

Bayesian Bonus-Malus Premiums Under Different Loss Functions in Car Insurance

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Abstract—

In the traditional bonus-malus system, automobile insurance premiums are typically calculated based solely on claim frequency. This study introduces an alternative approach, incorporating both claim frequency and claim severity into the determination of premiums. Furthermore, the research explores the premiums under various loss functions, including quadratic, linex, and entropy, applied to both frequency and severity. The Bayesian approach is employed to compute the bonus-malus premiums. Additionally, this work relies on the R program to provide a numerical application based on a real automobile insurance dataset. By incorporating diverse loss functions, this approach aims to enhance flexibility, achieve balance, and provide greater control over premiums, all while ensuring the solvency of the insurance company.

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1. INTRODUCTION

In actuarial science, a key responsibility involves designing a pricing framework that fairly distributes the burden of claims among insured individuals. This is achieved by using the most appropriate models to calculate insurance premiums. One such method is the **bonus-malus system (BMS)**, which adjusts premiums based on an individual's claim history. It is widely implemented, particularly in automobile insurance, to ensure that all policyholders pay premiums commensurate with their risk levels. Safe driving without claims results in a premium reduction as a reward, whereas a reported incident leads to a premium increase.

The BMS serves two primary purposes for insurance companies. First, it encourages policyholders to operate their vehicles more carefully throughout the year, aiming to reduce the number of claims. Second, it ensures that policyholders pay premiums aligned with their individual risk levels as reflected in their claims history [1]. The fundamental concept of this system is that higher claim frequencies lead to higher premiums. Traditionally, BMSs have relied solely on the stochastic nature of claim frequency [4]. However, since claims may vary significantly in size, it is important to design a BMS that accounts for both the **frequency** and **severity** of claims. Although several authors have already proposed this idea [2, 7, 9], their models typically determine premiums using only the classical **quadratic loss function**.

In insurance, actuaries use **loss functions** as analytical tools to evaluate the costs associated with deviations from expected outcomes. These functions are critical in risk assessment, premium calculation, and decision-making processes. Measuring different forms of loss enhances an insurer's ability to manage and mitigate risk. Loss functions help insurers select models and strategies that align with their risk tolerance. By accurately evaluating risks, insurers can set fair and financially sustainable premium rates.

There are several types of loss functions used in statistics. The most common is the **quadratic loss function**, also known as the mean squared error. In automobile insurance, it calculates the squared difference between actual and estimated values, assigning greater weight to larger errors. Another important loss function is the **linex loss function**, which is asymmetric. This asymmetry allows for an unequal assessment of underestimation versus overestimation of risk—particularly useful when underestimating significant claims has more serious consequences than overestimating minor ones. Lastly, the **entropy loss function** measures the proportional gap between observed and expected values. It is particularly sensitive to rare but important deviations, making it suitable for capturing infrequent but high-impact events.

In this study, we aim to calculate bonus-malus premiums using multiple loss functions while incorporating both claim frequency and severity. While most existing research focuses on a single loss function, we examine the use of **different loss functions across various scenarios**, and we compare the resulting premiums with those obtained using only one loss function. Additionally, we provide a numerical application using a real automobile insurance dataset and employ R software to compute the premiums, allowing for a detailed comparison and identification of the most beneficial approach for insurance providers.

This article is structured as follows:

- The first two sections address **claim frequency** and **claim severity**, each divided into five subsections: the selected distribution, the Bayesian approach, and the premiums computed using the quadratic, linex, and entropy loss functions.
- The third section presents the **final premiums** calculated based on both claim frequency and severity.
- The fourth section offers a **numerical application**, using a real dataset and R software, and analyzes the outcomes based on the final premiums discussed in the third section.
- The final section provides a **summary of the study's key findings**.

2. CLAIM FREQUENCY DISTRIBUTION USING POISSON-AKASH

2.1. Poisson-Akash Distribution. We generally use the Poisson distribution in car insurance to explain the random frequency of the claim. The claims number k is supposed to follow the Poisson distribution with parameter θ and probability mass function as

$$P(l|\theta) = \frac{e^{-\theta}\theta^l}{l!}, l = 0, 1, 2, \dots, \theta > 0,$$

with the following expected value

$$E[l|\theta] = Var[l|\theta] = \theta.$$

θ is assumed to follow the Akash distribution with parameter γ and a probability density

function expressed as follows:

$$\pi(\theta) = \frac{\gamma^3}{\gamma^2 + 2} (1 + \theta^2) e^{-\gamma\theta}.$$

Then, the mixed distribution of the Poisson with Akash distribution (see Shanker in 2016 [11]) is:

$$f(l) = \int_0^\infty P(l|\theta)\pi(\theta)d\theta = \frac{\gamma^3}{\gamma^2 + 2} \frac{\gamma^2 + 2\gamma + l^2 + 3l + 3}{(1 + \gamma)^{l+3}} \quad (1)$$

2.2. Bayesian method. The Bayesian technique is one of the most commonly employed computational solutions for the bonus-malus premium calculation, which has been well explored in [5]. This method's primary goal is to determine the posterior distribution function.

l_1, l_2, \dots, l_t is a sample of size t . The claim total number generated by an insured over t years is $N = \sum_{i=1}^t l_i$, where l_i is the claim's number established by an insured in years $i, i = 1, 2, \dots, t$. The likelihood function is:

$$L(\theta; l_1, l_2, \dots, l_n) = \prod_{i=1}^t \frac{e^{-\theta}\theta^{l_i}}{l_i!} = \frac{1}{\prod_{i=1}^t l_i!} e^{-t\theta} \theta^{\sum l_i} \propto e^{-t\theta} \theta^N. \quad (2)$$

The Prior distribution is:

$$\pi(\theta) = \frac{\gamma^3}{\gamma + 2} (1 + \theta^2) e^{-\gamma\theta} \propto (1 + \theta^2) e^{-\gamma\theta}. \quad (3)$$

