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Enhancing Zakat Collection Forecasting using Time Series Analysis

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Abstract
Zakat institutions face a major challenge: the lack of a reliable framework to analyze zakat collection trends. To address this, the study employs Holt-Winters and ARIMA models on 72 monthly observations of MAIK collections from January 2017 to December 2022, with a 70:30 train-test split. The data shows a clear upward trend and seasonality, confirmed by ADF tests and correlograms. Evaluation using MSE, RMSE, and MAPE shows that ARIMA$(0,0,1)(0,1,1)_{12}$ outperforms other models in forecasting zakat collection. In 2024, zakat is projected to reach RM228 million, aiding MAIK's strategic financial planning.

Keywords: Forecasting; Zakat Collection; ARIMA; Holt-Winters

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1.0 Introduction

The Islamic economic system encompasses profit-oriented and non-profit institutions (Alshater et al., 2021). Profit-oriented institutions include Islamic banks, takaful providers, service providers, and manufacturing companies. Non-profit institutions, such as zakat, waqf, and charitable organizations, play a crucial role in socio-economic development. Among them, zakat holds a central position. As one of the Five Pillars of Islam, zakat is a mandatory charitable obligation for eligible Muslims (Wahab & Rahim Abdul Rahman, 2015). It assists the poor and needy, addressing issues like poverty and inequality. Saad et al. (2020) emphasized that zakat not only reflects the relationship between the wealthy and the poor but also improves the quality of life. According to Syariah, it is a financial responsibility for capable Muslims (Ahmad, Othman & Salleh, 2015). Zakat institutions, usually overseen by government or state Islamic religious councils, are responsible for its collection and distribution.

In Malaysia, zakat collection grew from RM2.86 billion in 2018 to RM3.03 billion in 2020. However, in 2021, it dropped to RM1.13 billion due to the economic impact of COVID-19 (Jabatan Wakaf, Zakat dan Haji – JAWHAR). Shaharin et al. (2021) found that the pandemic increased the number of zakat recipients.

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A major challenge facing zakat institutions is the lack of effective forecasting tools. Without accurate predictions, planning and resource allocation become difficult. Studies by Mohd Fadlihisyam and Asmah (2020) and Akbarizan et al. (2016) show that time series forecasting can improve zakat management by revealing trends and helping institutions optimize their operations.

2.0 Literature Review

In Malaysia, zakat administration falls under the jurisdiction of individual states. The Sultans oversee Islamic laws and customs, including zakat, while the Federal Government handles this for federal territories (Ahmed, 2004; Hudayati & Tohirin, 2010; Mahamod, 2011; Saad & Abdullah, 2014). *State Islamic Religious Councils (Majlis Agama Islam Negeri, MAIN)* advise the Sultans and manage zakat institutions to suit local needs, enhancing efficient collection and distribution.There are two main types of zakat in Malaysia: zakat *fitrah* and zakat *harta*. Zakat *fitrah,* paid during Ramadan, is obligatory for all Muslims regardless of age or wealth (*Lembaga Zakat Selangor*, 2018). It may be paid in rice or cash equivalent, based on rulings by the *Islamic Legal Consultative Committee* and *National Fatwa Council*. Umar (2017) stated that rice, the staple food in Malaysia, is used to set the value. In 2017, zakat *fitrah* was RM7.00, based on 2.7 kg of *Beras Super Special Tempatan 5%* priced at RM2.60/kg. Zakat *harta* applies to income, assets, and savings. Muslims whose wealth meets the *Nisab,* the minimum threshold for zakat eligibility, are required to pay 2.5% of their wealth.

Globally, zakat systems vary. In Saudi Arabia, the *Ministry of Islamic Affairs* manages zakat (Sawmar & Mohammad, 2019), with rates tied to gold/silver values. In Indonesia, zakat is managed by two types of institutions: Badan Amil Zakat (BAZ), established by the government, and Lembaga Amil Zakat (LAZ), formed by non-governmental entities. Both are authorized to collect and distribute zakat under national regulations (Wahyuni et al., 2021; Mochammad Ardani & Arif Pujiyono, 2021; Harahap, 2022).

Forecasting is essential for efficient zakat planning. Akbarizan et al. (2016) used ARIMA and Holt's method in Indonesia; Razak et al. (2013) applied models to *Pusat Zakat Melaka*. Ubaidillah and Sallehuddin (2013) developed a forecasting model for *Pusat Zakat Pahang* using two Artificial Neural Network (ANN) training algorithms: Backpropagation (BP) and Levenberg-Marquardt (LM). Both models were evaluated for accuracy, and the BP model was found to be more effective based on lower mean square error and higher correlation values.

