Comparative study for Modeling and Forecasting life insurance premiums applying ETS, Holt Winter, NNETAR, and TBATS models

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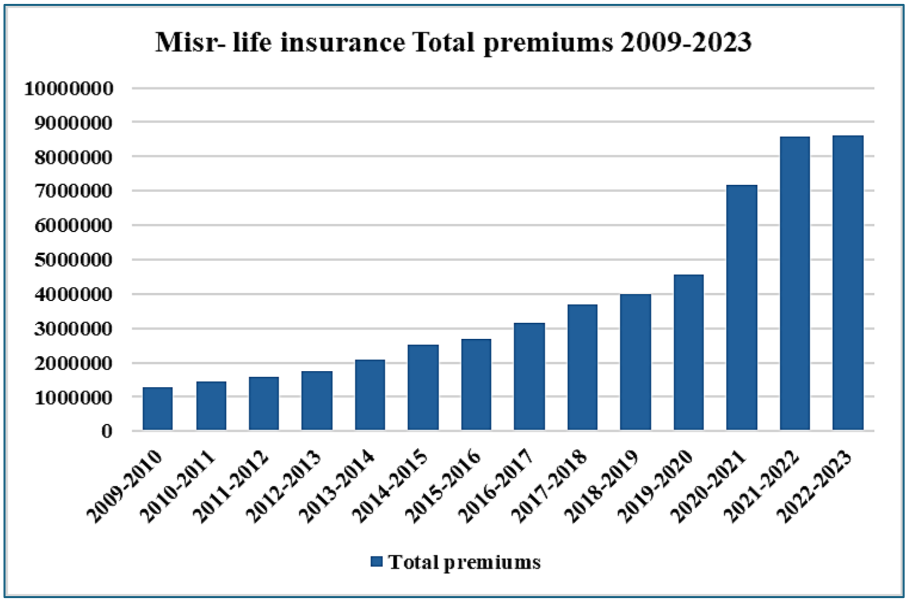
Abstract

Life insurance provides financial security to individuals, as well as helping to improve the stability of financial markets. It also offers advantages in terms of discipline and continuous savings. To achieve this, life insurance companies need to calculate and forecast premiums. The aim of this research is to model and forecast life insurance premiums by applying alternative forecasting models. The data set is extracted from the insurance statistical annual book data for the period 2009–2023 for Misr Life Insurance quarterly premiums and forecasts up to 2026. Four models were applied to determine what the best forecasting model was for this type of data. To address this, models were applied: Exponential Smoothing models (ETS), Holt Winter models, Neural Network Autoregressive NNETAR, and Trigonometric Seasonality Box-Cox Transformation ARIMA errors Trend Seasonal components TBATS. The primary findings of this research highlight the rise in premiums for Misr Life Insurance, a governmental company sector. In addition, among the applied models in this paper, NNETAR is the best model to forecast life insurance premiums with this type of data.

Key words: Life insurance- premiums- ETS- Holt Winter- TBATS- NNETAR.

1. Introduction

Life insurance provides financial security to individuals, also helping to improve the stability of financial markets. Also provides benefits in terms of saving money with discipline and continuity. To achieve this life insurance companies, need to calculate and forecast premiums. regardless, economic fluctuations, including inflation rates, income levels, and increases in population, provide the prediction of life insurance premiums a significant difficulty, particularly in growing economies like Egypt. Next figure shows the development of premiums for Misr life insurance company as a governmental company in insurance sector, for the period (2009-2023).



Source: prepared by the researcher based on insurance statistical annual book data.

Figure 1: development of Misr life insurance premiums (2009-2023)

Figure above shows the development of premiums over the period, there is a steady increasing in the premiums, this reflects an increase in the demand for life insurance policies, consequently influencing the growth of the insurance sector in Egypt and, by extension, the national economy, because insurance constitutes a fundamental determinant of the economy. The growth of insurance may directly influence economic development, generating value and long-term stability for all stakeholders in the business of insurance **(Namawejje & Geofrey, 2020).**

Recent improvements in actuarial science which apply mathematical, statistical forecasting approaches and machine learning. These models are capable of generate accurate forecasting of insurance premiums. As an example of these models the time series models: TBATS, NNETAR, ETS, and Holt-Winters, known for their accuracy in utilizing experience data and forecasting future trends. Therefore, it was essential to examine the accuracy of these models in forecasting life insurance premiums in Egypt, thereby assisting insurance companies in enhancing their pricing strategies and managing financial risks more effectively.

Based on the above, according to the dynamic nature of the Egyptian insurance sector, advanced time series models can provide more reliable insights of decision making. According to **(Peovski & Ivanovski, 2024)** insurance companies need accurate prediction to guarantee sustainability and competitiveness. So, they provide analyzing nonlife insurance gross written premiums, claims, technical premiums, also the number of contracts through a multi model univariate approach comparing SARIMA with Exponential Smoothing models (ETS). This comparison applied on time series from January 2012 to June 2023. This research confirmed that during the training phase, SARIMA model accuracy exceeded the accuracy of exponential smoothing models. In the test period ETS performance better than SARIMA. Considering an exception of predicting the quantity of contracts, the continuous one-step ahead prediction technique exceeded the traditional training-test split strategy in reliability.