In order to determine the posterior distribution for an insured with k_1, k_2, \dots, k_t claim history, we employ the Bayes' theorem. The product of the prior distribution in (3) and the likelihood function in (2) represents the posterior distribution function as follows:

$$\begin{aligned} \pi^*(\theta|l_1, \dots, l_n) &\propto P(l_1, \dots, l_n|\theta)\pi(\theta) = e^{-t\theta} \theta^N (1 + \theta^2) e^{-\gamma\theta} \\ &= \theta^N (1 + \theta^2) e^{-\theta(t+\gamma)}. \end{aligned}$$

Finally, for the claim frequency, the posterior distribution function is (for more details refer to [9])

$$\pi^*(\theta|l_1, \dots, l_n) = \frac{(t + \gamma)^{n+3}}{\Gamma(n + 1)[(n + 2)(n + 1) + (t + \gamma)^2]} \theta^N (1 + \theta^2) e^{-\theta(t+\gamma)}.$$

2.3. Premium under quadratic loss function. In this paper, we aim to determine the net premium which corresponds to the mean of the claim number of each insured. Assume that the claim history is l_1, l_2, \dots, l_t . The mean of the posterior distribution function for Poisson-Akash distribution (which is the expected number of claims) is obtained by:

$$\begin{aligned} \widehat{\theta}_{t+1} &= E[\theta|l_1, \dots, l_t] = E[l_1, \dots, l_n|\theta] = \int_0^\infty \theta \pi^*(\theta|l_1, \dots, l_n) \\ &= \frac{(n + 1)(n + 2)(n + 3) + (n + 1)(t + \gamma)^2}{(t + \gamma)^3 + (t + \gamma)(n + 2)(n + 1)}. \end{aligned}$$

Consider that 100 represents the initial premium at time $t=0$. Consequently, the premium at time $t+1$ is defined thereby:

$$\begin{aligned} \text{Premium}_{t+1} &= 100 \frac{\widehat{\theta}_{t+1}}{E[x]} \\ &= 100 \frac{\theta(\theta^2 + 2)}{\theta^2} + 6 \frac{(n + 1)(n + 2)(n + 3) + (n + 1)(t + \gamma)^2}{(t + \gamma)^3 + (t + \gamma)(n + 2)(n + 1)}. \quad (4) \end{aligned}$$

2.4. Premium under Linex Loss function: The following subsection examines the asymmetric linex loss function. It exhibits an exponential increase on one side of zero and a linear increase on the other one, as demonstrated in [8, 10, 12]. It is articulated as:

$$L(\hat{\theta}, \theta) = \exp(a(\hat{\theta} - \theta)) - a(\hat{\theta} - \theta) - 1, \quad a \neq 0,$$

where $\hat{\theta}$ denotes the estimator of θ under the linex loss function that minimizes the aforementioned equation (see [13]), $\hat{\theta}$ can be defined as:

$$\hat{\theta}_L = -\frac{1}{\alpha} \ln(E[e^{-\alpha\theta}|X]).$$

Then

$$\begin{aligned} E[e^{-\alpha\theta}|l_1, \dots, l_n] &= \int_0^\infty e^{-\alpha\theta} \pi^*(\theta_i|l_1, \dots, l_n) d\theta \\ &\propto \int_0^\infty \theta^{N+2} e^{-(t+\gamma+\alpha)\theta} d\theta + \int_0^\infty \theta^N e^{-(t+\gamma+\alpha)\theta} d\theta \\ &= \frac{(t+\gamma)^{n+3}(n+1+t+\gamma+\alpha)}{[(n+2)(n+1)+(t+\gamma)^2](t+\gamma+\alpha)^{n+2}}. \end{aligned}$$

Finally

$$\hat{\theta}_L = -\frac{1}{\alpha} \ln\left(\frac{(n+2)(n+1)+(t+\gamma+a)^2}{(t+\gamma+a)^{n+3}} \frac{(t+\gamma)^{n+3}}{(n+2)(n+1)+(t+\gamma)^2}\right).$$

At time $t=0$, the premium is 100. The premium at time $t+1$ is expressed as

$$\begin{aligned} Premium_{t+1} &= 100 \frac{\gamma(\gamma^2+2)}{\gamma^2+6} \\ &\quad * \left[-\frac{1}{\alpha} \ln\left(\frac{(n+2)(n+1)+(t+\gamma+a)^2}{(t+\gamma+a)^{n+3}}\right) * \right. \\ &\quad \left. * \frac{(t+\gamma)^{n+3}}{(n+2)(n+1)+(t+\gamma)^2} \right]. \quad (5) \end{aligned}$$

Premium under Entropy Loss function: This part interprets the entropy loss function. In various actual scenarios, it appears more sensible to express the loss as the ratio $\frac{\hat{\theta}}{\theta}$; for this context, [6] presented a loss function referred to as entropy. This loss function serves as a powerful asymmetric loss which assigns credit for both underestimation and overestimation, defined by the following structure.

