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Prediction of Insurance Claim Payouts in Malaysia with State Space Modelling

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Abstract

Insurance claim payouts represent a primary determinant in actuarial pricing models used to calculate policy premiums. However, high volatility in claims directly influences the accuracy of premium determination. Therefore, predicting insurance claim payouts is critical to insurance companies' solvency. This paper predicts insurance claim payouts in Malaysia from 2013 to 2023 across the categories of disability, medical, death, bonus, and others using a state-space model. Historical data for these categories are collected and pre-processed through cleaning and scaling to ensure consistency. The state-space model is formulated to capture the underlying dynamics of claim payouts. Subsequently, a prediction-error-based cost function is introduced to estimate model parameters, with the output and state-transition matrices updated via gradient descent. The model's performance is assessed using mean squared error (MSE). The results demonstrate that the state-space model closely tracks the trend of claim payout categories, yielding a significantly lower MSE, within 0.0001, compared to the simple moving average and exponential smoothing models, which yield MSEs within 0.01. Therefore, the state-space model provides an efficient and accurate computational framework for predicting claim payouts and is a robust tool for actuarial forecasting in the Malaysian insurance sector.

1. Introduction

Insurance claim payouts are payments made by insurers to insureds upon the filing of an insurance claim. It is commonly used to help individuals and businesses recover financially from covered incidents under their insurance policies [1]. Insurance claims are one of the most critical components in calculating the insurance policy premium. A high claim payout amount will lead to a higher policy premium in the subsequent periods, while a low payout amount will reduce the policy premium [2]. Several factors influence the claim payout amount, including medical cost inflation, policy structure, demographic shifts, and regulatory changes [3-6]. If any event covered under the policy occurs, such as an accident, illness, or property damage, the insured may submit a claim for reimbursement, also referred to as a claim payout [7]. Then, the insurer will determine the eligibility and the claim amount before making the payment. An accurate prediction of claim payouts is vital for insurance companies because it helps them set fair premiums, maintain financial stability, and manage operational efficiency [8]. However, the nonlinear patterns and volatility in the claim payout data have made prediction difficult using traditional forecasting techniques. Furthermore, policy changes, economic events, and seasonality occurrences have drastically affected claim payouts, introducing uncertainty in financial planning to insurance companies.

In past studies, predicting insurance claim payouts has been a frequent focus. [9] successfully applied an ARIMA (1,0,1) model to predict motor insurance claims, highlighting its applicability for long-term univariate forecasting. The model's predictive accuracy was confirmed by a high R-squared value (0.964) and an RMSE 26.7% lower than that of alternative ARIMA configurations. Additionally, [10] employed Holt-Winter Filtering and Residual Analysis to forecast short-term insurance claim payments. [11] applied machine learning techniques such as Support Vector Machines, Decision Trees, Boosting, and Random Forests in forecasting motor insurance claims. [12] explored the application of the selective state space model, which combines the structure of state space models with the nonlinear generalization power of neural networks, in the stock market prediction. Moreover, [13] also proposed the Dynamic Poisson State Space (DPSS) Model to predict the automobile insurance claim frequency. The results showed that the model captures the time-varying dynamics in claim frequency more effectively by updating its parameters online. To study the prediction of incurred but not reported (IBNR) claims, [14] used a state-space model such as the Kalman filter, Kalman smoother, and Simulation smoother. The key findings showed that the model outperformed traditional deterministic methods, and its framework is highly adaptable and broadly applicable. [15] applied the state-space model to insurance claim size modelling. In terms of accuracy, the model outperformed traditional methods, including static regression and the distributional approach.

Although many previous studies have examined insurance claim prediction, there are still gaps to be filled, especially in Malaysia. Previous studies have used neural networks to predict claims [16], and hidden Markov models to predict claim risks [17], but these methods do not normally consider payout prediction or the time-varying nature of claims. Other than this, Long-Short Term Memory (LSTM) networks are more accurate in their predictions, but they pay more attention to the reserve than to the payout severity [18]. In advanced markets, the traditional methods of actuaries continue to dominate, and the new time-series data methods are hardly employed in emerging markets such as Malaysia [19]. To fill these gaps, this paper suggests the adoption of state-space models, which not only offer interpretable, time-structured dynamic projections but also integrate the advantages of both traditional and modern methods, offering a robust prediction framework on insurance claim payments in the Malaysian context.