3.0 Methodology

The dataset employed in this research is collected from Majlis Agama Islam Kelantan encompassing the period from January 2017 to December 2022, with a total of 72 observations. The zakat collection data from Kelantan is split into two subsets, estimation and evaluation data, utilizing a 70:30 ratio. The estimation data serves the purpose of model development and training, whereas the evaluation data facilitates assessing the model's performance.

3.1 Autoregressive Integrated Moving Average (ARIMA) Modelling

According to Mohd Alias Lazim (2011), the ARIMA modelling procedure encompasses a few steps. The first step involved checking the data's stationarity to develop the ARMA *(p,q)* model. According to Mohd Alias Lazim (2011), the ARIMA modelling procedure encompasses five steps. The initial step is to assess the stationarity of the data, which lays the foundation for developing the ARMA (p,q) model. Following this, the second step entails scrutinizing the data for seasonal effects. This involves analysing the data patterns to ascertain whether there exists a recurring pattern over fixed intervals of time, such as monthly or annually. Should seasonality be present, the third step of seasonal differencing is initiated. Seasonal differencing aids in achieving stationarity by eliminating seasonal patterns. This process is conducted based on $z_t = y_t - y_{t-12}$ for monthly data, simplifying the modeling of the underlying trend and noise. If no seasonal effects are observed, the alternative is to perform a non-seasonal difference, marking the transition to the fourth step. This procedure renders the data series stationary, ensuring a constant mean and variance over time. Upon the completion of either seasonal or non-seasonal differencing, the fifth step involves re-evaluating the stationarity of the data series. If stationarity is achieved, the subsequent phase is to develop the ARIMA, with specifications of *(P, D, Q)* for the seasonal part and *(p,d,q)* for non-seasonal part.

3.2 Stationarity Checking and Testing in ARIMA

Since the Box-Jenkins method will be employed in this study, one of the most important assumptions is that the data is stationary. Therefore, in this study, stationarity checking becomes a crucial step to lay the foundation for the subsequent time series analysis. One of the stationarity checks is through plotting Autocorrelation (ACF) and Partial autocorrelation (PACF). Autocorrelation (ACF) and Partial autocorrelation (PACF) functions (Box Jenkins, 1970) are two of the approaches to determine the stationarity of the data. Both ACF and PACF are useful to plot against consecutive time lags for modelling and forecasting as the order of AR and MA are determined by these plots.

Unit root tests can be used for testing the stationarity in time series data. An Augmented Dickey-Fuller (ADF) test is one of them. This test is widely used in time series analysis to test for the presence of a unit root, which is a root of the characteristic equation of the autoregressive model. The null hypothesis represents the presence of a unit root and indicates that the time series is non-stationary, which means its statistical properties change over time. If the test statistic is less than the significance level, then the null hypothesis is rejected, indicating that the series is stationary. The following equation is used to calculate the test statistic of the ADF test:

$$\Delta y_t = \alpha + \beta t + \gamma y_t + \delta_1 \Delta y_{t-1} + \delta_2 y_{t-2} + \cdots + \delta_p y_{t-p} + \varepsilon_t \quad (1)$$

where Δy_t represents the difference time series at time *t*, α is the constant term, β is the coefficient of the trend, y_{t-1} and denotes the value of the time series at the previous time point *t-1*. The lagged difference of the time series, $\Delta y_{t-1}, \Delta y_{t-2}, \ldots, \Delta y_{t-p}$ and ε_t represents the error term.

Another unit root test is Philips-Perron (PP), which shares a similar purpose to the ADF test, testing the presence of a unit root in the time series. The equation for the Philips-Perron test can be represented as follows (Philips & Perron, 1998):

$$\Delta y_t = \rho\, y_{t-1} + \sum_{i=1}^{p-1} \beta_i\, \Delta y_{t-1} + \sum_{i=1}^{p-1} \gamma_i\, \Delta y_{t-1} + \varepsilon_t \quad (2)$$

Where Δy_t represents the first difference of the time series at time *t*, y_{t-1} is the lagged value of the time series, β_i and γ_i are the coefficients to be estimated, ρ is the lag length chosen for the test, and ε_t is the error term.