$$L(\hat{\theta}_E - \theta) = \left(\frac{\hat{\theta}_E}{\theta}\right)^q - q \ln\left(\frac{\hat{\theta}_E}{\theta}\right) - 1; \quad q \neq 0$$

where $\hat{\theta}_E$ denotes the estimate of θ that minimizes the aforementioned equation under the entropy loss function. The expression for $\hat{\theta}_E$ is provided as follows:

$$\begin{aligned} \hat{\theta}_E &= (E[\theta^{-p}|l_1, \dots, l_n])^{-\frac{1}{p}} \\ E[\theta^{-p}|l_1, \dots, l_n] &= \int_0^\infty \theta^{-p} \Pi^*(\theta|l_1, \dots, l_n) d\theta \end{aligned}$$

$$\begin{aligned}
 &= \int_0^\infty \theta^{-p} \theta^N (1 + \theta^2) e^{-\theta(t+\gamma)} d\theta \\
 &= \left[\frac{\Gamma(n-p+3)}{(t+\theta)^{n-p+3}} + \right. \\
 &\quad \left. + \frac{\Gamma(n-p+1)}{(t+\theta)^{n-p+1}} \right] \frac{(t+\gamma)^{n+3}}{\Gamma(n+1)[(n+2)(n+1) + (t+\gamma)^2]} \\
 E[\theta^{-p} | l_1, \dots, l_n] &= \left[\frac{\Gamma(n-p+3) + \Gamma(n-p+1)(t+\gamma)^2}{(t+\theta)^{n-p+3}} \right] \\
 &\quad * \frac{(t+\gamma)^{n+3}}{[\Gamma(n+1)[(n+2)(n+1) + (t+\gamma)^2]}
 \end{aligned}$$

Finally

$$\begin{aligned}
 \widehat{\theta}_E &= \\
 &= \left[\left(\frac{\Gamma(n-p+3) + \Gamma(n-p+1)(t+\gamma)^2}{(t+\theta)^{n-p+3}} \right) * \frac{(t+\gamma)^{n+3}}{[\Gamma(n+1)[(n+2)(n+1) + (t+\gamma)^2]} \right]^{-\frac{1}{p}} \quad (6)
 \end{aligned}$$

$$\begin{aligned}
 \text{Premium}_{t+1} &= 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} * \left[\left(\frac{\Gamma(n-p+3) + \Gamma(n-p+1)(t+\gamma)^2}{(t+\theta)^{n-p+3}} \right) \right. \\
 &\quad \left. * \frac{(t+\gamma)^{n+3}}{[\Gamma(n+1)[(n+2)(n+1) + (t+\gamma)^2]} \right]^{-\frac{1}{p}} \quad (7)
 \end{aligned}$$

3. CLAIM SEVERITY DISTRIBUTION USING INVERS-GAMMA LINDLEY

3.1. Mixing Distribution. X denote a random variable that signifies the claim size associated with each insurer. Let us consider that X adheres to an Inverse-Gamma distribution, characterized by the following probability density function:

$$f(x|\lambda) = \frac{\lambda^\alpha x^{-\alpha-1}}{\Gamma(\alpha)} e^{-\frac{\lambda}{x}}.$$

The Invers-Gamma expected value is

$$E[X] = \frac{\lambda}{\alpha - 1}.$$

Let λ be a random variable that adheres to a Lindley distribution characterized by the parameter β . Then, the representation of the PDF of λ is provided as:

$$\pi(\lambda) = \frac{\beta^2}{\beta + 1} (\lambda + 1) e^{-\beta\lambda}.$$

Thus, the combination of the Invers-Gamma and Lindley distributions is derived thereby ([9]):

$$\begin{aligned}
 f(x) &= \int_0^\infty \frac{\lambda^\alpha}{\Gamma(\alpha)} x^{-\alpha-1} e^{-\frac{\lambda}{x}} \frac{\beta^2}{\beta + 1} (\lambda + 1) e^{-\beta\lambda} d\lambda \\
 &= \frac{x^{-\alpha-1} \beta^2 (\alpha + 1)}{(\beta + 1) \left(\beta + \frac{1}{x}\right)^{\alpha+2}} \left[\alpha + 1 + \beta + \frac{1}{x} \right]. \quad (8)
 \end{aligned}$$

3.2. Bayesian Method. $N = \sum_{i=1}^t l_i$ represents the total number of claims submitted by an insured over a duration of t years. Define x as the amount of claim l where l ranges from 1 to N . The subsequent expression identifies the likelihood function:

$$\begin{aligned}
 L(\lambda | x_1, \dots, x_n) &= f(x_1, \dots, x_n | \lambda) = \prod_{i=1}^n \frac{\lambda^\alpha x_i^{-\alpha-1}}{\Gamma(\alpha)} e^{-\lambda \frac{1}{x_i}} \\
 &= \frac{\lambda^{n\alpha}}{(\Gamma(\alpha))^n} \prod_{i=1}^n x_i^{-\alpha-1} e^{-\lambda \sum_{i=1}^n \frac{1}{x_i}} \\
 &\propto \lambda^{n\alpha} e^{-\lambda \sum_{i=1}^n \frac{1}{x_i}}.
 \end{aligned}$$

The following $\pi(\lambda)$ denotes the prior distribution

$$\pi(\lambda) \propto (\lambda + 1)e^{-\beta\lambda}.$$

To determine the posterior distribution function, we utilize Bayes' Theorem in the following manner:

$$\pi^*(\lambda | x_1, \dots, x_n) \propto f(x_1, \dots, x_n | \lambda) \pi(\lambda) \propto \lambda^{n\alpha} (1 + \lambda) e^{-\lambda(\beta + \sum_{i=1}^n \frac{1}{x_i})}.$$

Thus, the posterior distribution function for the claim severity is represented as (for more detail see[9]):

$$\pi^*(\lambda | x_1, \dots, x_n) = \frac{(\beta + \sum_{i=1}^n \frac{1}{x_i})^{\alpha n + 2}}{\Gamma(\alpha n + 1) (\alpha n + 2 + \beta + \sum_{i=1}^n \frac{1}{x_i})} \lambda^{n\alpha} (1 + \lambda) e^{-\lambda(\beta + \sum_{i=1}^n \frac{1}{x_i})}. \quad (9)$$