Our study predicts insurance claim payouts in Malaysia across five insurance categories, namely disability, bonus, medical, death, and others, using state-space modelling. For this goal, insurance claim payout data from 2013 to 2023 are collected from the Life Insurance Association Malaysia (LIAM) annual reports. The data are pre-processed, and their dynamics are captured by formulating a continuous-state-space model. A prediction-error-based cost function is defined to estimate the model parameters, and the output and state-transition matrices are computed using the gradient descent method to generate a prediction solution at the time intervals. Accordingly, the objectives of the study are: (a) To analyse the historical insurance claim payout using descriptive statistics; (b) To predict the claim payouts occurring in Malaysia using a state space model, and (c) To assess the accuracy of the prediction results on the claim payout patterns.

2. Methodology

Consider a state space model [20] with the state equation

$$\dot{x} = Ax + b, \tag{1}$$

and the output equation

$$y = Cx + d, \tag{2}$$

where x and y are state and output variables, respectively, while A, b, C and d are the model parameters. Here, the matrix A determines the movement direction of the state evolves, the vector b is the model constant, the matrix C maps the state to the measured output, and the vector d is the output constant. The model solution is expressed in its discrete sequences as follows,

$$x_{k+1} = e^{A\Delta t} x_k - (I - e^{A\Delta t})A^{-1}b, \tag{3}$$

where k is the time-step and Δt is the sampling time. While the measured output is given by

$$y_k = Cx_k + d. \tag{4}$$

To predict the observed output denoted by y_s, we introduce a least squares optimization problem [21] as follows,

$$\text{Minimize } J(x) = \frac{1}{2}(y - y_s)^{\mathrm{T}}(y - y_s) \tag{5}$$

subject to the state equation (1) and the measured output (2), where $^{\mathrm{T}}$ represents the transposition operator. The aim is to estimate the model parameters A, b, C and d, and to find the optimal state estimate to predict the observed output y_s, such that the objective function J is minimized.

Consider the following gradients with respect to model parameters,

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$$\frac{\partial J}{\partial A} = C^{\mathrm{T}}(\hat{y} - y_s)(\hat{x}^{\mathrm{T}}), \tag{6}$$

$$\frac{\partial J}{\partial b} = C^{\mathrm{T}}(\hat{y} - y_s)(1^{\mathrm{T}}), \tag{7}$$

$$\frac{\partial J}{\partial C} = (\hat{y} - y_s)(\hat{x}^{\mathrm{T}}), \tag{8}$$

$$\frac{\partial J}{\partial d} = (\hat{y} - y_s)(1^{\mathrm{T}}), \tag{9}$$

By using the following recursion equations,

$$A^{i+1} = A^i - \alpha_1 \left(\frac{\partial J}{\partial A}\right)^i, \tag{10}$$

$$b^{i+1} = b^i - \alpha_2 \left(\frac{\partial J}{\partial b}\right)^i, \tag{11}$$

$$C^{i+1} = C^i - \alpha_3 \left(\frac{\partial J}{\partial C}\right)^i, \tag{12}$$

$$d^{i+1} = d^i - \alpha_4 \left(\frac{\partial J}{\partial d}\right)^i, \tag{13}$$

with $\alpha_1, \alpha_2, \alpha_3$ and α_4 are the learning rates and i is the iteration number, the optimal model parameters are estimated when the gradients are approximate zero.