In the context of forecasting life insurance premiums **(Jing, Du, Jin, & Xie, 2024)** investigated three types of neural networks models for predicting medical insurance premiums, Artificial Neural Network (ANN), Recurrent Neural Network (RNN), and Long Short – Term Memory (LSTM). The dataset of this study consists of 1070 training samples and 268 test samples. The assessment of models based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The main finding of this study is that ANN more effective in dealing with the non-time series data, leading to better accuracy for forecasting medical insurance premiums.

(Boonsom et al., 2023) applying four forecasting methods to forecasting life insurance sales, also evaluating the market and organizing customer campaigns. The methods are Holt Winter Additive, Holt Winter multiplicative, simple exponential smoothing, and double exponential smoothing. These methods are used to forecast life insurance premiums one year ahead from 2021. The data collected from the office of insurance commission, sales of life insurance from 2018 to 2022. The main findings of this study are that Holt Winters multiplicative methods as most accurate, with accuracy percentage of 97.56%. and that insurance companies significantly could enhance their sales forecasting by applying Holt Winter Multiplicative model.

Interestingly, **(Salem & Khalil, 2023)** present two methods for forecasting short-term insurance claim payments. First, Simple Exponential smoothing (SES) with constant level and no seasonality. Where second, the Holt-Winters additive algorithm, which extended exponential smoothing to deal with trends in the time series. The primary conclusion of this study is that the analysis of SES residuals reveals consistent variance in forecast errors and no evidence of significant autocorrelation, therefore confirming the model's integrity. The Holt-Winters additive algorithm is advised for forecasting short-term insurance claims payment data.

Moreover **(Rane et al., 2023)** aimed to use different methods to analyze and improve the prediction of mortality outcomes for COVID-19 patients. This study applies three machine learning models to predict mortality. First, Support Vector Machine (SVM) classified tasks, helping to identify the boundaries between classes survival and mortality. Second, Neural Network Auto Regression Technique (NNETAR) used for capturing complex patterns in the data series. Third, Decision Tree (DT) is classification model that uses tree structure to make decisions based on input features, helping in mortality forecasting. The result of this study is that NNETAR among applied machine learning models is an effective tool for forecasting COVID-19 mortality. Also effective in emphasizing the significance of biomarker selection, plus the potential impact on healthcare decision making.

On the other hand, **(Thayyib et al., 2023)** apply different advanced forecasting time series methods to forecast and analyze Goods and Services Tax (GST) in India. Also compare accuracy of single and hybrid forecasting models. The data were GST time series shows nonlinear fluctuations and linear fluctuations. The advanced forecast models are TBATS, ETS. TBATS included trigonometric seasonality and Box-Cox transformation, to interpret sophisticated seasonal patterns and non-linear correlations in the data. ETS, single time series model, which is effective and simple in capturing trend and seasonality. Also, apply Neural Networks models, Artificial Neural Networks (AAN), and Neural Networks for autoregression (NNAR). AAN is applying to constructed to include non-linear correlations inside the data, offering a more adaptable methodology for forecasting. NNAR is the same with AAN, but focus on autoregressive elements and let it learn from past values to predict. Finally applied hybrid models which integrated linear and nonlinear methods Hybrid Theta-TBATS is the most effective in forecasting accuracy.

The main findings of this study are that Hybrid Theta-TBATS model offer superior forecasting accuracy. And Single TBATS is the second-best model for forecasting accuracy.

(Banditvilai & Kuharattanachai, 2022) studying forecasting models for premiums of the first year of life insurance. Analyzed premium data applying both the multiplicative model and the decomposition method with initial values from 18 years. The data were collected from January 2003 to November 2021. The model construction process uses data from January 2003 to December 2020, while the accuracy computation focuses on data from January 2021 to November 2021. The main finding is that the multiplicative model is best for first-year premium forecasting.

(Das et al., 2022) analyzes consumer behavior towards life insurance during Covid-19, and predicts future premiums for life insurance companies. The data collected for this study from 24 Indian life insurance companies, from January 2015 to December 2020. Two techniques used first, Functional Link Artificial Neural Network (FLANN) which are designed to predict how consumers make decisions regarding insurance products based on their experiences during the pandemic. The FLANN model is optimized using a Genetic Algorithm (GA), which helps in adjusting the parameters of the FLANN to improve performance. Second, sliding window techniques provide a window moving over the time series data. The research indicated that the Covid-19 outbreak substantially impacted the premium collection of life insurance firms in India. The general trend in life insurance performance revealed changes because of the pandemic's impact. The FLANN model provides accurate projections of customer behavior and premium collections during the pandemic.

Additionally **(Priyanka et al., 2022)** illustrates an application of the Holt-Winters method for forecasting on seasonal time- series data on crop insurance registration, covering the management of structural outliers. Applying on time series of the number of farmers registered in different crop insurance programs, from 2000 to 2018. The model was run in Ms-Excel to comprehend the fundamentals of time series forecasting. Generate predictions of the number of farmers using R software. The results of this study that crop insurance data revealed seasonal trends and an exponential increase. Also, residual analysis indicated that the model adequately fitted the data, since the residuals exhibited a mean around zero, absence of autocorrelation, and a normal distribution.