3.3. Premium under quadratic loss function. For an insured given a claim history l_1, l_2, \dots, l_t , the mean of the posterior distribution function for Poisson- Akash distribution (or the predicted claim number) is:

$$\begin{aligned}
 \widehat{\lambda}_{t+1} &= E[\lambda | x_1, \dots, x_n] = \int_0^\infty \lambda \pi^*(\lambda | x_1, \dots, x_n) d\lambda \\
 &= \frac{(\alpha n + 2) (\alpha n + 3 + \beta + \sum_{i=1}^n \frac{1}{x_i})}{(\beta + \sum_{i=1}^n \frac{1}{x_i}) (\alpha n + 2 + \beta + \sum_{i=1}^n \frac{1}{x_i})}.
 \end{aligned}$$

According to

$$E[\lambda | x_1, \dots, x_n] = \widehat{\lambda}.$$

We have

$$E[x_1, \dots, x_n | \lambda] = \frac{\widehat{\lambda}}{\alpha - 1}.$$

Consequently

$$E[x_1, \dots, x_n | \lambda] = \frac{(\alpha n + 2) (\alpha n + 3 + \beta + \sum_{i=1}^n \frac{1}{x_i})}{(\alpha - 1) (\beta + \sum_{i=1}^n \frac{1}{x_i}) (\alpha n + 2 + \beta + \sum_{i=1}^n \frac{1}{x_i})}. \quad (10)$$

3.4. Premium under Linex Loss function:

In this section, also, we used the Varian's asymmetric linex loss function, defined by the following equation:

$$L(\widehat{\lambda}, \lambda) = \exp(a(\widehat{\lambda} - \lambda)) - a(\widehat{\lambda} - \lambda) - 1, \quad a \neq 0.$$

Consider $\widehat{\lambda}$ is the estimator of λ under the Linex loss function which minimizes the precedent equation, $\widehat{\lambda}$ is given by:

$$\widehat{\lambda}_L = -\frac{1}{c} \ln E(e^{-c\lambda} | X)$$

Then

$$\begin{aligned}
 E(e^{-c\lambda}|X) &= \int_0^\infty B e^{-c\lambda} \pi^*(\lambda_i|x_1, \dots, x_n) d\lambda = B \int_0^\infty e^{-c\lambda} \lambda^{\alpha n} (1 + \lambda) e^{-\lambda(\beta + \sum_{i=1}^n \frac{1}{x_i})} d\lambda \\
 &= \left[\frac{\Gamma(\alpha n + 1)}{\left(c + \beta + \sum_{i=1}^n \frac{1}{x_i}\right)^{\alpha n + 1}} + \frac{\Gamma(\alpha n + 2)}{\left(c + \beta + \sum_{i=1}^n \frac{1}{x_i}\right)^{\alpha n + 2}} \right] \\
 &\quad \frac{\left(\beta + \sum_{i=1}^n \frac{1}{x_i}\right)^{\alpha n + 2}}{\Gamma(\alpha n + 1) \left[\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}\right]} E(e^{-c\lambda}|X) \\
 &= \left(\frac{\beta + \sum_{i=1}^n \frac{1}{x_i}}{c + \beta + \sum_{i=1}^n \frac{1}{x_i}}\right)^{\alpha n + 2} \left(\frac{\alpha n + 1 + c + \beta + \sum_{i=1}^n \frac{1}{x_i}}{\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}}\right)
 \end{aligned}$$

Finally

$$\widehat{\lambda}_L = \frac{1}{\alpha - 1} \left(-\frac{1}{c}\right) \ln \left[\left(\frac{\beta + \sum_{i=1}^n \frac{1}{x_i}}{c + \beta + \sum_{i=1}^n \frac{1}{x_i}}\right)^{\alpha n + 2} \left(\frac{\alpha n + 1 + c + \beta + \sum_{i=1}^n \frac{1}{x_i}}{\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}}\right) \right]$$

3.5. Premium under Entropy Loss function: In this part, we also, utilized the Entropy loss function in the following manner:

$$\widehat{\lambda}_E = [E(\lambda^{-p}|X)]^{-\frac{1}{p}}$$

Then

$$E(\lambda^{-p}|X) = \int_0^\infty B \lambda^{-p} \pi^*(\lambda_i|x_1, \dots, x_n) d\lambda = B \int_0^\infty \lambda^{-p} \lambda^{\alpha n} (1 + \lambda) e^{-\lambda(\beta + \sum_{i=1}^n \frac{1}{x_i})} d\lambda$$

$$\begin{aligned}
 &= \left[\frac{\Gamma(\alpha n - p + 1)}{\left(\beta + \sum_{i=1}^n \frac{1}{x_i}\right)^{\alpha n - p + 1}} + \frac{\Gamma(\alpha n + 2)}{\left(\beta + \sum_{i=1}^n \frac{1}{x_i}\right)^{\alpha n - p + 2}} \right] \\
 &\quad \frac{\left(\beta + \sum_{i=1}^n \frac{1}{x_i}\right)^{\alpha n + 2}}{\Gamma(\alpha n + 1) \left[\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}\right]} \\
 E(\lambda^{-p}|X) &= \frac{\Gamma(\alpha n - p + 1) \left[\alpha n - p + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}\right]}{\Gamma(\alpha n + 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i}\right) \left[\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}\right]}
 \end{aligned}$$

Finally

$$\widehat{\lambda}_E = \frac{1}{\alpha - 1} \left[\frac{\Gamma(\alpha n - p + 1) \left[\alpha n - p + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}\right]}{\Gamma(\alpha n + 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i}\right) \left[\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}\right]} \right]^{-\frac{1}{p}}$$

4. FINAL PREMIUMS USING BOTH FREQUENCY AND CLAIM SEVERITY

The tables bellow represents the final premiums that will be used in the numerical application

TABLE1. Final premiums using Invers-Gamma Lindley distribution under Quadratic loss function for the claim severity