On the other hand, consider the gradient with respect to the state variable,

$$\frac{\partial J}{\partial x} = C^{\mathrm{T}}(\hat{y} - y_s), \tag{14}$$

the optimal state estimate can be obtained by applying the recursion equation

$$\hat{x}^{i+1} = x^i - \alpha_5 \left(\frac{\partial J}{\partial x}\right)^i, \tag{15}$$

with α_5 is the learning rate, and x is the solution to the state equation (1) and $\hat{x}$ is the state estimate (15). We modify the analytical solution and the measured output for prediction purposes, which is as follows:

$$\hat{x}_k = e^{A\Delta t} x_k - (I - e^{A\Delta t}) A^{-1} b, \tag{16}$$

$$\hat{y}_k = C\hat{x}_k + d, \tag{17}$$

where $\hat{y}_k$ is the output estimate. The performance of the model is evaluated by minimizing the mean squared error (MSE) [22], defined as

$$\mathrm{MSE} = \frac{1}{n}(\hat{y} - y_s)^{\mathrm{T}}(\hat{y} - y_s), \tag{18}$$

with n is the total number of data points. It is remarked that a lower MSE indicates a higher prediction accuracy.

Therefore, the calculation procedure as an iterative algorithm is summarized below.

Step 1 Solve the state equation (1) from (3) and measure the model output (2) from (4). Set the iteration number $i = 0$ to begin the iteration.

Step 2 Compute the state estimate $\hat{x}_k$ and the output estimate $\hat{y}_k$ from (16) and (17), respectively.

Step 3 Evaluate the objective function J^{i+1} from (5).

Step 4 Calculate the gradients with respect to the model parameters from (6) to (9), and update the model parameters from (10) to (13).

Step 5 Calculate the gradient with respect to the state variable from (14) and update the state estimate $\hat{x}^{i+1}$ from (15).

Step 6 Test the convergence. If $\| J^{i+1} - J^i \| <$ tolerance, stop the iteration; otherwise, set $i = i + 1$, and $x^i = \hat{x}^i$, go to Step 2 and repeat the iteration.

3. Result and Discussion

This section presents the visualization for all five categories of claim, which are disability, medical, death, bonus and others. The disability category is selected because it is volatile, and its prediction results are discussed using different prediction ratios and model parameter estimates. After that, the prediction results for five categories are obtained and compared with those from the simple moving average and the exponential smoothing.

3.1 Data Description and Visualization

The insurance claim payout data for all five insurance categories: disability, bonus, medical, death and others, from 2013 to 2023 are presented in Table 1. Their trends are shown in Fig. 1 to Fig. 5, respectively.

Table 1 Insurance Claim Payout Data (RM) (2013-2023)

Year	Disability	Bonus	Medical	Death	Others
2013	140,118,897	2,973,936,097	1,991,509,614	974,455,695	862,168,593
2014	140,832,582	3,441,593,472	2,736,482,357	1,048,707,941	1,056,524,751
2015	126,167,416	3,609,357,545	3,153,823,419	1,142,175,201	1,154,778,363
2016	85,868,248	3,577,266,832	3,408,176,898	1,222,411,558	1,364,276,198
2017	116,338,752	3,635,523,002	3,660,715,515	1,336,279,422	1,419,470,204
2018	121,945,710	3,675,023,537	4,088,416,357	1,422,474,881	1,523,663,948
2019	112,575,767	3,644,139,331	4,939,645,443	1,518,538,660	1,720,410,364
2020	119,285,276	3,492,025,312	4,508,524,205	1,496,939,637	1,944,308,423
2021	89,540,934	3,346,160,919	4,610,672,441	1,830,154,284	2,003,810,013
2022	107,946,280	3,162,473,293	6,163,799,351	1,814,532,683	2,144,558,651
2023	152,662,549	3,306,450,789	7,780,606,751	1,727,050,751	2,423,393,443

