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Design and Implementation of a Bonus-Malus System for Vehicle Insurance in Nigeria

Rufai A. U., Okunoye O. B., and Imohi E.

University of Lagos, Nigeria
Emails of authors: arufai@unilag.edu.ng; bokunoye@unilag.edu.ng; immanuel.imohi@gmail.com

Abstract:
Insurance companies often categorize risks based on observable factors when determining premium rates. However, many unobservable factors can also impact risk. In a competitive market, it's challenging to cross-subsidize different risk categories. To enhance profitability and growth, insurance companies must prioritize efficient pricing models. Experience rating, also known as No Claim Discount or Bonus-Malus Systems, adjusts premiums based on claims history. This study employed a risk-based adjustment model that incorporates decisions about costs fairly and equitably based on individual characteristics. Data on risk criteria, claims impact, and placement decisions for motor insurance liability portfolios in Nigeria were collected and analysed using a 5-by-5 matrix computational approach. The study concluded that motor insurance risks are influenced by individual risk criteria and that a risk-based adjustment pricing approach is essential for fair and equitable cost allocation among insured individuals.

Keywords: *Bolus-Malus Systems (BMS), Insurance, Gamma Lindley Distribution (GaL*

1. **Introduction**

Insurance companies operates in uncertain environments, based informed decision-making. In launching new products, the issues balance pricing, competitiveness, and security are taken into consideration. For non-life insurance, the estimation of future claim costs is essential in underwriting profitability. Automobile insurance presents diverse policyholder risk profiles, necessitating nuanced risk assessment. Actuaries develop tariff structures to distribute claims burdens fairly among policyholders. Insurers aim to balance premiums with projected claims, operational costs, desired profits, and capital expenditures. Risk-based pricing is vital in motor insurance, considering varying risk levels. This is achieved through risk-sensitive pricing strategies aligned with individual risk profiles. In mature markets, risk-based pricing ensures efficiency and profitability. To achieve fair premiums, insurers classify risks based on observable policyholder characteristics. However, unobservable factors like driving aggressiveness and accident-proneness are difficult to integrate into risk assessment.

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Effective risk prediction is essential for sustainability, but Nigeria's auto insurance industry faces challenges. Unlike developed markets, Nigeria relies on guided tariffs, neglecting key risk factors. Research emphasizes the need for a comprehensive risk assessment framework. Automobile insurance employs premium reductions for claim-free policyholders, leveraging experience or merit rating. By promoting responsible driving practices, Bolus-Malus System (BMS) has improved road safety, minimized claims, and reduced accidents. Recent studies contradict the traditional assumption that claim frequency and severity are independent. Insurance models need to account for the dependence between frequency and severity [1].

Actuaries face the challenge of designing fair charge structures. BMS plays a crucial role in achieving this goal, adjusting premiums according to individual claim histories. Bayesian approaches facilitate accurate parameter estimation for driving risk. Bivariate random effect models incorporate two random effects, capturing the connection between claim frequency and severity. Designing a robust BMS considering both factors becomes complex. Researchers have explored using frequency and severity data for setting premiums. Bonus-Malus System designs vary depending on insurance regulations. Well-designed BMS achieves financial balance and fairness for policyholders [1].

i. This research designed a risk-assessment framework to determine fair and equitable expected premium rates, reflecting the underlying risks and how what decisions to be considered before offering insurance services
ii. Researchers have designed a conceptual model to determine risk-based premium adjustments, optimizing actuarial fairness.
iii. The study's findings indicate that common risk factors drive both claim frequency and severity, contradicting the long-held assumption in actuarial literature that these components should be evaluated separately.
iv. The study derived risk scores, providing valuable insights into policyholder characteristics for enhanced risk assessment and stratification.

1. Related Works

A Gamma Lindley Distribution (GaL) work was done establishing Poisson-GaL distribution with the combination. This mixture improves the claim frequency modelling and Exponential-GaL mixture enhances claim severity modelling which offers increased flexibility, enabling more accurate and nuanced analysis of complex data and created more complexity in adoption [2].

