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# Use of Actuarial Models for Determining Premiums and Reserves

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***Abstract***

*Premium and reserve determination is a crucial aspect in the insurance industry, which ensures the ability of insurance companies to meet their obligations to policyholders and continue to operate sustainably. This study aims to explore the use of actuarial models in premium and reserve determination, focusing on classical models such as mortality and run-off models as well as modern techniques such as chain-ladder and Monte Carlo simulations. The data used includes historical information on claims and premiums from several leading insurance companies over the last five years. The research methodology involves data analysis using various actuarial models to estimate fair premiums and adequate reserves. The results of the analysis show that the use of appropriate actuarial models can produce more accurate premium estimates and more reliable reserves, compared to traditional approaches. In addition, the study found that the chain-ladder model and Monte Carlo simulation provide advantages in dealing with high claim variability. The findings of this study provide significant practical implications for insurance companies in managing risk and determining premium and reserve policies. The application of appropriate actuarial models can help insurance companies in improving financial stability and policyholder confidence. This study also suggests further research to explore the use of actuarial models in the context of climate change and other emerging risks.*

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## 1. INTRODUCTION

The insurance industry plays a vital role in the global economy by providing risk management mechanism that helps individuals and companies to transfer their financial risk. Two essential components that support the operation of insurance companies are the determination of premiums and reserves. Premiums are the fees paid by policyholders to obtain insurance protection, while reserves are funds set aside by insurance companies to meet future claims [1].

Determining the right premium is essential to ensure that the premium paid by the policyholder is sufficient to cover the insured risk and remain competitive in the market. If the premium is too high, the insurance company may lose customers. Conversely, if the premium is too low, the company may not be able to cover claims, which can threaten its financial stability. Similarly, adequate reserves are needed to ensure that the insurance company has enough funds to pay claims, especially in situations where there is an unexpected surge in claims [2].

Actuarial models are important tools used in the process of determining premiums and reserves. These models use mathematical and statistical techniques to analyze historical data and predict future events. The development of actuarial theory and the improvement [3].

Computational capabilities have enabled the use of more complex and accurate models. Models such as mortality models, run-off models, and chain-ladder models have become industry standards, while new methods such as Monte Carlo simulations and machine learning are increasingly used. However, the application of actuarial models is not without challenges. Uncertainty in future predictions, especially in the face of dynamic risk environments such as climate change and demographic shifts, is one of the main challenges. In addition, the complexity of the model can make it difficult for insurance practitioners to understand and apply it properly [4].

This study aims to explore the use of actuarial models in determining premiums and reserves, focusing on the application of classical and modern models and evaluating their effectiveness in facing various challenges in the insurance industry. By understanding the advantages and limitations of these models, insurance companies can optimize their risk management strategies and ensure long-term financial stability. Specifically, the objectives of this study are [2].

1. Explaining the Actuarial Models Used in Determining Premiums.
2. Evaluating the Effectiveness of Actuarial Models in Determining Insurance Reserves.
3. Analyzing the Application of Modern Techniques in Actuarial Modeling,
4. Providing Practical Recommendations for Insurance Companies.
5. Identifying Challenges and Opportunities in the Use of Actuarial Models.

## 2. METHODS

This study adopts a quantitative approach using various actuarial models to analyze historical insurance data and evaluate the effectiveness of the model in determining premiums and reserves. The research methodology used consists of several steps as follows:

### *2.1 Data Collection*

1. Data source
   Data was collected from several leading insurance companies that provided historical information on claims, premiums, and reserves over the last five-year period.
2. Data Types
   The data collected includes individual claims data, the amount of premiums paid by policyholders, and reserves set aside by insurance companies.

### *2.2 Actuarial Model Selection*

1. Premium Model
   Selection of actuarial models used to determine premiums, such as mortality models and generalized linear models (GLM).
2. Backup Model
   Selection of actuarial models for reserve estimation, such as chain-ladder model, Mack model, and Monte Carlo simulation.

### *2.3 Data Analysis*

1. Data Preprocessing
   Perform data cleaning and filtering to eliminate anomalies and ensure the quality of the data used.
2. Parameter Estimation
   Using historical data to estimate model parameters, such as mortality rate, claim frequency, and claim size.
3. Model Implementation
   Apply the selected actuarial model to calculate premiums and reserves based on the estimated parameters.