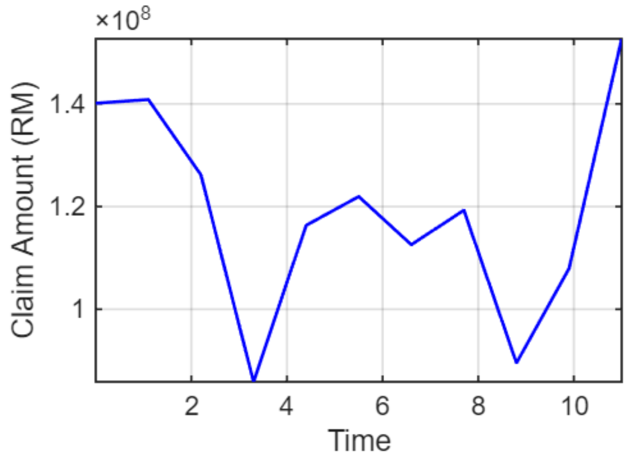

Fig. 1 Disability

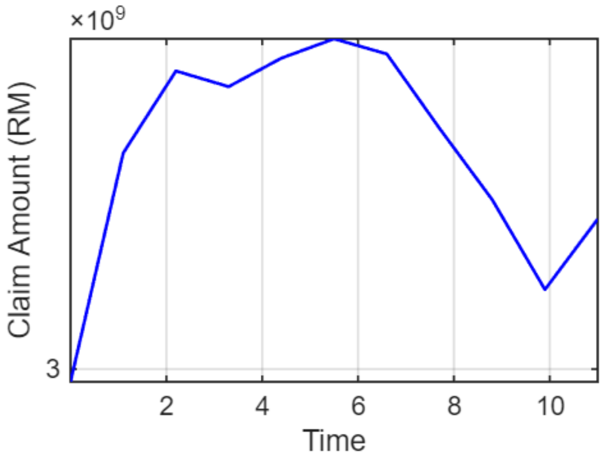

Fig. 2 Bonus

As shown in Fig. 1, the standardized Disability claims do not exhibit a clear upward or downward trend, instead showing high volatility. Over the time interval, the data trend alternates between sharp increases and sharp decreases, with no in between. The Bonus category exhibits moderate volatility, as shown in Fig. 2. The claims grew steadily for the first few years, then fluctuated in the middle period before declining in the last few years. In Fig. 3, the claim payout for the medical category rises consistently, from nearly RM2 billion in 2013 to RM 7.78 billion in 2023, with a slight decrease in 2020. This trend is expected, as medical insurance has become an essential part of our daily lives. Over time, the Death claims, as shown in Fig. 4, have grown steadily, with some minor fluctuations toward the end. This trend might be due to changes in claim frequency or severity caused by epidemics, policy adjustments, or unusual incidents that year. In Fig. 5, the other category shows a continuous upward trend, exhibiting a smooth, exponential-like pattern that points to either systematic increases in claims or predictable business expansion. This trend indicates a steady growth in these kinds of claims.