(Gecili et al., 2021) perform four time series models: Holt Winter, ARIMA, RBATS, and cubic smoothing spline model based on stochastic state space model which allows the use of a likelihood model for estimating the smoothing parameter. The time period from 22 February 2020 to 29 April 2020 for data from USA and Italy. Evaluated forecasting performance done by Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), and Akiake Information Criteria AIC for evaluated model fit. The results of this study are the cubic smoothing spline models and ARIMA had smaller prediction error and narrow prediction intervals rather than Holt and TBATS models. Also, the accuracy of the forecasting for all models enhanced as more data became available over time.

Since **(Perone, 2020)** apply hybrid forecasting models, ARIMA, ETS, NNAR and TBATS, in forecasting the second wave of COVID-19 hospitalizations in Italy. The data set is the number of patients hospitalized in intensive care with mild symptoms. The time series is from 21 February 2020 to 13 October 2020. The main findings show that hybrid models best at present linear, nonlinear and seasonal pandemic patterns, considerably exceeding the individual models for each time series.

Similarly, **(Namawejje et al., 2020)** predict life insurance premiums in Uganda, and analyze penetration rates over annual data from 2000 to 2018. Applying ARIMA model for forecasting life insurance premiums, the main finding is that the individual life premiums will increase while group life premiums remain constant. Also, Uganda has the lowest insurance penetration in East Africa.

Moreover **(Li et al., 2020)** in their study examines the evolution of life insurance premiums in China from 2001 to 2019 and generates a time and incentive-aware LSTM model for prediction. Furthermore, robust foundational methodologies. The primary conclusion of this study is that the suggested LSTM-TI model exceeds strong baseline techniques. This shows that merging time effects and incentive signals into the model improves its forecast accuracy for life insurance prices. The empirical assessment of the dataset demonstrates markedly higher accuracy for LSTM-TI. Highlighted the importance of understanding the role of time and incentives mechanisms, which may lead to better strategies for premiums prediction and market analysis.

(Lima et al., 2019) Seek to evaluate the accuracy of the additive and multiplicative Holt-Winters models while enhancing forecasting accuracy for economic time series data. The data consisted monthly indices of e-commerce retail sales in Portugal, spanning from January 2000 to February 2018. This study determined that the multiplicative model outperformed the additive model in predicting e-commerce retail sales. Forecast intervals are computed based on Mean Square Error.

Depending on all the above, forecasting life insurance premiums has a crucial role, hence the non-accurate forecasting may led to financial problems affect the ability of companies to face its obligations. Premiums are affected by many factors such as economic changes, inflation, and income levels. So, it is important to apply new forecasting methods, to capture linear and nonlinear trends and capturing seasonality in the data, which helps to accurate pricing, and estimate risks.

2. Research Objectives

The aim of this research is briefly summarized as follows:

1. Forecasting life insurance premiums using four methods: ETS, Holt-Winter, NNETAR, and TBATS.
2. Compare between these models to determine which model fits real data.

3. Research Importance

This research has important implications in many aspects:

1. For insurance companies: provide forecasting methods to improve the accuracy values, to promote financial stability and reduce financial risks.
2. For national economy, it supports economic growth as financial and investment planning.
3. Provide comparative analysis for different forecasting models.

4. Methodology

4.1. Exponential Smoothing Methods ETS

Exponential Smoothing forecasts are weighted average of past observations, with exponentially decline weights over time. This model used when there is seasonality and trend in data **(Teköz, 2022).** The model generates basic exponential smoothing techniques using both additive and multiplicative approaches. This model integrated three determinants: Trend: long term components, seasonal pattern, errors **(Thayyib et al., 2023).** Seasonal components can be (A) additive, (M) multiplicative, or (N) none **(Kuan, 2022).** The equation for ETS for additive error is as follows:

- Forecast equation

$$\hat{y}_{(t+1|t)} = l_t \qquad (1)$$

Since:

l_t: new estimated level.

$\hat{y}_{(t+1|t)}$: each one step-ahead prediction for time t_{+1}.

- Smoothing equation

$$l_t = l_{t-1} + \alpha(y_t - l_{t-1}) \qquad (2)$$

Since:

α: is the smoothing parameter, it limits the rate of decline of the weights.

$y_t - l_{t-1}$: the error at the time t

This model provides accurate forecasts for a short period of time, however the quality decreased when the forecasting periods increased.

4.2. Holt-Winter

It is the most advanced method of Smoothing methods, which are used to minimize the effect of random noise in time series. Also called triple exponential smoothing. The model general frame equation is (Yakovyna & Bachkai, 2018).

$$\hat{y}_{(t+h|t)} = l_t + b_t h + s_{t-m+h_m^+} \qquad (3)$$
$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \qquad (4)$$
$$b_t = \beta(l_t - l_{t-1}) + (1 - b_{t-1}) \qquad (5)$$
$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \qquad (6)$$

Since:

$\hat{y}_{(t+h|t)}$: a forecast of y_{t+h} for h periods ahead, where $h_m^+ = [(h-1) mod\ m] + 1$

m: is the term of seasonality.

l_t: presents the level of the series.

b_t: the growth parameter.

s_t: seasonal component.