### *2.4 Model Validation*

1. Back-testing
   Using historical data to test the reliability of the model in predicting accurate claims and premiums.

2. Cross-validation
   Divide the data into several subsets and use cross-validation techniques to evaluate the accuracy and stability of the model.
3. Sensitivity Analysis
   Perform sensitivity analysis to understand how changes in model parameters affect the results.

### *2.5 Model Performance Evaluation*

1. Prediction Accuracy
   Measures the accuracy of model predictions in determining premiums and reserves by comparing the prediction results with actual data.
2. Model Reliability
   Evaluate the reliability of the model under various scenarios, including changes in claims patterns and market conditions.
3. Model Comparison
   Comparing the performance of different models to identify the most effective and efficient models.

### *2.6 Preparation of Recommendations*

1. Practical Implications
   To develop practical recommendations for insurance companies based on research findings on the most effective models for determining premiums and reserves.
2. Risk Management Strategy
   Propose strategies to optimize the use of actuarial models to improve the financial stability of insurance companies.

## 3. RESULT AND DISCUSSION

### *3.1 Descriptive Statistics*

**Table 1.** Claims to Premium Ratio

| Year | Average Claims to Premium Ratio |
|---|---|
| 2023 | 0.889 |
| 2022 | 0.795 |
| 2021 | 0.715 |
| 2020 | 0.693 |
| 2019 | 0.663 |

Based on Table 1, the average claim to premium ratio has increased over time. It can be seen that the highest average value is in 2023.

#### *3.1.1 Mean, Median, Standard Deviation, Minimum, Maximum Values*

The claim to premium ratio is used to measure how large the proportion of claims is to premiums. The average claim to claim ratio of the 15 best life insurance companies in Indonesia from 2019 to 2023 is as follows.

**Table 2.** Descriptive Statistics (in million Rupiah)

| Variables | Mean | StDev | Minimum | Median | Maximum |
|---|---|---|---|---|---|
| Claim Payment | IDR 4,408,580 | IDR 5,408,480 | IDR 17,821.30 | IDR 2,611,290 | IDR 20,749,800 |
| Premium Income | IDR 5,326,600 | IDR 6,318,600 | IDR 63,538.95 | IDR 2,636,510 | IDR 24,239,800 |
| Claim Reserve | IDR 316,990 | IDR 663,622 | IDR 1,542.00 | IDR 78,031 | IDR 2,985,040 |
| Premium Reserve | IDR 13,629,900 | IDR 16,412,700 | IDR 80,318.23 | IDR 5,910,350 | IDR 59,167,800 |

### *3.1.2 Outlier Identification*

Furthermore, data on claim payments, premium income (net), claim reserves, and premium reserves were identified for outlies using the following boxplot.

