started increasing around the year 2009 up to the end of the study period. The formation of the Government of National Unity (GNU) in the year 2009 coupled with the introduction of multiple currencies, may have contributed to the increase in tourist arrivals. However, all the tourism series look noisy, with increasing variance. Thus, a logarithm transformation is used to tame the variance.

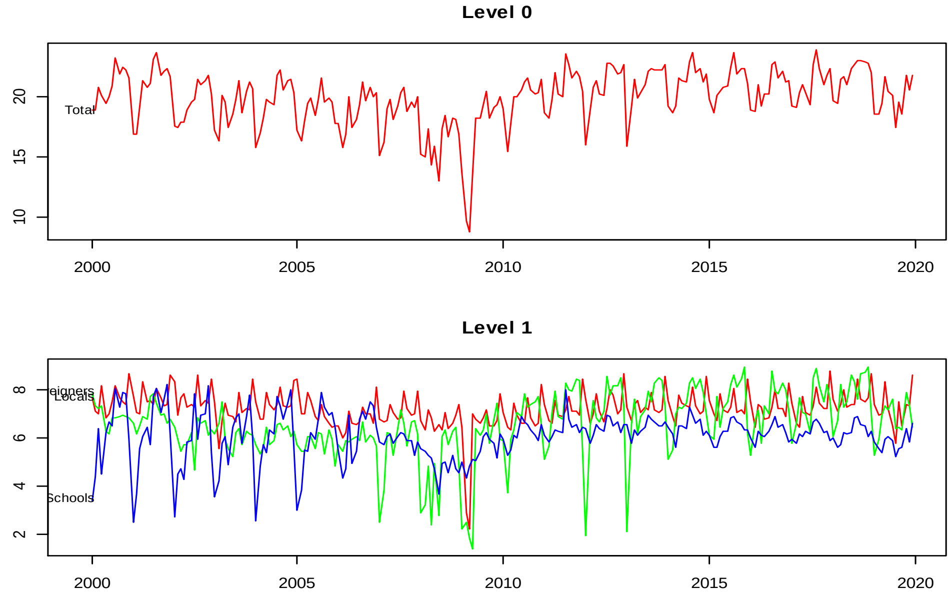

Figure 4: Time series plot of log-transformed series

Figure 4 exhibits a time-series plot of log-transformed data. The log-transformed data are used for modelling and prediction purposes.

Forecasting method evaluation

The ES and ARIMA models are the two methods used in forecasting individual series. Evaluation done on three-step-ahead, six-step-ahead, and twelve-step ahead forecasts is presented. The RMSE is calculated for both individual models and the SACM. The approaches being considered are bottom-up (BU), top-down with average historical proportions (TDAHP), top-down with the proportion of historical averages (TDPHA), top-down with forecast proportions (TDFP), optimal combination (OC) and SACM. The RMSE results are shown in Table 2.

Table 2: ES and ARIMA RMSE results

	Step ahead	3	6	12	3	6	12	3	6	12	3	6	12
	Approach	**Totals**			**Locals**			**Foreigners**			**Schools**		
ARIMA	BU	0.65	0.50	0.76	0.25	0.25	0.36	0.47	0.44	0.41	0.16	0.14	0.35
	TDAHP	0.41	0.67	0.91	0.47	0.51	0.60	0.60	0.79	0.69	0.30	0.26	0.41
	TDPHA	0.41	0.67	0.91	0.50	0.53	0.60	0.60	0.76	0.67	0.30	0.26	0.41
	TDFP	0.41	0.67	0.91	0.27	0.29	0.41	0.32	0.49	0.43	0.24	0.18	0.39
	OC	0.25	0.42	0.78	0.21	0.22	0.36	0.32	0.46	0.41	0.13	0.10	0.36
	SACM	**0.22**	**0.35**	**0.66**	**0.15**	**0.17**	**0.30**	**0.31**	**0.42**	**0.39**	**0.11**	**0.08**	**0.28**
ES	BU	0.66	0.98	1.36	0.23	0.36	0.57	0.38	0.78	0.69	0.20	0.18	0.31
	TDAHP	1.01	1.15	1.67	0.69	0.72	0.89	0.57	0.81	0.72	0.40	0.29	0.61
	TDPHA	1.01	1.15	1.67	0.73	0.74	0.89	0.55	0.77	0.70	0.40	0.29	0.60
	TDFP	1.01	1.15	1.67	0.25	0.38	0.67	0.47	0.81	0.77	0.36	0.28	0.42
	OC	0.82	1.05	1.51	0.22	0.36	0.59	0.48	0.81	0.76	0.28	0.22	0.36
	SACM	0.71	0.86	0.94	0.21	0.33	0.46	0.35	0.63	0.57	0.18	0.13	0.31

From the results in Table 2, the ARIMA forecasting approach has lower RMSE values. The lower RMSE values are indicated in bold. The SACM under the ARIMA method has the lowest RMSE when compared to other models. The results show the superiority of the SACM over other individual models. The results are in line with those of Stock and Watson (2004) and Timmermann (2006) who indicated that nothing could beat the SACM. Tourist arrival forecasts for the next 60 months are projected using the three hierarchical forecasting approaches (bottom-up, top-down and optimal combination) under the ARIMA method and combined using the SACM. The logarithm transformed data are used in forecasting but an anti-logarithm transformation is applied to the forecasts to come up with the tourism forecasts. Table 3 displays the SACM estimates for the next 60 months.