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is another unit root test to determine the stationarity of a time series. KPSS test is different from ADF and PP tests, in which the KPSS test directly tests for stationarity. The KPSS test statistic is calculated using the following equation (3) (Imam, Habiba, & Atanda, 2016):

$$KPSS = \frac{\sum_{t=1}^{T} \hat{e}_t^2}{T \times \hat{\sigma}^2} \quad (3)$$

where $\hat{e}_t$ is the residual at time *t*, $\hat{\sigma}^2$ is the estimated variance of the residuals, and *T* is the number of observations. The test statistic is compared to the critical value at the significance level to determine whether to accept or reject the null hypothesis. If the test statistic exceeds the significance level, the null hypothesis of stationarity is rejected, indicating that the data is non-stationary.

Seasonal ARIMA is an extension of the ARIMA technique for time series data in which a pattern repeats seasonally over time. It is expressed as ARIMA *(p, d, q)(P, D, Q)*, where *(p, d, q)* represents the non-seasonal component of the model, *(P, D, Q)* represents the seasonal component of the model and *s* denotes the number of periods per season. Pongdatu and Putra (2018) express that *P* stands for the Seasonal Autoregressive (SAR) term, *D* for the number of seasonal differences performed and *Q* for the Seasonal Moving Average (SMA) term in the seasonal component. The Seasonal ARIMA model can be represented using the following general notation:

$$(1-B)^d (1-B)^D Y_t = \mu + \frac{\theta(B)\,\theta_s(B^s)}{\phi(B)\,\phi_s(B^s)}\, \varepsilon_t \quad (4)$$

where *B* is a backward shift operator, θ_s are Seasonal Moving Average (SMA), ϕ_s are the Seasonal Autoregressive (SAR) polynomials.

3.3 Model Selection in ARIMA

An appropriate model is crucial in time series analysis to ensure accurate and reliable predictions. This study will use model selection criteria, including the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria are essential for evaluating the goodness-of-fit and sufficiency of proposed models. The AIC equation given as in (5) (Mohd. Alias Lazim, 2011) is shown below,

$$AIC = e^{\frac{2k}{T}} \frac{\sum_{t=1}^{T} e_t^2}{T} \quad (5)$$

Next, the Bayesian Information Criterion (BIC) was developed by Schwarz (1978) to select models that achieve the most accurate evaluation data by balancing between the model's complexity and goodness of fit. As a result, the model with the lowest BIC values is the best, as determined by the same criterion as AIC. The BIC value is calculated as in (6) (Mohd. Alias Lazim, 2011),

$$BIC = T^{\frac{k}{T}} \frac{\sum_{t=1}^{T} e_t^2}{T} \quad (6)$$

where $k = p+q+P+Q$ represents the number of parameters estimated in the model, p is a respective term for AR process, q is a respective term for MA process, P and Q represent the seasonality part of the ARIMA model, T is the total number of observations in the data series, e_t^2 is a penalty function whose aim is to avoid model overfitting.

3.4 Holt-Winters Modelling

The Holt-Winters methods include seasonal factor estimations for each period, denoted by S. The parameter p specifies the annual number of seasonal periods. For instance, if $p = 12$, it would indicate adjustments for monthly seasonality, while $p = 4$ would indicate adjustments for quarterly seasonality. Below are the fundamental formulas for the additive model as presented by Lidiema (2017),

$$L_t = \alpha\left(Y_t - S_{t-s}\right) + (1-\alpha)\left(L_{t-1} + b_{t-1}\right) \tag{7}$$

$$b_t = \beta\left(L_t - L_{t-1}\right) + (1-\beta)\ b_{t-1} \tag{8}$$

$$S_t = \gamma\left(Y_t - L_t\right) + (1-\gamma)\, S_{t-s} \tag{9}$$

$$F_{t+m} = L_t + b_t m + S_{t-s+m} \tag{10}$$

where s is the length of seasonality in months, L_t denotes the level of the series period ahead, α, β, γ are the smoothing parameters, constrained to lie between 0 and 1, b_t represents growth, S_t is the seasonal element, F_{t+m} is the forecast for m-step ahead.

3.5 Model Comparison

It is essential to minimise error when developing a statistical model, as this helps determine whether the model is appropriate for the problem at hand and can provide accurate forecasts. When comparing ARIMA and Holt-Winters Exponential Smoothing methods, the performance of each model can be calculated by Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). The error metrics used in this study are outlined as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2}{n}} \tag{11}$$

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{\left(y_t - \hat{y}_t\right)}{y_t}\right|}{n} \times 100 \tag{12}$$

where y_t is the actual value and $\hat{y}_t$ is the fitted value at time t, respectively.