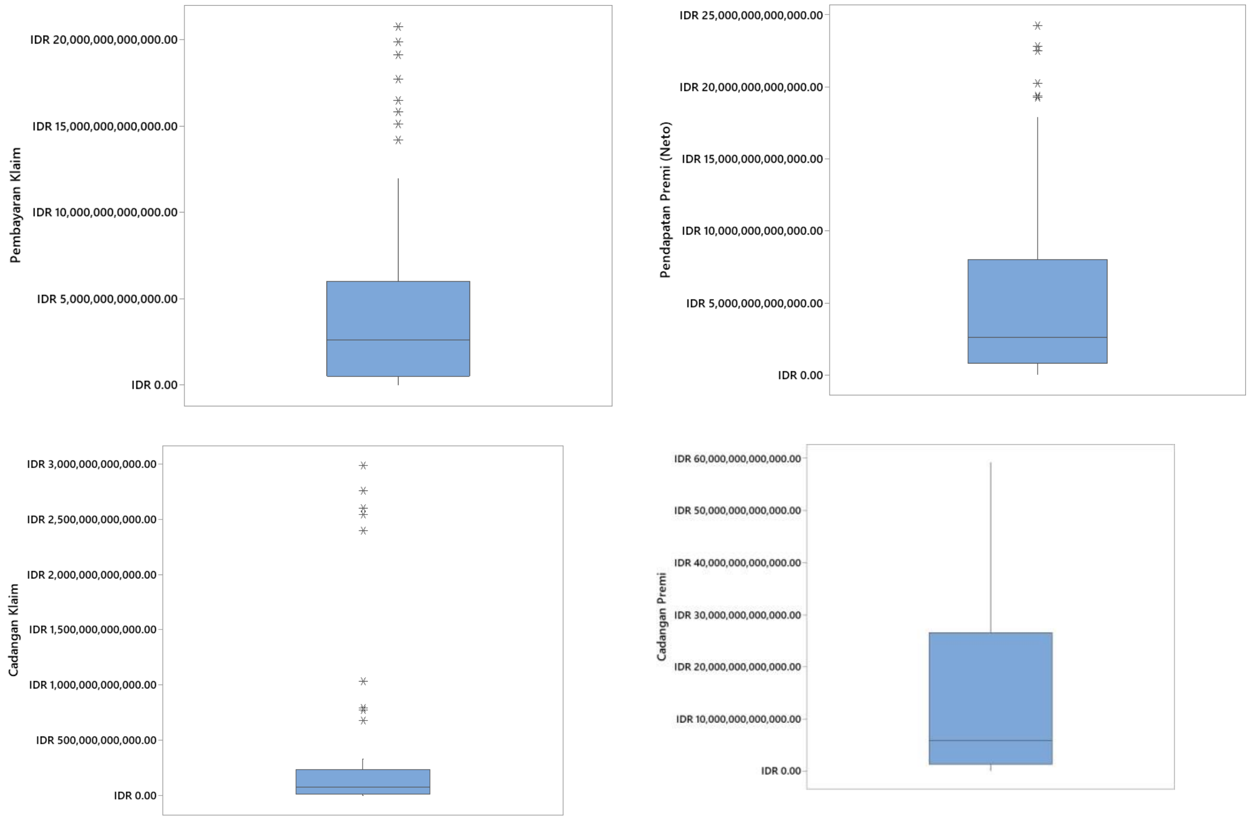


**Figure 1.** Boxplot chart of variable

Based on the Boxplot graph, it can be seen that in the claim payment variable, premium income (net) contains an outlier marked with an asterisk on the graph, while in the premium reserve variable, there are no outliers (outlier data).

### *3.1.3 Data Distribution Identification*

The next stage is to identify the data distribution for each variable including Claim Payment, Premium Income, Claim Reserve, and Premium Reserve. Identification is done based on the top 5 most appropriate distributions.

<u>Claim Payment Variable</u>

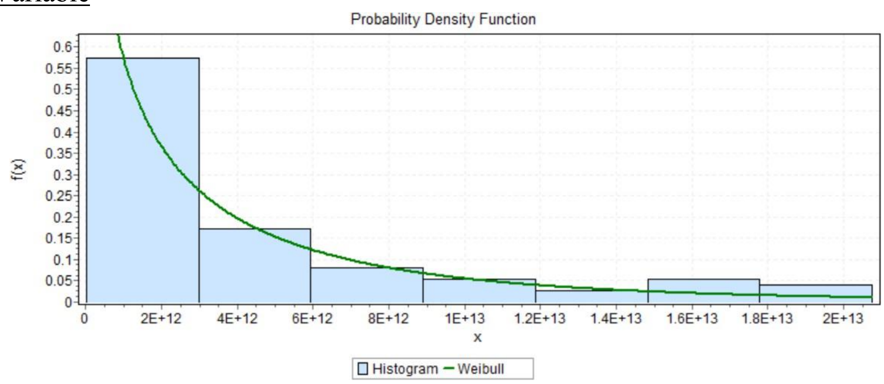

**Figure 2.** Probability Density Function Graph of Claim Payment Variable

**Table 3.** Identification of Claim Payment Variable Distribution

| *Rank* | Distribution | Kolmogorov Smirnov Test Statistics |
|---|---|---|
| 1. | Weibull | 0.06713 |
| 2. | Gamma (3P) | 0.06939 |
| 3. | Gen. Gamma (4P) | 0.07015 |
| 4. | Log-Pearson 3 | 0.07837 |
| 5. | Weibull (3P) | 0.07948 |