Equation number (3) includes: level, trend, seasonal, and components.

4.3.Neural Network Autoregressive NNETAR

Is one of the Machine Learning statistical models. It is non- linear parametric forecasting model. Two phases are essential for forecasting using this model, *first*, autoregression order for the chosen time series. The number of past values that the current value of the time series depends on, determined by the order of auto-regression. *Second*, training the neural network (NN). The predicted values indicate the output of the model. Error and trial are used to determine the number of hidden layers.

Data preparation is the first step in time series modelling. The data classified in two groups testing and training. Testing data is used for evaluating model performance. And training data used for fitting the model. After training, the model can forecast future values of the time series data. NN generates forecasted values for the following time step. Final stage of NNETAR evaluating performance, by comparing model with baseline model to determine significancy increases forecasting accuracy **(Rane et al., 2023).** There are two fitted models **(Chukwueloka & Nwosu, 2023)**

a. Non seasonal data fitted model: referred to as $NNAR(p, k)$
   k is the number of hidden layers, which comparable to $AR\ (p)$ model.
b. Seasonal data fitted model: referred to as $NNAR(p, P, k)[m]$ model, which is comparable to an $ARIMA(p, 0,0)(P, 0,0)[m]$ model but nonlinear.

4.4. Trigonometric Seasonality Box- Cox Transformation ARIMA errors Trend Seasonal components TBATS

This model integrates different approaches: trigonometric term for seasonality modeling, Boc-Cox transformation for addressing heterogeneity, ARMA errors for capturing short term dynamics, show trends and seasonal components if found. These models have many properties:

1. Dealing with complex seasonal patterns.
2. Consider nonlinear time series patterns.
3. Handling any type of autocorrelation in residuals.

It is important to highlight that integrated different time series models to forecast, optimizes the likelihood of identifying seasonal, linear, and nonlinear patterns. achieving better performance and forecast accuracy. The basic TBATS equation is **(Thayyib et al., 2023):**

$$y_t^{(\omega)} = 1_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t \tag{7}$$

Where:

$y_t^{(\omega)}$: Box-Cox transformation parameter, (ω) applied to the observation y_t at time t.

i_t: the local level.

ϕ: damped trend.

b: long run trend.

T: seasonal pattern.

$s_t^{(i)}$: ^{i}th seasonal component.

m_i: seasonal periods.

d_t: $ARMA(p, q)$ process of residuals.

4.5. Evaluation metrics

To assess the performance of different forecasting model the following metrics were used **(Thayyib et al., 2023)**

1. Root Mean Square Error RMSE= $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

   This matrix measures the average difference between the forecasted values and the actual values from the real data.
2. Mean Absolute Error MAE= $\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$

   This matrix calculate the average absolute difference between the real data and forecasted. Also measures the average of errors ignoring their direction. A lower MAE indicates better model performance.

3. Mean Absolute Percentage Error MAPE= $\frac{1}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{y}_i|}{y_i} * 100\%$

   Assess the average percentage difference between the forecasted value and actual.

5. Forecasting life insurance premiums with four methods

In this section four forecasting models applied to forecast life insurance premiums using R program. The data are extracted from the annual statistical insurance book. Time period (2009-2023) quarterly life insurance premium data, for governmental sector. ETS, Holt-Winters, NNETAR, TBATS, applied respectively to forecast premiums to 2026, as follow:

5.1. ETS

Applying ETS on the data results in the following model output:

Table 1: ETS (A, A, N) output

Smoothing parameters	Model coefficients (initial values)	Residual Standard Deviation σ
Alpha α = 0.3867 Beta β= 0.3867	l = 654.1369 b = 67.9725	297.2417

Source: prepared by researcher based on R program output.

From the table above both α *and* β the model appropriately integrates historical data while adapting to changes in time. The model coefficients starting with 654.1369 and increasing by 67.9725 per period, this corresponds with the increasing trend in the data. Value of σ shows some variations in residuals. Next table for Ljung- Box Test to check residual independence.

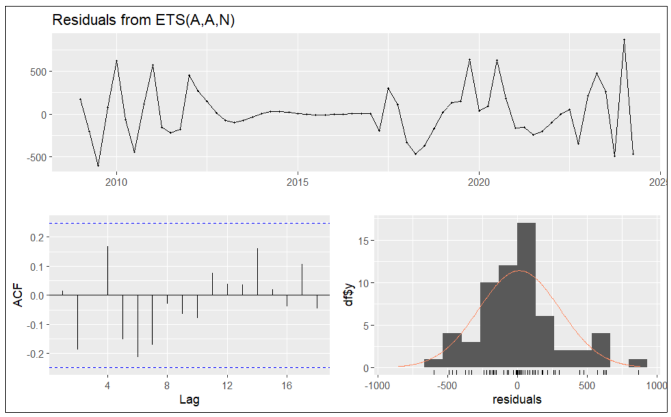
Table 2: Ljung- Box Test

Model df: 0. Total lags used: 8

Q^*	Degree of freedom df	P- value
11.32	8	0.1842

Source: prepared by researcher based on R program output.