4.0 Findings and Discussion

4.1 Stationarity Checking and Testing in ARIMA Modelling

The time series plot of the zakat collection in Kelantan from January 2017 to December 2022 is presented in Fig. 1. The figure shows two main trends indicating a rise in Muslim contributions in Kelantan. There is also a seasonal trend in the graph, where a notable increase in zakat collection occurs during Ramadan due to the obligatory charity, zakat *fitrah*, given during this time. It causes a sharp rise, followed by a significant drop in the collections after Ramadan, returning to normal until the next Ramadan. This pattern repeats yearly, making the data non-stationary as the mean and variance change over time. Fig. 2(a) and Fig. 2(b) show the ACF and PACF plots for zakat collection. The ACF plot reveals notable correlations at lag 12 and 24, suggesting a recurring pattern or seasonality in the data, indicating non-stationarity. After performing a seasonal differencing of order one, D = 1, Fig. 3(a) and Fig. 3(b) indicate that most lags fall within the confidence limits, signifying stationary data, thereby confirming stationarity. The ACF and PACF plots of the seasonal differenced series are used to identify the order of p, q, P, and Q. For non-seasonal components, the ACF shows significant correlation at lag 1, suggesting q=1 and p=1. For seasonal components, Q and P are observed from ACF and PACF at lags 12 and 24. The ACF shows no significant correlation at lags 12 and 24, while PACF shows a significant correlation at lag 12, leading to initial seasonal assumptions of Q=0 and P=1. The suggested model is ARIMA$(1,0,1)(1,1,0)_{12}$.

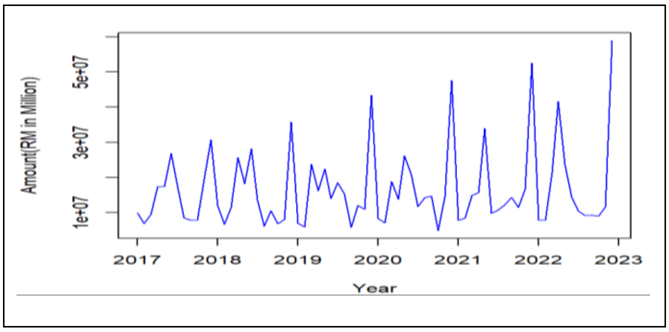
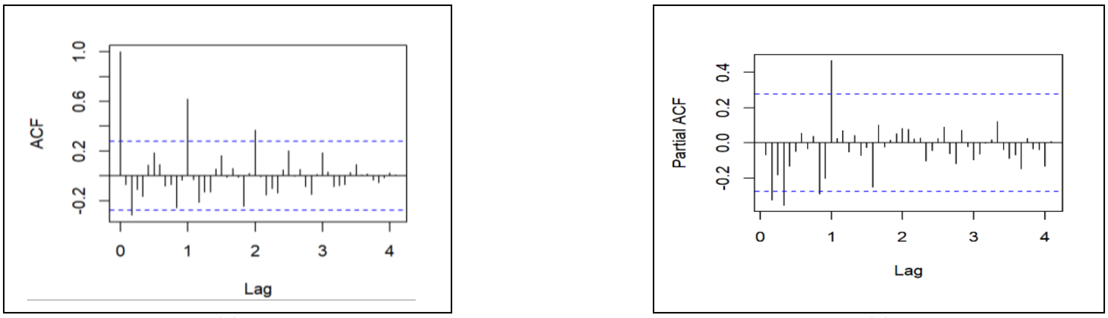
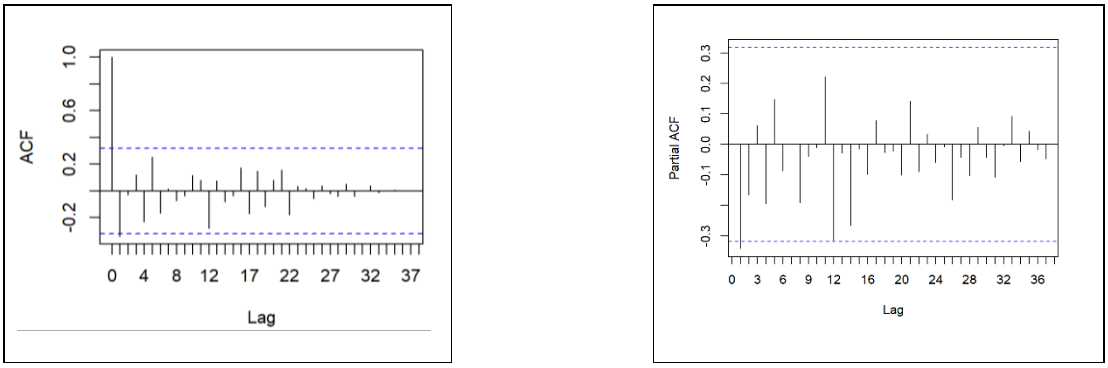