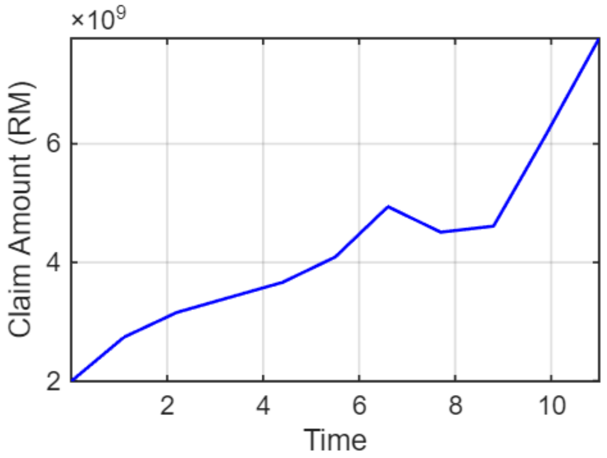

Fig. 3 Medical

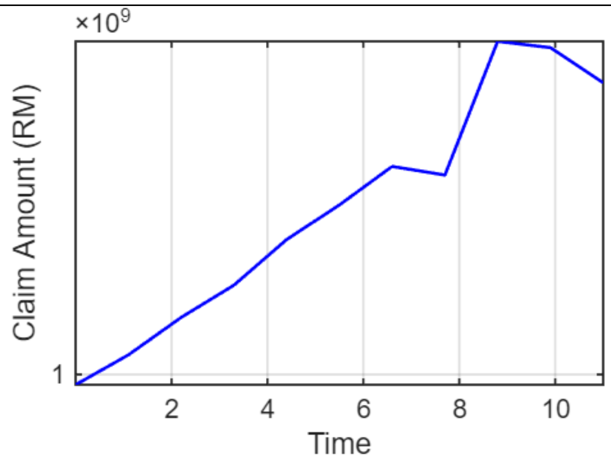

Fig. 4 Death

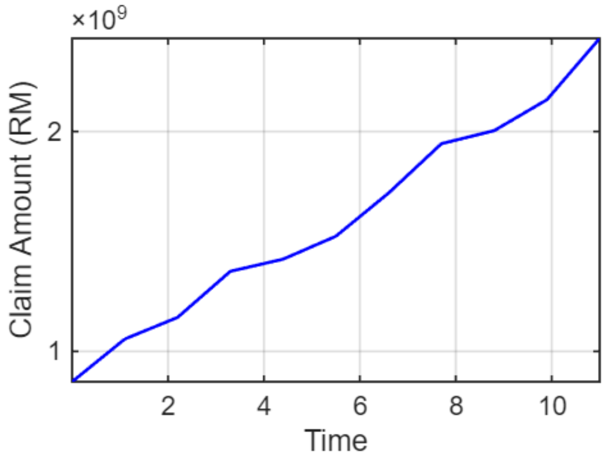

Fig. 5 Others

3.2 Prediction Results

Since the disability category has a high volatility, we consider suggesting a state space model for predicting the historical data of the disability category from 2013 to 2023. The state space model,

$$\dot{x} = -0.455x + 0.05, \tag{19}$$

$$y = 0.5x, \tag{20}$$

with the initial state $x_0 = 0.31$, is employed as an initial model to predict the trend of the disability category before running the iterative algorithm. Figure 6 shows the initial model output when the state space model, consisting of (19) and (20), is solved. The output trajectory decreased from 0.155 to 0.0556. Since the model output is derived from the state equation without accounting for the trend in the historical data, there is a significant difference between the model output and the historical data. Fig. 7 shows the output that is estimated at the second iteration using the estimated parameters. The output has observable time changes, whereby there is an early decrease and subsequent minor fluctuations and slight incremental changes towards the latter time points, as a pointer to initial model responsiveness. Nevertheless, the extent of these variations is smaller, implying that the model is yet to master the underlying data dynamics.

Having optimized the parameters, the presented results of the prediction in Fig. 8 indicate that the standardization of data does not have a negative impact on the work of the model, as the predicted values are close to the observed tendency. The precise coincidence of peaks and troughs is an indicator of the fact that the model is an effective estimator of the underlying system dynamics. Fig. 9 shows the prediction error that was obtained using the standardized data, with the value of the error increasing with time and with the greatest error in the first time point, and then gradually decreasing with time to the subsequent observations. The error is positive in the first four points and thereafter changes to negative values, which denotes that it overestimated the initial stage, and thereafter, in later periods, it underestimated the outcome. Such an asymmetric error pattern suggests that this model has an idea of the overall trend but has a time bias that still has not been completely mitigated at an optimization stage.