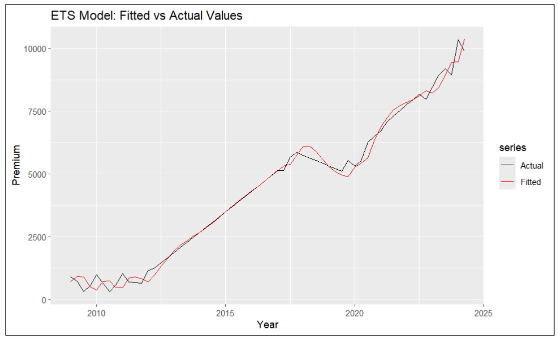
From the table, since $p > 0.05$ then residuals appear independent and random, which means that model fitted well to the data. That indicates no significant autocorrelations in residuals. Next figure plotting the residuals for more clarification.



Source: R program outputs.

Figure 2: residuals for ETS (A, A, N) model

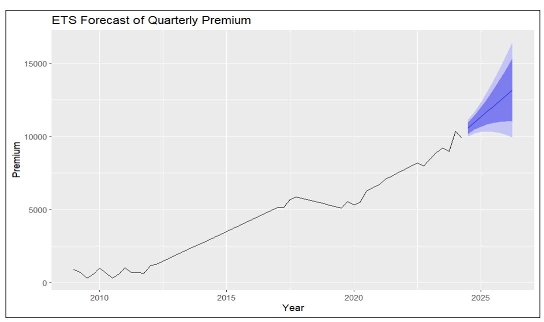
- Top panel presents residual time series: the residuals fluctuate around zero, there are peaks at periods (2009-2012) and (2020-2022). The variance of residuals exhibits irregularity, indicating that the model may not fully account for all underlying dynamics.
- The bottom left panel presents residual histogram, which reflects nearly normal distribution, with limited skewness and heavy tails. This indicates that the model may not fully capture outliers in premium data.
- The bottom right panel presents normality check, shows the existence of outliers and skewness that might indicate requiring more dynamic approach. The next step express the ETS model fitted and actual values. The residuals are **mostly uncorrelated**, meaning the ETS(A,A,N) model is a reasonable fit.



Source: R program outputs.

Figure 3: ETS model Fitted and actual values.

Figure above shows that the actual premiums values (black color) fit the forecasted ETS values (red color) and followed the trend closely. There are deviations in the periods 2018 and 2020, since the actual premiums values shows short term fluctuations. The data has upward trend, which reflect steady increase in life insurance premiums over time. Next figure present the forecasted of quarterly premiums, as follow:



Source: R program outputs.

Figure 4: ETS quarterly life insurance premiums forecast

Figure above shows that for forecasting periods which is blue shaded region continued increasing as past premiums trend. While the expanding of interval prediction reflecting increasing uncertainty moving into future predictions. From the above, the *dark blue region* represents a high-confidence forecast range, since the *lighter blue region* represents a wider range indicating more uncertainty.

5.2. Holt- Winters

Next table shows Holt-Winters model output

Table 3: Holt- Winters model outputs

Smoothing Parameters	Model coefficients	
	Initial values	Seasonal effects
Alpha $\boldsymbol{\alpha} = \mathbf{0.5445}$ Beta $\boldsymbol{\beta} = \mathbf{0.3776}$ Gamma $\boldsymbol{\gamma} = \mathbf{1}$	$a = 9869.75824$ $b = 277,28283$	$s1 = 204.78742$ $s2 = -173.67302$ $s3 = 558.47286$ $s4 = 29.24176$

Source: prepared by researcher based on R program output.

From the table the value of α presents that model assigns a moderate significance to new observations for modifying the overall level. β reflects the upward trend component is revised with a degree of inertia, showing that historical trends continue to affect predictions. $\gamma = 1$ meaning the model depends only on the most recent seasonal data without using trends from prior years. Initial value $a = 9869.76$ indicating that the dataset's total scale is significant. Since $b = 277.28$ positive and reflect increasing trend in data.

For the seasonal effects coefficients present variation, Q_1 the first quarter has a small positive seasonal effect $s1$. Q_2 related to $s2$ has a negative seasonal effect, meaning the data decrease in the Q_2. Where Q_3 present in $s3$ has the highest seasonal increase in the observed data. Q_4 in the context of $s4$ closer to base level. Next table shows the results of Ljung Box test

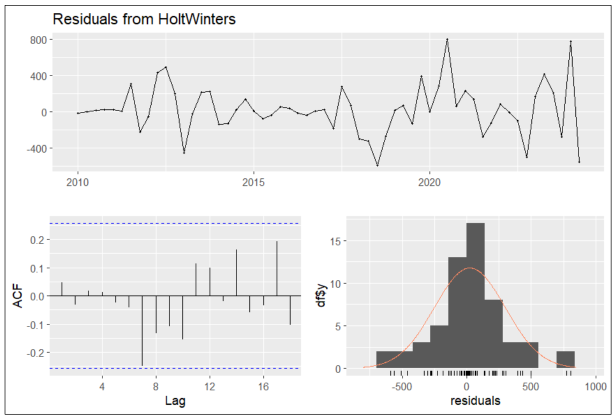
Table 4: Ljung Box test

Model df: 0 total lags used: 8

$\boldsymbol{Q^*}$	Degree of freedom df	P- value
5.8982	8	0.6586

Source: prepared by researcher based on R program output.