Fig. 1. Zakat collection



(a) (b)

Fig. 2. (a) ACF plot of zakat collection; (b) PACF plot of zakat collection



(a) (b)

Fig. 3. (a) ACF plot of seasonal difference; (b) PACF plot of seasonal difference

The data were further examined for stationarity using the three most widely applied tests: ADF, PP, and KPSS. Table 1 presents the unit root test results for both the original and seasonally differenced zakat collection series. The ADF test produces a p-value of 0.2987, above the 0.05 significance level, indicating possible non-stationarity. In contrast, the Philips-Perron (PP) test yields a p-value of 0.01, suggesting stationarity. The KPSS test, with a p-value of 0.1, does not provide sufficient evidence to confirm non-stationarity. Visual inspection of the ACF and PACF plots (Figures 2(a) and 2(b)) also indicates non-stationarity. Considering the test results and plots, the data are concluded to be non-stationary. Therefore, seasonal differencing is applied, and all tests confirm stationarity in the transformed series, making it suitable for modelling.

Table 1. Unit root tests

	Test	ADF test	P-P test	KPSS test
Original series	p-value	0.2987	0.01	0.1
	Decision	p-value>0.05	p-value<0.05	p-value>0.05
	Conclusion	Non-stationary	Stationary	Stationary
Seasonal differenced, D=1 series	p-value	0.02642	0.01	0.1
	Conclusion	Stationary	Stationary	Stationary

4.2 Model Selection in ARIMA

After manually estimating the model parameters for ARIMA using ACF and PACF plots, the "auto.arima" function was utilized to automatically obtain the suggested ARIMA model.

Table 2. Comparisons of ARIMA models

Model	AIC	BIC	Log-likelihood
ARIMA$(1,0,1)(1,1,0)_{12}$	1291.72	1298.27	-641.86
ARIMA$(0,0,1)(0,1,1)_{12}$	1288.83	1295.38	-640.42

Based on Table 2 and utilizing metrics such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and log-likelihood, the assessment for the best-fitting models to the data has been made. Lower values of AIC and BIC and a higher log-likelihood value indicate a better model fit. Comparing ARIMA$(0,0,1)(0,1,1)_{12}$ and ARIMA$(1,0,1)(1,1,0)_{12}$, it is found that ARIMA$(0,0,1)(0,1,1)_{12}$ has a lower AIC (1288.83) and BIC (1295.38) values, and a higher log-likelihood (-640.42) compared to ARIMA$(1,0,1)(1,1,0)_{12}$ with AIC (1291.72), BIC (1298.27), and log-likelihood (-641.86). Therefore, ARIMA(0,0,1)(0,1,1) is determined to be a better-fitting model for the given time series data based on these criteria, outperforming ARIMA$(1,0,1)(1,1,0)_{12}$ in terms of AIC, BIC, and log-likelihood.

4.3 Holt-Winters Modelling

In this study, the Exponential Smoothing technique, specifically Holt-Winters, is considered for modelling the zakat collection. This method is posited to adeptly capture the data's inherent patterns, trends, and seasonality, thereby demonstrating its effectiveness in predictive performance and precise forecasting. As depicted in Fig. 1(a), the interaction between the trend and seasonal components adheres to an additive assumption.

4.4 Model Comparison

The comparative performance of the Additive Holt-Winters Smoothing model and the selected ARIMA model is evaluated using error measures: Mean Error (ME), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). These metrics are tabulated to ascertain the model exhibiting superior performance. Table 4 encapsulates the comparative analysis between the Additive Holt-Winters Smoothing and selected ARIMA models.