In the proposal of an optimal BMS framework using a quadratic error loss function to implement BMS, a zero-utility premium calculation resulted, and this gave a negative binomial distribution claims frequency and Poisson Inverse Guassian distribution for claim frequency [3].

In the works of Pitrebois *et al.* [4], tying insurance premium to history was implemented while adopting an underreporting of minor accident. This encouraged responsible driving habits but was focused on reporting only minor incidents for effective premium evaluation.

Pitrebois *et al*. [5] considered adopting a comprehensive approach to premium evaluation but pointed that the traditional BMS has significant flaw. They considered both accident frequency and severity when determining insurance premiums but differentiate between policyholders who experience minor accidents and those involved in more severe incidents.

The utilization of posteriori ratemaking system for BMS was implemented considering rewards for accident-free driving and adherence to traffic regulations. This promotes safe driving but undermine its credibility as a risk differentiation tool [6].

In the works of Vepsalainen [8] in designing a Brazil’s motor insurance framework, the model divides policyholders into seven classes and was able to achieve the ease of navigation but the system's ability to incentivize safe driving is uncertain, At-fault claims trigger single-tier penalties.

According to Pinquet [9], a BMS premium model was explored to diverse distributions to optimize the Bayelsian BMS framework. This ended up in refining premium calculations and improving actuarial decision-making but lack of differentiation between premium payments for minor and major.

Miller & James [10] analysed survival probabilities and surplus distribution characteristics, a non-homogeneous claim occurrence was used considering a crucial effective risk assessment, but the system was complex to adopt in real life scenario. The introduction of a mixed Poisson cluster model using Fuzzy methodology to improve the prediction accuracy through non-homogenous Poisson processes was implemented by Stiglitz [7]. It was found useful with an unstable probability result. A Tunisian BMS based system which centralized the information repository on risk classes but was inaccessible of the private insurers [11].

Willmot,[12] a proposed mixed Poisson distributions with diverse prior distributions to better model claim frequency was implemented which addressed more complex distributions like negative binomial and mixed Poisson are commonly employed but exhibited overdispersion (variance exceeding the mean).

Pinquet [9], designed an optimal BMS by mixing the Poisson distribution with the inverse Gaussian distribution using Mixed Poisson.
According to Boucher *et al*.[13], a unique BMS was developed using a recursive partitioning technique to each type of insured. This was able to address number of claims reported with a smaller claim size consideration.

In the works of Pitrebois *et al*. [4], a BMS was derived to incorporate a *posteriori* and the *a priori* classification criteria.

2.2 Motor Insurance Policy in Nigeria

According to Mowbray [14], motor insurance emerged in the late 19th century, following the introduction of automobiles. By the early 20th century, specialized insurance companies and the motor tariff were established. In Nigeria, motor insurance has grown significantly, driven by urbanization and legislative changes. Nigerian motor insurance offers comprehensive coverage, including third-party protection and damage coverage. Third-party insurance is mandatory for vehicle owners. Key features include mandatory coverage, two primary categories, and additional options for enhanced protection [15].

Third-party insurance covers death, injury, and property damage to third parties. Third-party fire and theft offer coverage for specific incidents. Nigeria's motor tariff outlines underwriting standards and general regulations for all motor vehicles.

Obasi [16] categorized motor insurance based on vehicle usage. emphasized the importance of fair pricing based on sufficient proof and statistics. Insurance pricing involves making assumptions about expected costs, leading to uncertainty. Asokere and Nwankwo [17] identified factors like adequacy, reasonableness, equity, technical profitability, and induced loss prevention as crucial for effective pricing.

Despite accounting for most premiums, motor insurance usage in Nigeria is low compared to the number of motor vehicles. This represents a significant untapped opportunity. A major concern is the high prevalence of fake compulsory insurance policies sold by unregistered companies.
The motor insurance business in Nigeria is expected to grow by 7% in the next three years, with an estimated 40 million vehicles on the roads by 2020. This growth will likely lead to an increase in accidents, posing challenges for the insurance industry.