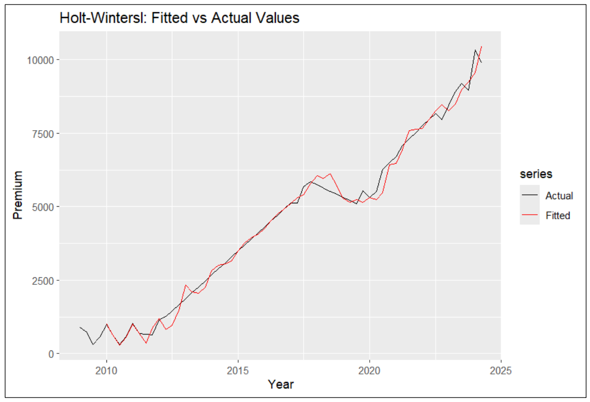
From the table, since p value greater than 0.05, this means no significant correlation in residuals, so Holt- Winters model successfully captured trend and seasonality. Next figure provide more interpretation.



Source: R program outputs.

Figure 5: residuals for Holt- Winter model

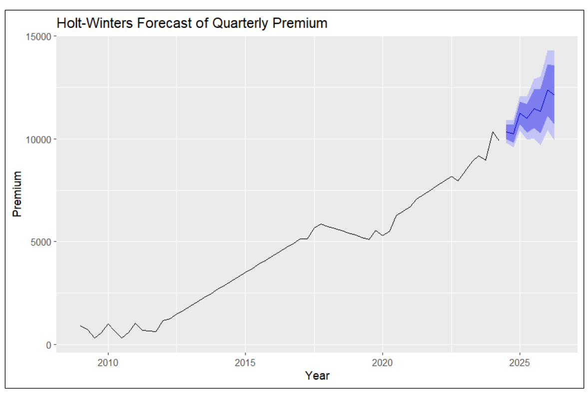
- The top panel residuals time series plot shows the randomness of residuals, with no obvious trends. Also, many peaks indicate significant periodic forecast errors; however, they have an obvious trend. There is no significant autocorrelation appear.
- The bottom left panel autocorrelation function exhibits that most autocorrelation values are close to zero. A few small peaks found within the confidence bands indicates that model has effectively captured seasonality.
- The bottom right panel residual histogram shows that residuals have a bell-shaped pattern, indicating a nearly normal distribution. Also, there are certain extreme values, however they are not extreme. Meaning the model forecasts are statistically reliable.



Source: R program outputs.

Figure 6: Holt- Winter model Fitted and actual values.

Figure above shows that the actual premiums values fit the forecasted Holt-Winter values and followed the trend closely. There are deviations in the periods 2018 and 2020, since the actual premiums values show short term fluctuations. The data has increasing trend, which reflects steady increase in life insurance premiums over time. And next figure present the forecasted of quarterly premiums, as follow:



Source: R program outputs.

Figure 7: Holt-Winter quarterly life insurance premiums forecast

The line shows steadily increasing, indicating long-term growth in premiums. Blue line represents forecasted values for future quarters. The increasing trends provide the possibility that premiums keep rising. Darker blue indicates higher certainty, where lighter blue suggests greater uncertainty in future out predictions.

5.3. NNETAR

Applying the model result in the $NNAR(1,1,2)[4]$, where 1 past lag as an input, 1 one seasonal lag quarterly seasonality is present, 2 there are two hidden neurons in the hidden layer. [4] quarterly data seasonal frequency. Calculated the variance of residual errors $\sigma^2 = 53952$ this higher value indicates more variability in predictions, compared to previous models. Next step is to analyze residuals by Ljung Box

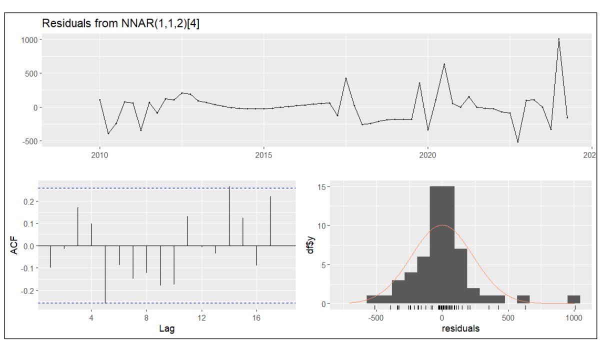
Table 5: Ljung Box test

Model df: 0   total lags used: 8

Q^*	Degree of freedom df	P- value
10.618	8	0.2243

Source: prepared by researcher based on R program output.

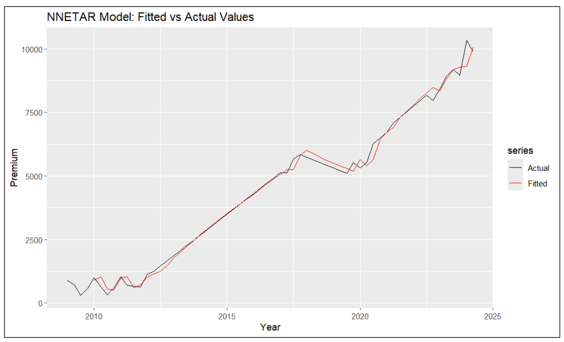
Since p value =0.2243, greater than 0.05 this means no significant correlation in residuals, but while there is no significant correlation, it still has large errors. Next figure provides three panel for analyse residuals



Source: R program outputs.