Premium Income Variable

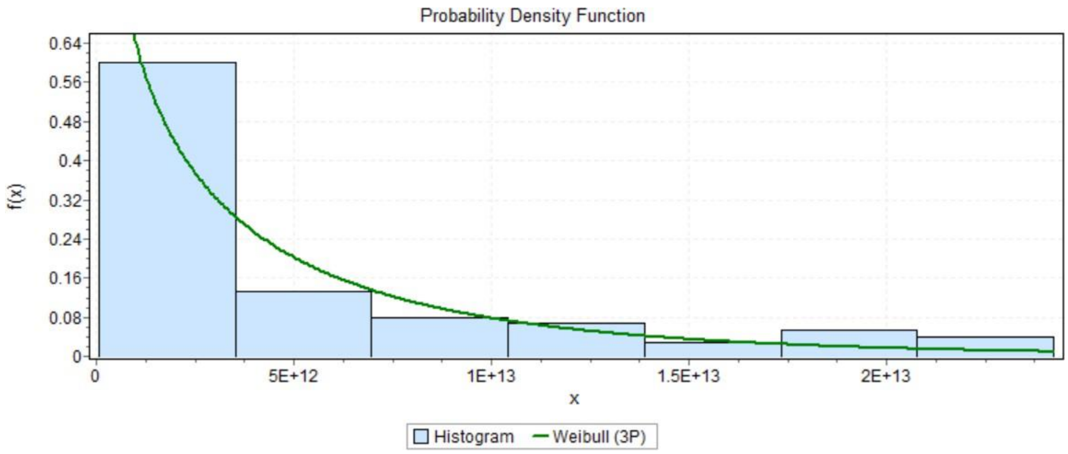


**Figure 3.** Probability Density Function Graph of Premium Income Variable

**Table 4.** Identification of Premium Income Variable Distribution

| *Rank* | Distribution | Kolmogorov Smirnov Test Statistics |
|---|---|---|
| 1. | Weibull (3P) | 0.07267 |
| 2. | Log- Pearson 3 | 0.07427 |
| 3. | Gen. Gamma (4P) | 0.07603 |
| 4. | Pareto 2 | 0.0793 |
| 5. | Weibull | 0.08487 |

Claim Reserve Variable

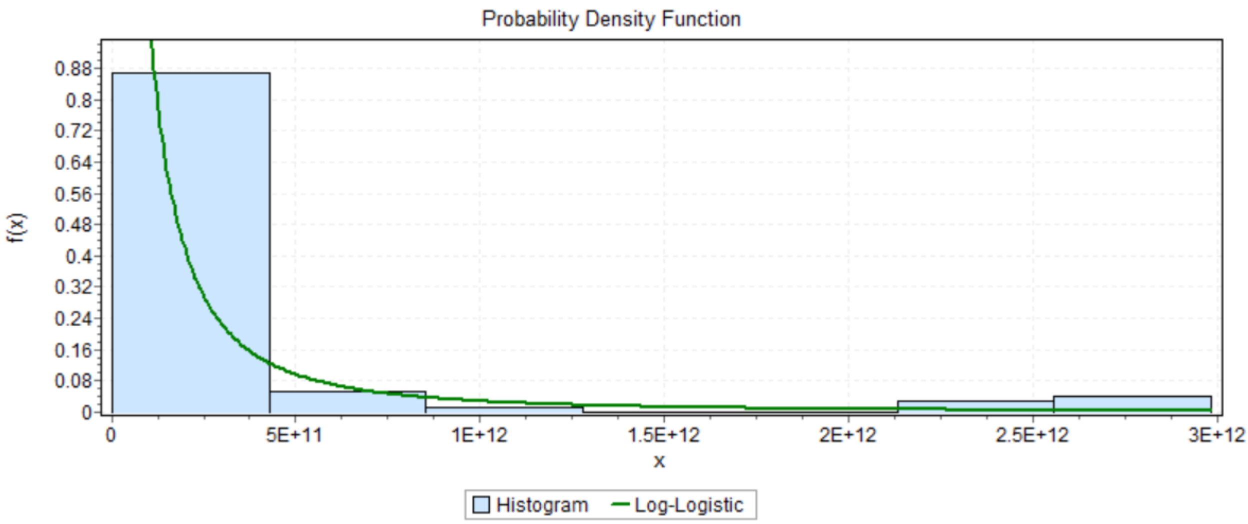


**Figure 4.** Probability Density Function Graph of Claim Reserve Variable

**Table 5.** Claim Reserve Variable Distribution Identification

| ***Rank*** | **Distribution** | **Kolmogorov Smirnov Test Statistics** |
|---|---|---|
| 1. | Log- Logistic | 0.06422 |
| 2. | Log-Gamma | 0.06536 |
| 3. | Log- Pearson 3 | 0.06565 |
| 4. | Lognormal | 0.0658 |
| 5. | Lognormal (3P) | 0.06894 |