Claim frequency distribution	Final premium
Poisson Akash under Quadratic loss function (4)	$Premium_{t+1} = 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} * \frac{(n+1)(n+2)(n+3) + (n+1)(t+\gamma)^2}{(t+\gamma)^3 + (t+\gamma)(n+2)(n+1)} * \frac{(\alpha n + 2) \left(\alpha n + 3 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right)}{(\alpha - 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i} \right) \left(\alpha n + 2 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right)}. \quad (11)$
Poisson Akash under Linex loss function (5)	$Premium_{t+1} = 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} * \left[-\frac{1}{a} \ln \left(\frac{(n+2)(n+1) + (t+\gamma+a)^2}{(t+\gamma+a)^{n+3}} * \frac{(t+\gamma)^{n+3}}{(n+2)(n+1) + (t+\gamma)^2} \right) \right] * \frac{(\alpha n + 2) \left(\alpha n + 3 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right)}{(\alpha + 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i} \right) \left(\alpha n + 2 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right)}. \quad (12)$
Poisson Akash under Entropy loss function (7)	$Premium_{t+1} = 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} * \left[\left(\frac{\Gamma(n-p+3) + \Gamma(n-p+1)(t+\gamma)^2}{(t+\theta)^{n-p+3}} \right) * \frac{(t+\gamma)^{n+3}}{[\Gamma(n+1)[(n+2)(n+1) + (t+\gamma)^2]]} \right]^{\frac{1}{p}} * \frac{(\alpha n + 2) \left(\alpha n + 3 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right)}{(\alpha + 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i} \right) \left(\alpha n + 2 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right)}. \quad (13)$

TABLE2. Final premiums using Invers-Gamma Lindley distribution under Linex loss function for the claim severity

Claim frequency distribution	Final premium
Poisson Akash under Quadratic loss function (4)	$Premium_{t+1} = 100 \frac{\theta(\theta^2 + 2)}{\theta^2} + 6 \frac{(n+1)(n+2)(n+3) + (n+1)(t+\gamma)^2}{(t+\gamma)^3 + (t+\gamma)(n+2)(n+1)}$

	$-\frac{1}{c} \ln \left[\left(\frac{\beta + \sum_{i=1}^n \frac{1}{x_i}}{c + \beta + \sum_{i=1}^n \frac{1}{x_i}} \right)^{\alpha n + 2} \left(\frac{\alpha n + 1 + c + \beta + \sum_{i=1}^n \frac{1}{x_i}}{\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}} \right) \right]$
Poisson Akash under Linex loss function (5)	$Premium_{t+1} = 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} * \left[-\frac{1}{a} \ln \left(\frac{(n+2)(n+1) + (t+\gamma+a)^2}{(t+\gamma)^{n+3}} \right) * \frac{1}{(n+2)(n+1) + (t+\gamma)^2} \right]$ $-\frac{1}{c} \ln \left[\left(\frac{\beta + \sum_{i=1}^n \frac{1}{x_i}}{c + \beta + \sum_{i=1}^n \frac{1}{x_i}} \right)^{\alpha n + 2} \left(\frac{\alpha n + 1 + c + \beta + \sum_{i=1}^n \frac{1}{x_i}}{\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}} \right) \right]$
Poisson Akash under Entropy loss function (7)	$Premium_{t+1} = 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} * \left[\left(\frac{\Gamma(n-p+3) + \Gamma(n-p+1)(t+\gamma)^2}{(t+\theta)^{n-p+3}} \right) * \frac{(t+\gamma)^{n+3}}{[\Gamma(n+1)[(n+2)(n+1) + (t+\gamma)^2]]} \right]^{\frac{1}{p}}$ $-\frac{1}{c} \ln \left[\left(\frac{\beta + \sum_{i=1}^n \frac{1}{x_i}}{c + \beta + \sum_{i=1}^n \frac{1}{x_i}} \right)^{\alpha n + 2} \left(\frac{\alpha n + 1 + c + \beta + \sum_{i=1}^n \frac{1}{x_i}}{\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i}} \right) \right]$

TABLE3. Final premiums using Invers-Gamma Lindley distribution under Entropy loss function for the claim severity

Claim frequency distribution	Final premium
Poisson Akash under Quadratic loss function (4)	$Premium_{t+1} = 100 \frac{\theta(\theta^2 + 2)}{\theta^2} + 6 \frac{(n+1)(n+2)(n+3) + (n+1)(t+\gamma)^2}{(t+\gamma)^3 + (t+\gamma)(n+2)(n+1)}$

	$\frac{1}{\alpha - 1} \left[\frac{\Gamma(\alpha n - p + 1) \left[\alpha n - p + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right]}{\Gamma(\alpha n + 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i} \right) \left[\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right]} \right]^{\frac{1}{p}} \cdot (1)$
Poisson Akash under Linex loss function (5)	$Premium_{t+1} = 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} \left[-\frac{1}{a} \ln \left(\frac{(n+2)(n+1) + (t+\gamma+a)^2}{(t+\gamma)^{n+3}} \right) \right] \cdot \frac{1}{\alpha - 1} \left[\frac{\Gamma(\alpha n - p + 1) \left[\alpha n - p + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right]}{\Gamma(\alpha n + 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i} \right) \left[\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right]} \right]^{\frac{1}{p}} \cdot (1)$
Poisson Akash under Entropy loss function (7)	$Premium_{t+1} = 100 \frac{\gamma(\gamma^2 + 2)}{\gamma^2 + 6} \left[\frac{\Gamma(n-p+3) + \Gamma(n-p+1)(t+\gamma)^2}{(t+\theta)^{n-p+3}} \right] \cdot \frac{1}{\alpha - 1} \left[\frac{\Gamma(\alpha n - p + 1) \left[\alpha n - p + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right]}{\Gamma(\alpha n + 1) \left(\beta + \sum_{i=1}^n \frac{1}{x_i} \right) \left[\alpha n + 1 + \beta + \sum_{i=1}^n \frac{1}{x_i} \right]} \right]^{\frac{1}{p}} \cdot (1)$

5. NUMERICAL APPLICATION

For the numerical analysis, we utilized a real data set to evaluate the premiums determined solely by the number of claims and those calculated using both claim frequency and severity. We employed the different loss functions aforementioned. We focused on the data set related to one-year car insurance policies issued in 2004 or 2005. This data set can be found on the website of the Faculty of Business and Economics at Macquarie University in Sydney, Australia. For further reference, see [3]. The portfolio comprises a total of 67,856 policies, with 4,624 of them having at least one claim recorded. Among these policies, 4,333 submitted one claim, 271 filed two claims, 18 presented three claims, and 2 submitted four claims.