Table 3. Comparison between Additive Holt-Winters and selected ARIMA models

Model	Performance Measure		
	MAE	RMSE	MAPE
Additive Holt-Winters Smoothing Model	3346140	**4125569**	25.68926
ARIMA $(0,0,1)(0,1,1)_{12}$	**2745566**	4233899	**22.20556**

Based on Table 3, the ARIMA$(0,0,1)(0,1,1)_{12}$ model, with a lower Mean Absolute Error (MAE) of 274566 and a lower Mean Absolute Percentage Error (MAPE) of 22.20556, demonstrates better accuracy compared to the Holt-Winters Additive model with MAE of 3346140 and MAPE of 25.68926. However, the Holt-Winters model has a lower Root Mean Square Error (RMSE) of 4125569, indicating better predictive accuracy compared to the ARIMA model's RMSE of 4233899. Despite this, the lower MAE and MAPE values favour the ARIMA$(0,0,1)(0,1,1)_{12}$ model for more accurate forecasting in this dataset. The best model is employed for the forthcoming forecast of the Zakat collection. Fig. 4 delineates the projected zakat collection in Kelantan over the ensuing years. A solid line depicts the actual data, while the forecasted data is represented by a dashed line. The shaded regions embody the forecast's 80% and 95% confidence intervals, illustrating some uncertainty regarding future predictions. Nonetheless, the overarching trend of the graph implies an anticipated augmentation in the zakat collection in the forthcoming years.

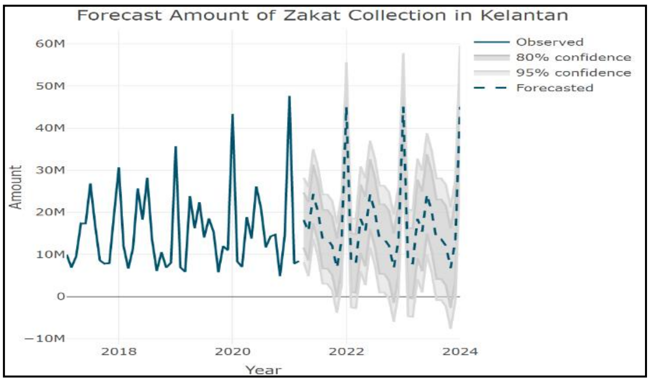


Fig. 4. Future forecast of Zakat collection for 2023-2024

4.0 Conclusion

This study finds that the ARIMA$(0,0,1)(0,1,1)_{12}$ model is the best for forecasting zakat collections and has significant implications for zakat institutions. The study's findings align with the research conducted by Streimikiene et al. (2018), which uses time series techniques to forecast tax revenues in Pakistan. They found that the ARIMA model outperforms other approaches, proving better-forecasted values for the total tax revenues of Pakistan. Additionally, similar research conducted by Ofori, Fumey et al. (2021) investigated using different time series models for forecasting value-added tax revenue in Ghana. They also found that ARIMA models outperformed other approaches, providing more accurate and reliable forecasts. Forecasting zakat collection plays a vital role in the significance of this study and holds great potential for Majlis Agama Islam Kelantan (MAIK). In 2024, Kelantan's projected zakat collection is RM228,017,148.00, with its peak value anticipated in December at RM46,855,194. It reflects a 1.24% and 1.7% increase from 2022 and 2023, respectively. Accurate forecasting allows Lembaga Zakat to allocate its staff and financial resources effectively, particularly during peak seasons like Ramadan. By identifying expected surges in zakat collection, MAIK can ensure they have enough staff to manage collection centres, reducing waiting times and providing superior customer service. Forecasting also helps determine the optimal time to open the zakat counter based on the anticipated zakat collection peak periods. It ensures that MAIK can accommodate the increased number of contributors during these times, making it easier for payers to fulfill their obligations immediately. With the insights gained from this study, MAIK can embrace the time series analysis method for zakat collection and strengthen its mission to help those in need. For future studies, it is recommended to explore the utilization of multivariate time series analysis as a promising approach for forecasting zakat collection. This method simultaneously analyses the relationships between zakat collection and multiple socioeconomic variables. Researchers can obtain a more comprehensive understanding of the underlying dynamics and drivers of zakat contributions by considering various factors that could influence zakat collection.

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Paper Contribution to Related Field of Study

The study contributes a new perspective by modeling seasonality in the zakat collection dataset using time series approaches. The study's findings are expected to assist zakat institutions in making data-driven strategic decisions.

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