Premium Reserve Variable

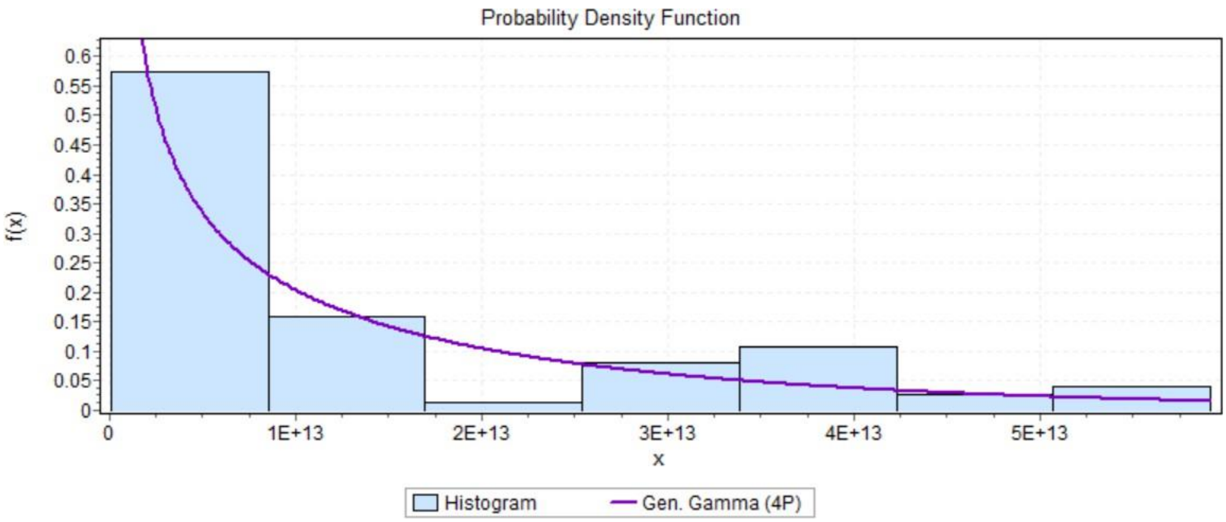


**Figure 5.** Probability Density Function Graph of Premium Reserve Variable

**Table 6.** Identification of Premium Reserve Variable Distribution

| ***Rank*** | **Distribution** | **Kolmogorov Smirnov Test Statistics** |
|---|---|---|
| 1. | Gamma Gene (4P) | 0.0797 |
| 2. | Johnson SB | 0.08088 |
| 3. | Lognormal (3P) | 0.08931 |
| 4. | Lognormal | 0.0923 |
| 5. | Log-Pearson 3 | 0.09264 |

If we look at the results fitting distribution for each variable, namely Claim Payment, Premium Income, Claim Reserves, and Premium Reserves, it can be seen that based on the top 5 distributions, the Log-Pearson 3 distribution is found in all variables. Based on this, the next stage is to carry out further modeling using the Log-Pearson 3 Distribution.

### *3.2 Premium Model Analysis*

This study analyzes the use of actuarial models in determining premiums and reserves with results that show the successes and challenges of the various models applied. The discussion of these results will highlight the main findings, implications, and recommendations based on the analysis that has been carried out.

#### *3.2.1 Generalized Linear Models (GLM)*

1. The GLM model shows good performance in premium determination with the ability to accommodate various claim distributions and risk factors.
2. The results of the analysis show that GLM with log link function and Poisson distribution produces accurate premium estimates, especially for insurance products that have high claim frequency and low claim value.