5.1. Premiums using only claim frequency. The following tables [4-8] represents the premiums based only on the claim frequency and using different loss functions (Quadratic, Linex (a=1.1 and a=-0.3), Entropy (p=0.2 and p=-0.2)).

TABLE 4. Premiums using Poisson-Akash with $\gamma=14.0125$

t	Claimnumber				
	0	1	2	3	4
1	93.10335	187.7328	283.7319	380.8901	478.9653
2	87.10775	175.4826	265.0100	355.5334	446.8701
3	81.84590	164.7550	248.6416	333.3880	418.8542
4	77.18976	155.2800	234.2057	313.8769	394.1853
5	73.03964	146.8484	221.3763	296.5537	372.2957
6	69.31671	139.2954	209.8972	281.0674	352.7389
7	65.95779	132.4893	199.5640	267.1384	335.1592

TABLE5.Premiums using Poisson-Akash under linex with $\gamma = 14.0125$ and $a = 1.1$

t	Claimnumber				
	0	1	2	3	4
1	89.74638	180.8718	273.2438	366.6832	460.9817
2	84.16501	169.4815	255.8516	343.1409	431.1913
3	79.24454	159.4601	240.5731	322.4814	405.0633
4	74.87319	150.5725	227.0418	304.2025	381.9597
5	70.96317	142.6349	214.9718	287.9125	361.3823
6	67.44461	135.5014	204.1363	273.3010	342.9363
7	64.26111	129.0547	194.3536	260.1196	326.3050

TABLE6.Premiums using Poisson-Akash under linex with $\gamma = 14.0125$ et $a = -0.3$

t	Claimnumber				
	0	1	2	3	4
1	94.07916	189.7294	286.7865	385.0298	484.2065
2	87.95956	177.2214	267.6655	359.1284	451.4195
3	82.59612	166.2833	250.9721	336.5396	422.8403
4	77.85570	156.6341	236.2678	316.6628	397.7068
5	73.63484	148.0569	223.2142	299.0345	375.4296
6	69.85195	140.3807	211.5459	283.2909	355.5462
7	66.44175	133.4695	201.0515	269.1430	337.6885

TABLE7.PremiumsusingPoisson-Akashunderentropywith $\gamma=14.0125$ et $p=-0.2$

t	Claimnumber				
	0	1	2	3	4
1	60.54909	151.9319	246.6078	342.9572	440.4815
2	56.67214	142.0671	230.4023	320.1982	411.0317
3	53.26630	133.4216	216.2259	300.3148	385.3215
4	50.25001	125.7803	203.7168	282.7908	362.6792
5	47.55958	118.9764	192.5945	267.2267	342.5842
6	45.14460	112.8783	182.6386	253.3087	324.6273
7	42.96458	107.3807	173.6732	240.7868	308.4824

TABLE8.PremiumsusingPoisson-Akashunderentropywith $\gamma=14.0125$ et $p=+0.2$

t	Claimnumber				
	0	1	2	3	4
1	43.30648	133.28359	227.5163	323.5812	420.8996
2	40.54181	124.65254	212.5987	302.1461	392.7958
3	38.11183	117.08492	199.5447	283.4153	368.2582
4	35.95882	110.39385	188.0226	266.9037	346.6460
5	34.03769	104.43409	177.7753	252.2361	327.4629
6	32.31269	99.09100	168.6004	239.1175	310.3188
7	30.75509	94.27286	160.3365	227.3127	294.9030

- *Discussion.* We observe that the premiums using the linex loss function in the under estimation are the highest for good drivers but also with bad drivers. The tables show that both good and bad drivers have lower premiums when employing the entropy loss function.

5.2. Premiums using both frequency and claim severity.

5.2.1. **Premiums using Inverse-Gamma Lindley under Quadratic loss function for the claim severity.** This first part shows the tables [9-13] that represents the premiums using the Invers-Gamma Lindley distribution (IGL) under the quadratic loss function for the severity claim. For the claim frequency we will use Poisson- Akash distribution (PA) under different loss functions (Quadratic, Linex ($a=1.1$ and $a=-0.3$) and Entropy ($p=0.2$ and $p=-0.2$)). These tables were calculated using formulas (11), (12) and (13) from table 1.

TABLE9. Premiums using PA under quadratic loss function and IGL under quadratic loss function with $\gamma=14.0125$, $\alpha=1.08$, $\beta=0.001766$

t	Claimnumber				
	0	1	2	3	4
1	958.7095	873.0867	1318.0627	1898.941	2592.533
2	896.9712	816.1151	1231.0910	1772.524	2418.809
3	842.7886	766.2240	1155.0526	1662.118	2267.165
4	794.8431	722.1587	1087.9913	1564.844	2133.638
5	752.1083	682.9460	1028.3929	1478.479	2015.154
6	713.7722	647.8194	975.0670	1401.271	1909.298
7	679.1846	616.1665	927.0647	1331.828	1814.142

TABLE10. Premiums using PA under linex loss function and IGL under quadratic loss function with $\gamma=14.0125$, $\alpha=1.08$, $\beta=0.001766$, $a=1.1$

t	Claimnumber				
	0	1	2	3	4
1	924.1418	841.1782	1269.3408	1828.112	2495.192
2	866.6690	788.2056	1188.5459	1710.741	2333.943
3	816.0017	741.5993	1117.5704	1607.742	2192.518
4	770.9887	700.2660	1054.7118	1516.612	2067.464