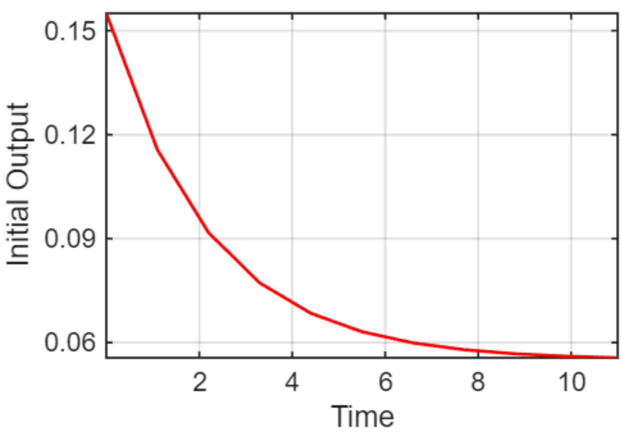

Fig. 6 Initial Model Output

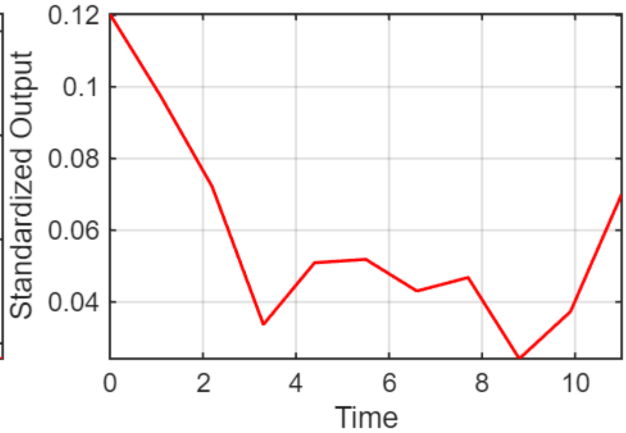

Fig. 7 Prediction Result at Two Iterations

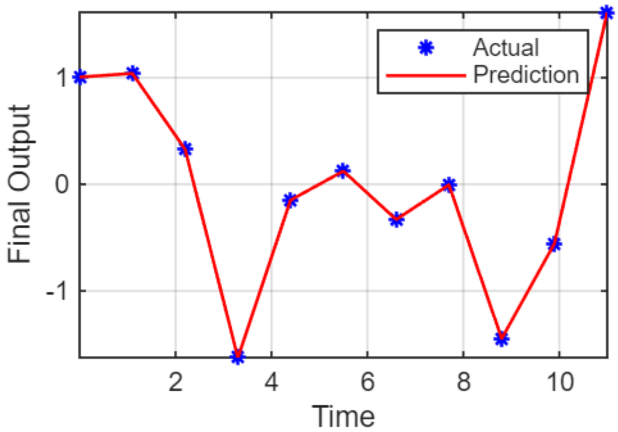

Fig. 8 Prediction Result at 80 Iterations

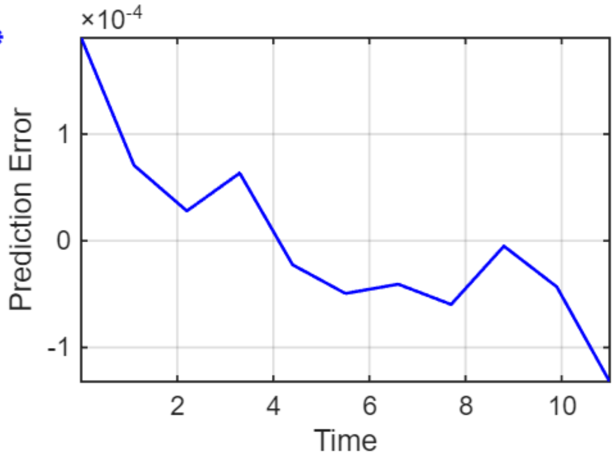

Fig. 9 Prediction Error

3.3 Validation

The process of validation is carried out on the Disability insurance category, which shows the greatest variation between the datasets. The prediction ratio indicates that the first number is the percentage of data used for prediction, and the second is the percentage used for testing during validation. The performance of this model is summarized in Table 2 under the various prediction ratios. The results show that the model has the highest performance with a prediction ratio of 40-60, as shown by minimum mean squared error (MSE), low elapsed time, and a moderate number of iterations.

Table 2 Model Performance on Various Prediction Ratios

Prediction Ratio	Iteration Number	Elapsed Time (seconds)	Mean Squared Error
20-80	37	0.009848	1.2×10^{-3}
40-60	75	0.006601	6.1234×10^{-5}
50-50	88	0.007847	6.1763×10^{-4}
60-40	215	0.008311	1.4377×10^{-4}
80-20	282	0.011305	1.7479×10^{-4}
100-0	80	0.039176	8.0675×10^{-4}

The prediction ratio of 40-60 is large enough to allow the model to get to know the underlying claim dynamics, but is not too large to offer a reliable and consistent estimate of the prediction error. This balance between training and test data is associated with a better parameter estimate and non-varying convergence.

The model, on the contrary, does not work well at the 20-80 prediction ratio, which should not be surprising given that there is a limited number of training data. Lack of sufficient training data limits the fitness of the model to explain the underlying trend and dynamic organization of the Disability claims, hence underfitting and high prediction error.

The MSE is relatively larger with the prediction ratio of 100-0. As much as the model has been trained on the whole data, the lack of a test dataset does not allow the assessment of predictive performance from being adequately tested. The error of generalization is therefore not an issue, and could be overfitting of the generalization ability when the reported error is used on unseen data.