Figure 8: residuals for NNETAR model

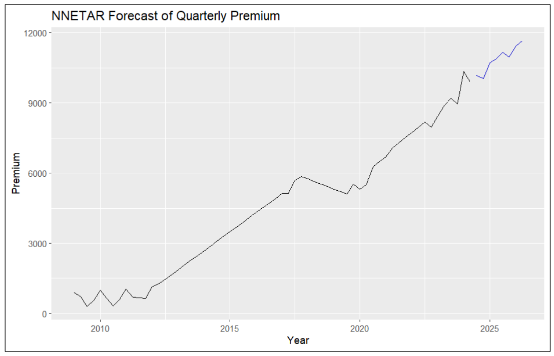
- The top panel time series plot of residuals shows that residuals fluctuate around zero, many peaks reflect seasonal high forecasting errors.
- The bottom left panel autocorrelation function shows that most autocorrelation are within confidence intervals.
- The bottom right panel histogram of residuals appears approximately normal with some skewness. There are some extreme errors considering outliers on the right side. The curve follows normal distribution and confirms the hypothesis of white noise residuals.



Source: R program outputs.

Figure 9: NNETAR model Fitted and actual values.

This graph shows almost matching between fitted and actual values. Which indicates that model capturing the trend and seasonal patterns. Also, models follow the overall increasing trend in the data, which particularly visible from 2010 to 2025. Although the fit is overall adequate, a few variations are obvious, especially in 2020 and 2024, as the actual values marginally deviate from the calculated values. Which indicates short term fluctuations. Next figure show quarterly life insurance premiums forecasting.



Source: R program outputs.

Figure 10: NNETAR quarterly life insurance premiums forecast

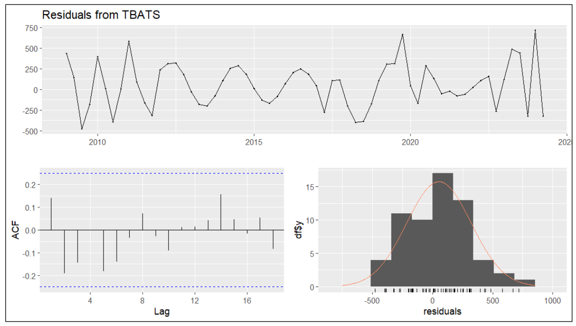
This figure shows consistent increase over time, reflecting the underlying growth pattern. The forecasted values continue this trend expecting steady increase in the future. Notice that there are no prediction intervals which help quantify the uncertainty to the forecast.

5.4. TBATS

This model has specific parameters, the model is $BATS(1, \{0,0\}, 0.863. -)$ where:

- 1 indicate single exponential smoothing state.
- $\{0,0\}$: indicates no significant seasonal pattern was found.
- Damped factor 0.863 the trend slow down over time, without unexpected exponential increase.
- Alpha (-0.1084)negative which reflects data overfitting.
- Beta moderate trend smoothing $= 0.6561$, indicates that the model should adjust to trend fluctuations, although with limitation.
- Sigma high residual variability $= 271.29$, indicating that model has some forecasting errors and uncertainty in predictions.

Next figure for TBATS residuals

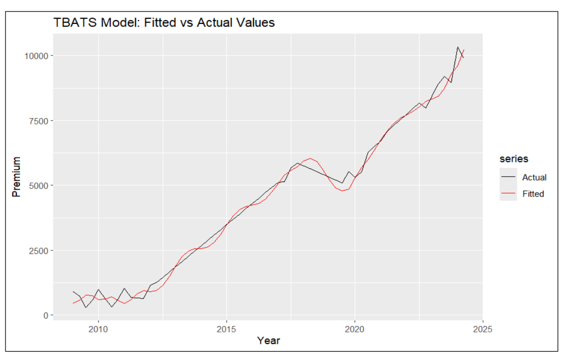


Source: R program outputs.

Figure 11: residuals for TBATS model

This figure for three panels

- The top panel represents a residual time series plot which reveals periodic variations, indicating that certain patterns persist in the residuals.
- The bottom left panel autocorrelation functions many bars over cross the confidence bounds reflecting serial correlation, indicating some data still in residuals.
- The bottom right panel residual distribution shows deviations with potential skewness.



Source: R program outputs.

Figure 12: TBATS model Fitted and actual values.

The figure above shows that the actual premiums values fit the forecasted TBATS values and followed the trend closely. There are peaks in the actual series not match the fitted series. There are deviations in the periods 2018 and 2020, since the actual premiums values show short term fluctuations. The data has increasing trend, which reflects steady increase in life insurance premiums over time. From the graph the TBATS model provide strong fit to the data.