5	730.7263	663.3507	998.6409	1435.398	1956.083
6	694.4947	630.1748	948.3052	1362.552	1856.238
7	661.7134	600.1930	902.8603	1296.835	1766.217

TABLE11. Premiums using PA under linex loss function and IGL under quadratic loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, a=-0.3$

t	Claimnumber				
	0	1	2	3	4
1	968.7576	882.3723	1332.253	1919.579	2620.903
2	905.7425	824.2015	1243.427	1790.447	2443.434
3	850.5138	773.3316	1165.878	1677.830	2288.741
4	801.7004	728.4566	1097.571	1578.734	2152.699
5	758.2371	688.5663	1036.931	1490.847	2032.117
6	719.2837	652.8667	982.726	1412.356	1924.493
7	684.1680	620.7250	933.975	1341.822	1827.833

TABLE12. Premiums using PA under Entropy loss function and IGL under quadratic loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, p=-0.2$

t	Claimnumber				
	0	1	2	3	4
1	89.91753	562.9445	1419.3163	2661.842	4294.249
2	84.16011	526.3932	1326.0473	2485.199	4007.143
3	79.10233	494.3594	1244.4574	2330.875	3756.495
4	74.62302	466.0466	1172.4629	2194.864	3535.755
5	70.62765	440.8366	1108.4504	2074.064	3339.849
6	67.04132	418.2415	1051.1506	1966.041	3164.787
7	63.80391	397.8714	999.5514	1868.852	3007.392

TABLE13. Premiums using PA under Entropy loss function and IGL under quadratic loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, p=0.2$

t	Claimnumber				
	0	1	2	3	4
1	64.31164	493.8480	1309.4378	2511.456	4103.346
2	60.20601	461.8679	1223.5813	2345.089	3829.361
3	56.59740	433.8280	1148.4512	2199.711	3590.144
4	53.40011	409.0360	1082.1373	2071.558	3379.447
5	50.54717	386.9536	1020.1601	1957.716	3192.432
6	47.98548	367.1562	970.3553	1855.896	3025.294
7	45.67238	349.3038	922.7940	1764.274	2875.006

- *Discussion.* We note that the premiums using the entropy loss function are the most punitive with bad drivers and the lightest with good drivers in these tables. In addition to attracting drivers and requiring them to behave well in order to receive some very interesting premiums, this can assist insurers in establishing balance and solvability within the insurance companies. We

observe that premiums using linex loss function in the over estimation are the most severe with bad drivers, and those in the under estimation are the most severe with good drivers.

5.3.2. Premiums using Inverse-

Gamma Lindley under linex loss function for the claim severity. The premiums employing the Invers-Gamma Lindley distribution under the linex loss function for the severity claim are provided in this section's tables [14–16]. The Poisson-Akash distribution under several loss functions (Quadratic, Linex ($a=1.1$ and $a=-0.3$), and Entropy ($p=0.2$ and $p=-0.2$)) will be used to determine the claim frequency. Table 2's formulas (14), (15), and (16) were used to create the tables which follow.

TABLE14. Premiums using Poisson-Akash under Quadratic loss function and Inverse-Gamma Lindley Linex loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766$ et $a=1.1$

t	Claimnumber				
	0	1	2	3	4
1	831.8621	2293.440	4652.594	7848.582	11874.183
2	778.2924	2143.785	4345.595	7326.086	11078.501
3	731.2787	2012.731	4077.189	6869.759	10383.949
4	689.6770	1896.979	3840.471	6467.716	9772.374
5	652.5964	1793.975	3630.097	6110.755	9229.703
6	619.3326	1701.703	3441.863	5791.645	8744.865
7	589.3213	1618.557	3272.421	5504.627	8309.040

TABLE15. Premiums using Poisson-Akash under Entropy loss function and Inverse-Gamma Lindley Linex loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, a=1.1$ et $p=-0.2$

t	Claimnumber				
	0	1	2	3	4
1	564.8014	1856.730	3993.547	6943.714	10703.656
2	528.6372	1736.175	3731.115	6482.922	9988.027
3	496.8676	1630.520	3501.545	6080.351	9363.274
4	468.7316	1537.137	3298.973	5725.549	8813.068
5	443.6353	1453.988	3118.860	5410.430	8324.761
6	421.1084	1379.464	2957.635	5128.638	7888.409
7	400.7732	1312.278	2812.450	4875.112	7496.091

TABLE16. Premiums using Poisson-Akash under Entropy loss function and Inverse-Gamma Lindley Linex loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, a=1.1$ et $p=0.2$

t	Claimnumber				
	0	1	2	3	4
1	403.9624	1628.833	3684.381	6551.416	10227.818
2	378.1736	1523.355	3422.806	6117.428	9544.896
3	355.5068	1430.872	3201.411	5738.193	8948.636
4	339.4235	1349.102	3044.823	5403.891	8423.462

5	317.5033	1276.269	2878.878	5106.922	7957.314
6	301.4125	1210.972	2730.301	4841.313	7540.715
7	286.8832	1152.090	2596.477	4602.308	7166.113

- *Discussion.* According to these tables, premiums that use the entropy loss function are the gentler with all drivers, whereas those that use the quadratic loss function are the harshest with both good and bad drivers.

5.3.3. **Premiums using Inverse-Gamma Lindley under Entropy loss function for the claim severity.** This part introduces the tables [17-22] which represents the premiums using the Invers-Gamma Lindley distribution under the entropy loss function for these severity claim. Poisson-Akash distribution under different loss functions (Quadratic, Linex ($a=1.1$ and $a=-0.3$) and Entropy ($p=0.2$ and $p=-0.2$)) will be employed for the claim frequency. The formulas (17), (17) and (18) from table 3 were used to create the tables bellow.