SACM forecasts in Table 3 suggest a slow increase in tourist arrivals at GZNM. The estimates are done without considering the Covid-19 pandemic because the data was collected before the pandemic. The estimates show that under normal circumstances, the GZNM will be dominated by local tourist arrivals. Entertainment facilities to satisfy the needs of domestic tourist arrivals may be put in place. More education cultural activities may be increased at GZNM, so as to attract more school tourists. Marketing strategies targeting foreign tourist arrivals are needed to attract tourists. These strategies are needed beyond the pandemic to revive the tourism industry.

Table 3: SACM future forecasts

Month	Total	Locals	Foreigners	Schools	Month	Total	Locals	Foreigners	Schools
Jan-20	1795	1556	121	359	Jul-22	5796	1969	3067	760
Feb-20	582	627	222	177	Aug-22	7522	3737	2864	920
Mar-20	2649	1242	1054	353	Sep-22	5316	2015	2596	706
Apr-20	4039	2801	698	540	Oct-22	6583	2350	3330	902
May-20	2431	1303	659	469	Nov-22	6805	2407	3639	759
Jun-20	3290	1304	1483	502	Dec-22	8120	5591	1501	1027
Jul-20	5373	1824	2796	753	Jan-23	2192	1750	33	409
Aug-20	7121	3588	2618	915	Feb-23	1300	931	103	266
Sep-20	4932	1885	2354	693	Mar-23	3288	1461	1417	409
Oct-20	6201	2234	3109	858	Apr-23	4656	3031	1022	604
Nov-20	6451	2296	3421	734	May-23	3014	1502	983	529
Dec-20	7766	5478	1316	972	Jun-23	3844	1482	1806	556
Jan-21	1870	1635	146	381	Jul-23	5889	1987	3119	783
Feb-21	993	825	68	236	Aug-23	7611	3753	2916	942
Mar-21	2996	1373	1239	384	Sep-23	5399	2031	2646	722
Apr-21	4381	2937	860	584	Oct-23	6656	2368	3381	907
May-21	2750	1423	823	505	Nov-23	6877	2423	3688	766
Jun-21	3595	1409	1647	539	Dec-23	8184	5609	1549	1025
Jul-21	5663	1919	2956	787	Jan-24	2257	1762	81	415
Aug-21	7395	3684	2765	946	Feb-24	1362	943	148	271
Sep-21	5189	1971	2502	715	Mar-24	3347	1474	1460	413
Oct-21	6452	2312	3246	894	Apr-24	4713	3042	1062	608
Nov-21	6681	2372	3558	752	May-24	3068	1513	1023	533
Dec-21	7994	5557	1431	1006	Jun-24	3896	1491	1845	560
Jan-22	2079	1715	37	401	Jul-24	5939	1996	3156	786
Feb-22	1192	899	35	258	Aug-24	7658	3761	2952	945
Mar-22	3184	1434	1351	399	Sep-24	5444	2039	2681	724
Apr-22	4557	3002	960	595	Oct-24	6700	2375	3414	911
May-22	2920	1478	922	521	Nov-24	6918	2430	3720	768
Jun-22	3754	1459	1747	547	Dec-24	8224	5614	1581	1028

Conclusions and recommendations

In this paper, tourist arrivals at GZNM are grouped according to tourism source, a grouping suitable for hierarchical forecasting approach. The monthly disaggregated original tourist arrivals data are more volatile as indicated by the time-series plot. A logarithm transformation is done to tame the volatility in the data. Hierarchical forecasting approaches (bottom-up, top-down and optimal combination) are considered in analysing the data. The forecasting accuracy of hierarchical methods is compared to that of SACM. It is found that the SACM outperforms the individual models as supported by smaller RMSE values. The SACM is used in combining hierarchical forecasts to come up with future projections for the following five years. An overall slow increase in tourist arrivals, particularly, in local tourist arrivals, followed by an increase in foreign tourist arrivals is noted.

The projected forecasts are not taking into account the COVID-19 pandemic period because the data was collected before this international disaster. Combining tourism forecasts improve forecasting accuracy. We, therefore, recommend tourism stakeholders to adopt this approach in tourist arrival projections. Combining forecasts is well known for generating more accurate estimates crucial for decision-making.

International disasters such as the COVID-19 pandemic outbreak significantly affect the tourism industry. In the meantime, the government and the Ministry of Tourism may partner so that they carefully strategise and plan to ensure improvement in the tourism sector after the pandemic. It will take a lot of effort to recover from the pandemic and for Zimbabwe to claim its fair share of tourists. The study results are useful, they reduce the chance of an oversupply, permit the best use of the resources at hand, increase tourism demand, and control the number of visitors.

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