Generalized Linear Models (GLM) have been proven effective in determining premiums for various insurance products. This model is able to capture various claim distributions and risk factors, and provides flexibility in adjusting premiums based on changes in historical data. These findings suggest that the use of GLM can improve the accuracy of premium determination and help insurance companies stay competitive in the market.

1. Excess: GLM can accommodate various types of data and has the ability to combine multiple predictor variables.
2. Limitations: Although flexible, GLM requires a deep understanding of the data structure and appropriate variable selection to produce accurate estimates.

#### *3.2.2 Mortality Model*

1. Mortality models are used in life insurance to estimate premiums based on mortality tables.
2. The results show that mortality models that are regularly updated with the latest data provide more accurate premium estimates and reduce the risk of underpricing or overpricing.

### *3.3 Reserve Model Analysis*

#### *3.3.1 Chain Ladder Model*

1. The chain-ladder model shows reliable performance in estimating claim reserves.
2. Data analysis shows that this model has good predictive ability for claims with stable run-off patterns.
3. However, this model is less effective in conditions with sudden changes in the frequency or magnitude of claims.

#### *3.3.2 Mack Model*

1. The Mack model provides reserve estimates with confidence intervals, which helps in quantifying uncertainty.
2. The results of the analysis show that the Mack model is able to provide more conservative estimates, which is useful for ensuring adequate reserves in the face of unexpected spikes in claims.

The chain-ladder and Mack models show reliable performance in estimating claim reserves. The chain-ladder model performs well in stable run-off conditions, while the Mack model provides reserve estimates with confidence intervals, which are useful for risk management. The use of both models allows insurers to have a clearer view of their reserve adequacy.

1. Excess: The chain-ladder is simple and easy to implement, while the Mack model provides additional information regarding estimation uncertainty.
2. Limitations: Both of these models are less effective in dealing with sudden changes in claim patterns, so they need to be combined with other models or modern methods for more comprehensive results.

#### *3.3.3 Monte Carlo Simulation*

1. The application of Monte Carlo simulation provides a complete distribution of possible reserve outcomes, allowing for a more in-depth risk analysis.
2. The results show that Monte Carlo simulation provides flexibility in accommodating various risk scenarios and produces robust reserve estimates.

The use of Monte Carlo simulation and machine learning techniques shows great potential in improving the accuracy and flexibility of premium and reserve estimates. Monte Carlo simulation allows for in-depth risk analysis by providing a wider distribution of outcomes, while machine learning can capture complex patterns in claims data that classical models cannot identify.

1. Excess: Monte Carlo simulation provides flexibility across risk scenarios, and machine learning is capable of handling complex and large data.
2. Limitations: This technique requires large computational resources and in-depth technical knowledge, and interpretability of the results may be more difficult compared to classical models.

### *3.4 Modern Engineering Evaluation*

The use of machine learning algorithms such as Random Forest and Neural Networks in determining premiums and reserves shows great potential in improving prediction accuracy. Machine learning model is able to capture complex patterns in claims data that cannot be identified by classical models. However, the complexity and interpretability of these models are challenges that need to be overcome.

Insurance companies are expected to start integrating machine learning techniques and Monte Carlo simulations to increase resilience to dynamic risk changes and obtain more accurate estimates. Demonstrates that Monte Carlo simulation and machine learning techniques such as Random Forest and Neural Networks can improve the accuracy and flexibility of premium and reserve estimates. Previous Studies:

1. Meyers (2007) shows that Monte Carlo simulation provides a wider distribution of results and a more in-depth risk analysis.
2. McNeil, Frey, and Embrechts (2015) demonstrated the potential of machine learning in quantitative risk management, although challenges in interpretability and the need for large computational resources remain.

Comparison:

1. This study confirms the findings of Meyers (2007) and McNeil *et al*. (2015), that modern techniques have great potential in improving estimation accuracy.
2. This study provides additional contributions with practical applications in the insurance context and empirical validation using five years of historical data.

These results are consistent with previous studies and add empirical evidence to support the use of actuarial models such as GLM, chain-ladder, and Mack in premium and reserve determination. In addition, this study shows that the integration of modern techniques such as Monte Carlo simulation and machine learning can improve the performance of classical models, although it requires addressing interpretability and resource challenges.