3.4 Parameter Exploration

Table 3 shows the model's prediction performance for the Disability category when different parameters are estimated. Three cases are considered: all parameters are estimated, only A and C are estimated, and only A is estimated.

Table 3 Model Parameter Analysis

Case	Iteration Number	Elapsed Time (seconds)	Mean Squared Error
All parameters estimated	70	0.023620	8.0675×10^{-4}
A and C estimated	71	0.010916	5.3552×10^{-4}
Only A estimated	31	0.006781	7.8892×10^{-4}

The findings suggest that the lowest value of mean squared error (MSE) is obtained when the state transition matrix A and the observation matrix C are estimated. Conversely, the model shows that the largest MSE occurs when all parameters are estimated. The bias-variance trade-off can be used to explain the behaviour of the cases considered. The estimation of variance is decreased with the number of free parameters being minimized by fixing some parameters, thus creating a better prediction stability. This biasing effect might be important with the Disability category, but the overall decrease in variance of fixing b and d is greater, which results in a smaller MSE. On the other hand, the freedom to estimate all the parameters makes the data more sensitive to noise, amplifying the prediction variance and worsening predictive performance.

This finding, in insurance terms, implies that the controlled parameter flexibility of a stable modelling of Disability claim dynamics can be useful since excessively complex parameter estimation can also present unwarranted randomness into the claim payout forecasting.

3.5 Prediction Performance

Table 4 shows the model performance of the state-space model and the two benchmark methods, exponential smoothing and simple moving average, for predicting the insurance claim categories.

Table 4 Mean Squared Error for the Prediction of Different Techniques

Categories	**State Space Model**	**Exponential Smoothing**	**Simple Moving Average**
Disability	8.0675×10^{-4}	0.196026	0.329132
Bonus	9.2342×10^{-4}	0.146984	0.158343
Medical	8.8655×10^{-4}	0.059360	0.060002
Death	7.9932×10^{-4}	0.041331	0.043204
Others	6.5002×10^{-4}	0.036396	0.027921

The state-space model always reported low values of the MSE across all types of insurance, meaning that it gives accurate prediction of claim payments, which is essential in the insurance risk assessment and planning. Specifically, categories like Medical, Death, and Others show comparatively smaller prediction errors under the state-space model. This indicates that these categories have a more predictable and consistent patterns of claims.

Relative to these, the benchmark processes, which are exponential smoothing and simple moving average, also generate significantly greater MSE values and are more variable by category. Categories that display relatively larger prediction errors include Disability and Bonus, meaning that both categories exhibit more variability in claims and less predictable payout behaviour. Insurance-wise, this underscores the need to use models that can represent the inherent claim dynamics because more volatile categories need sound predictive models in order to facilitate well-established financial planning and risk management.

4. Conclusion

This study successfully applied a state-space model to predict insurance claim payouts in Malaysia from 2013 to 2023. The findings were presented in tabular and graphical forms, illustrating the accuracy and reliability of the state-space model. Consequently, the study achieved its primary objective of developing a robust model to predict insurance claim payouts. In conclusion, this study demonstrated the effectiveness of the state-space model in predicting insurance claim payouts, achieving its objectives, and contributing to the field of insurance. The findings highlight the potential of state space modelling for broader applications and provide a foundation for future research in predictive analytics and insurance forecasting.

However, the state space model implemented in this study can only predict one claim category at a time. Besides, other modern prediction techniques, such as machine learning, are not being studied. Hence, future research should consider extending the model to predict multiple claim categories simultaneously. Furthermore, implementing a nonlinear state space model, hybrid statistical-machine-learning methods, or other optimization methods could also improve the convergence and stability of the model, producing a more accurate result.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Lee Heng Yuan;* ***data collection:*** *Lee Heng Yuan;* ***analysis and interpretation of results:*** *Lee Heng Yuan, Kek Sie Long;* ***draft manuscript preparation:*** *Lee Heng Yuan, Kek Sie Long. All authors reviewed the results and approved the final version of the manuscript.*

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