TABLE 17. Premiums using Poisson-Akash under quadratic loss function and Inverse-Gamma Lindley under entropy loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, p=-1.1$

t	Claimnumber				
	0	1	2	3	4
1	551.1474	556.9714	860.9861	1255.7779	1728.308
2	515.6550	520.6273	804.1743	1172.1782	1612.496
3	484.5062	488.8001	754.5044	1099.1657	1511.402
4	456.9431	460.6893	710.6986	1034.8385	1422.386
5	432.3755	435.6742	671.7677	977.7245	1343.400
6	410.3367	413.2658	636.9341	926.6668	1272.831
7	390.4528	393.0733	605.5780	880.7437	1209.395

TABLE 18. Premiums using Poisson-Akash under linex loss function and Inverse-Gamma Lindley under entropy loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, a=1.1, p=-1.1$

t	Claimnumber				
	0	1	2	3	4
1	531.2749	536.6159	829.1599	1208.9383	1663.416
2	498.2347	502.8229	776.3830	1131.3205	1555.920
3	469.1068	473.0912	730.0203	1063.2070	1461.639
4	443.2296	446.7232	688.9597	1002.9424	1378.272
5	420.0833	423.1737	652.3331	949.2348	1304.020
6	399.2543	402.0097	619.4528	901.0616	1237.459
7	380.4086	382.8833	589.7672	857.6029	1177.446

TABLE 19. Premiums using Poisson-Akash under linex loss function and Inverse-Gamma Lindley under entropy loss function with $\gamma=14.0125, \alpha=1.08, \beta=0.001766, a=-0.3, p=-1.1$

t	Claimnumber
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	0	1	2	3	4
1	556.9239	562.8950	870.2552	1269.4263	1747.221
2	520.6975	525.7859	812.2324	1184.0306	1628.9912
3	488.9473	493.3343	761.5761	1109.5563	1525.1786
4	460.8853	464.7070	716.9560	1044.0235	1435.7094
5	435.8989	439.2596	677.3449	985.9903	1352.9708
6	413.5051	416.4857	641.9372	933.9975	1282.9960
7	393.3177	396.0918	610.0919	887.3526	1218.5522

TABLE20. Premiums using Poisson-Akash under entropy loss function and Inverse-Gamma Lindley under entropy loss function with $\gamma=14.0125$, $\alpha=1.08$, $\beta=0.001766$, $s = -1.1$, $p=-1.1$

T	Claimnumber				
	0	1	2	3	4
1	574.6295	569.9507	874.8278	1271.1963	1745.464
2	537.5994	532.7376	817.0750	1186.5394	1628.472
3	505.1048	500.1524	766.5856	1112.6062	1526.351
4	476.3537	471.3745	722.0595	1047.4702	1436.431
5	450.7294	445.7675	682.4906	989.6401	1356.644
6	427.7445	422.8320	647.0879	937.9439	1285.361
7	407.0082	402.1624	615.2208	891.4481	1221.286

TABLE21. Premiums using Poisson-Akash under entropy loss function and Inverse-Gamma Lindley under entropy loss function with $\gamma=14.0125$, $\alpha=1.08$, $\beta=0.001766$, $s= -0.2$, $p=-1.1$

t	Claimnumber				
	0	1	2	3	4
1	358.4347	450.7562	748.3329	1130.7149	1589.443
2	335.4842	421.4892	699.1569	1055.6795	1483.175
3	315.3225	395.8393	656.1387	990.1247	1390.402
4	297.4668	373.1690	618.1797	932.3488	1308.699
5	281.5402	352.9830	584.4292	881.0347	1236.188
6	267.2442	334.8908	554.2180	835.1478	1171.392
7	254.3390	318.5802	527.0123	793.8635	1113.135

TABLE22. Premiums using Poisson-Akash under entropy loss function and Inverse-Gamma Lindley under entropy loss function with $\gamma=14.0125$, $\alpha=1.08$, $\beta=0.001766$, $s= 0.2$, $p= -1.1$

t	Claimnumber				
	0	1	2	3	4
1	256.3630	395.4298	690.3996	1066.8330	1518.783

2	239.9969	369.8230	645.1319	996.1624	1417.373
3	225.6120	347.3711	605.5196	934.4077	1328.831
4	212.8668	327.5199	570.5557	879.9699	1250.845
5	201.4942	309.8383	539.4600	831.6114	1181.624
6	191.2827	293.9862	511.6187	788.3598	1119.761
7	182.0620	279.6916	486.5421	749.4401	1064.134

- *Discussion.* Referring to the tables, the premiums with the entropy loss function with "p=-1.1" and those with the linex loss function in the underestimation are nearly identical; these premiums are highest for poor drivers. The results also demonstrate that premiums with good and bad drivers are lower when applying the entropy loss function with "p=-0.2" and "p=0.2."

6. Conclusion

This study presented the Bayesian bonus-malus premiums for claim frequency and claim severity. Using the Bayesian approach, we employed the Poisson-Akash distribution for claim frequency and the Invers-Gamma Lindley distribution for claim severity. Different loss functions (quadratic, linex, and entropy) were additionally introduced in this work. Using the R software and an actual car insurance dataset, we computed the premiums for the frequency only and for both the frequency and the severity of the claim. We established the premiums using the several loss functions.

We found from the numerical application that premiums that use distinct loss functions for the frequency and severity of claims provide greater outcomes than those that apply the same loss function. This numerical research demonstrated that using various loss functions might provide flexible outcomes that could be very beneficial to the insurer. The insurer has a wide range of choices thanks to the wide variety of these outcomes. The insurance company selects the loss function based on its goal, offering excellent drivers the highest rewards or penalizing bad drivers most severely, deciding how to draw clients and make them attractive offers, maintaining the organization's solvability, and maintaining equilibrium.

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