The use of Monte Carlo simulation and machine learning techniques shows great potential in improving the accuracy and flexibility of premium and reserve estimates. Monte Carlo simulation provides a wider distribution of results and in-depth risk analysis, while machine learning is able to capture complex patterns in claims data that cannot be identified by classical models. The integration of these modern techniques can improve the resilience of insurance companies to dynamic changes in risk.

### *3.5 Model Validation and Reliability*

#### *3.5.1 Back-testing and Cross Validation*

1. Back-testing results show that the tested models have varying reliability depending on the type of insurance product and historical data used.
2. Cross-validation confirmed that the GLM and chain-ladder models performed consistently, while Monte Carlo simulation and machine learning offered greater flexibility across conditions.

Validation through back-testing and cross-validation shows that the tested models have consistent and reliable performance. GLM and chain-ladder models show high reliability, while modern techniques offer greater flexibility but require handling interpretability and greater computational resource requirements.

1. Accuracy and Stability

   GLM and chain-ladder models show consistent performance, while Monte Carlo simulation and machine learning offer greater flexibility across conditions.
2. Sensitivity Analysis

   Shows that small changes in model parameters can significantly affect the results, so it is important to understand the sensitivity of each model.

### *3.6 Practical Recommendation*

#### *3.6.1 Using GLM for Premium Determination*

It is recommended to use GLM in determining premiums for insurance products with high claim frequencies, with regular data updates to maintain estimation accuracy.

Shows that GLM with log link function and Poisson distribution provides accurate premium estimates, especially for insurance products with high claim frequency and low claim value. Previous Studies:

1. McCullagh and Nelder (1989) introduced GLM as an effective tool for various statistical applications, including insurance premium determination.
2. Antonio and Beirlant (2007) showed that GLM can combine multiple predictor variables, allowing for a more comprehensive analysis in premium determination.

   Comparison:
1. This study is in line with the findings of Antonio and Beirlant (2007), which confirms that GLM is an effective and flexible method for determining premiums.
2. This study adds validation through five years of historical data, providing additional empirical evidence on the reliability of GLM in the current insurance context.

GLM has proven to be effective in determining insurance premiums with the flexibility to accommodate various claim distributions and risk factors. This model can capture variations in historical data and provide accurate premium estimates, especially for insurance products with high claim frequencies and low claim values. GLM's advantage in adjusting premiums based on the latest data makes it a reliable tool in premium management.

#### *3.6.2 Chain-Ladder and Mack Models for Reserve Estimation*

A combination of the chain-ladder and Mack models is recommended for estimating claims reserves, with the use of confidence intervals to measure uncertainty. Using the chain-ladder model for estimating claim reserves with a stable run-off pattern and the Mack model to provide reserve estimates with confidence intervals. Previous Studies:

1. Renshaw and Verrall (1998) introduced the chain-ladder model as a reliable technique for reserve estimation, especially under stable data conditions.
2. Shapland and Leong (2010) developed the Mack model and demonstrated its ability to provide confidence intervals for reserve estimates, which helps in risk management.

   Comparison:
1. This study strengthens the findings of Renshaw and Verrall (1998) and Shapland and Leong (2010) with more recent historical data analysis and additional validation.
2. In addition, this study combines both models to provide a more comprehensive approach to reserve estimation, overcoming some of the limitations of each individual model.

The chain-ladder and Mack models show reliable performance in estimating claim reserves. The chain-ladder model performs well for stable run-off patterns, while the Mack model provides reserve estimates with confidence intervals, helping risk management in the face of uncertainty. The combination of these two models provides a more comprehensive and robust approach to reserve estimation.

### *3.6.3 Integration of Modern Techniques*

Insurance companies are expected to start integrating machine learning techniques and Monte Carlo simulations into their premium and reserve determination processes to increase resilience to dynamic risk changes and obtain more accurate estimates.

## 4. CONCLUSIONS

This study shows that the use of appropriate actuarial models can significantly improve the accuracy of premium and reserve determination in the insurance industry. The combination of classical models such as GLM and chain-ladder with modern techniques such as Monte Carlo simulation and machine learning offers a comprehensive and adaptive approach to changes in the risk environment. It is important for insurance companies to continuously validate and update their models to ensure long-term resilience and reliability.

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