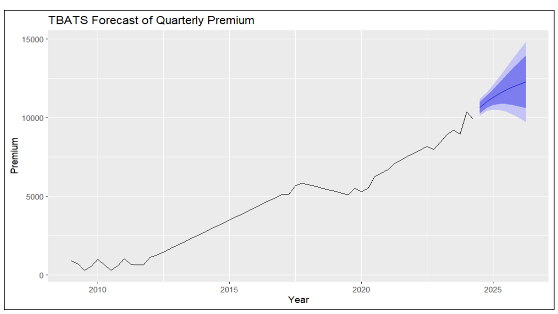
Table 6: Ljung Box test

Model df: 0 total lags used: 8

Q^*	Degree of freedom df	P- value
9.1763	8	0.3276

Source: prepared by researcher based on R program output.

according to Ljung Box test, since p value > 0.05, so the residuals not show significant autocorrelation. Consider that the model statistically valid in context of residual randomness, this is good sign for model forecasting ability. Next figure provide more clarification for residual.



Source: R program outputs.

Figure 13: TBATS quarterly life insurance premiums forecast

Figure above shows that for forecasting periods which is blue shaded region continued increasing as past premiums trend. While the expanding of interval prediction reflecting increasing uncertainty moving into future predictions. From the above, the *dark blue region* represents a high-confidence forecast range, since the *lighter blue region* represents a wider range indicating more uncertainty.

5.5. Metrics evaluation for four models

This section for comparing four models to determine which model is fitted for forecasting life insurance premiums data, the evaluation by applying performance matrix as follow

Table 7: performance matrix for forecasting life insurance models

	Model			
Performance matrix	**ETS**	**Holt- Winter**	**NNETAR**	**TBATS**
RMSE	287.493	273.377	232.2757	271.2882
MAE	202.212	191.9387	148.9283	218.9582
MAPE(%)	13.4699	6.18972	6.864636	13.38208

Source: prepared by researcher based on R program output.

From the table above, *ETS* has highest RMSE, MAE and MAPE, meaning larger prediction errors and poorest predictive accuracy respectively. RMSE for *Holt Winter* modestly high than TBATS. MAPE for the model is the lowest among four models. The lowest RMSE and MAE is for NNETAR model, this is prove that this model has strong predictive performance. And 6.86% provide good accuracy. *TBATS* has moderate RMSE and higher MAE. High MAPE indicates less accurate prediction.

Conclusion

The study shows an increase in premiums for Misr Life Insurance, indicating an increasing demand for life insurance.

The ETS model is an effective instrument for forecasting life insurance rates, accurately representing the long-term trend. Short-term forecasts are accurate; yet long-term forecasts need exhaustive studies due to increasing uncertainty. Holt-Winters is appropriate for modeling seasonality.

Among the four models, NNETAR is the most effective at forecasting life insurance premiums with this dataset. TBATS exhibits moderate performance, although weak predictability. The ETS model is the least efficacious model.

Recommendation

1. Incorporated external factors such as economic indicators, policy changes, demographic shifts to enhance accuracy of prediction.
2. Integrate models to develop hybrid models that indicate linear trends and nonlinear patterns.
3. Integrating classical models with machine learning models and hybrid time series.
4. Develop models to incorporate the effects of circumstances such as pandemics on life insurance premiums.

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تطبيق نماذج ETS، Holt- Winter، NNETAR ، وTBATS لنمذجة والتنبؤ بأقساط التأمين على الحياة: دراسة مقارنة

ملخص البحث:

يوفر التأمين على الحياة الأمان المالي للأفراد، كما يساهم في استقرار الأسواق المالية، بالإضافة إلى أنه يعتبر أداة جيدة للادخار. ولتحقيق ذلك تحتاج شركات تأمين الحياة للتنبؤ الدقيق بالأقساط. يتمثل الهدف من هذا البحث في التنبؤ بأقساط تأمين الحياة من خلال تطبيق نماذج تنبؤ مختلفة، وذلك بالتطبيق على البيانات الربع سنوية للفترة الزمنية (٢٠٠٩-٢٠٢٣) لشركة مصر لتأمينات الحياة، للتنبؤ بالأقساط الربع سنوية حتى العام ٢٠٢٦. تم تطبيق أربع نماذج تنبؤ مختلفة والمفاضلة فيما بينهم لتحديد أي هذه النماذج هو الأفضل في التنبؤ لهذا النوع من البيانات. الأربع نماذج المطبقة تباعاً هي: نماذج التمهيد الأسي (ETS) Exponential Smoothing models، نماذج Holt- Winter، الانحدار الذاتي للشبكات العصبية Neural Network Autoregressive NNETAR، الموسمية المثلثية لتحويل Box-Cox لأخطاء ARIMA الاتجاه الموسمي Trigonometric Seasonality Box-Cox Transformation ARIMA errors Trend Seasonal components TBATS. أتت نتائج هذا البحث لتوضح أن هناك زيادة في أقساط شركة القطاع العام مصر لتأمينات الحياة. أما بالنسبة فيما يتعلق بمقارنة النماذج كان نموذج NNETAR أفضل نموذج للتنبؤ للتطبيق في حالة هذا النوع من البيانات.

الكلمات المفتاحية: تأمينات الحياة- الأقساط- ETS- Holt Winter- TBATS- NNETAR