2.3 Rating System Experience

Experience ratings were introduced in Europe in the early 1960s, following research by Buhlmann [18]. Numerous studies have explored the design of optimal experience rating systems.

Loimaranta [19] developed formulas for some asymptotic properties of bonus systems, viewing them as Markov chains. Vepsäläinen applied this method to study bonus systems in various European countries. Lemaire [20], derived an algorithm for finding the optimal strategy for a policyholder and compared bonus systems in several European countries. Hastings formulated a simple model using Markov decision problems to analyse claim frequency and severity.

Markovian analysis has been widely used in actuarial applications, including bonus-malus systems (BMS). Several studies have explored optimal scale calculations. Lemaire conducted an analysis of experience rating mechanisms for motor insurance. Lemaire proposed five guidelines for constructing effective Bonus-Malus systems (BMS).

Lemaire [21] analysed 30 BMS from around the world and concluded that economic development and culture influence their design. Lemaire [22] evaluated the consumer-friendliness of 16 Asian BMS, considering cultural and economic variables. They found that the Common Law legal system and cultural variables like uncertainty avoidance influence BMS. Norris [23] conducted a Markovian study of the no-claim discount in India, using data from the Insurance Regulatory and Development Authority of India. They found that the probability of claims and the difference in NCD rates are not parallel.

2.4 Bonus-Malus System or No-Claim Discount (NCD) In Nigeria

There are various experience rating systems, including bonus-malus systems, merit-demerit systems, participating policies, and commissions in reinsurance. These systems vary widely across countries, from completely unregulated to government imposed. Some systems are considered soft, while others are severe, depending on their transition rules. When an insured person obtains a driving license, they enter the initial class of the NCD system. Throughout their driving career, transition rules are applied at each renewal to determine their new class based on their claim history. This system assumes that NCD forms a Markov chain.

The Nigeria Insurance Association (NIA) has six discount levels for private cars: 0%, 20%, 25%, 33.5%, 40%, and 50%. At the end of each policy year, policyholders move up a discount level if they have no claims. However, if they have made at least one claim, they lose all discounts and start at the 0% level. This means that regardless of their current discount level, making a claim resets their discount to 0%.

Table 1: NIA Transition Rule Description: Level of NCD System of NIA Source: NIA [24]

Starting Level	No Claim Discount
0	0%
1	20%
2	25%
3	33.5%
4	40%
5	50%

To summarise the transition matrix showing the probabilities movement among each level, the transition table below would be used to demonstrate to movement. Let P0 be the probability of no claim and (1 P0) be the probability of at least one claim.

Here,

$P=(P_i)_{5x5}$, $P_{i0} = (1-P_0)$, $i = 0, 1, 2, ..., 5; = P_0$, $i = 0, ..., 4$ and $P_{55} = P_0$

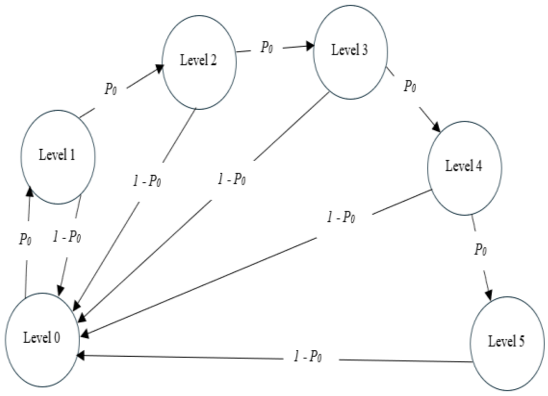

Fig. 1. Transition Diagram of discount levels of NIA Source: NIA [24]

3. Methodology

This study investigates the relationships between risk factors in motor insurance claims and their frequency of occurrence, focusing on risk-based adjustment models.

The insurance market is characterized by information asymmetry, leading to incomplete risk evaluation, adverse selection, and positive risk-coverage correlation. To ensure equitable pricing, insurers must incorporate these correlations into their risk assessment. The primary goal of pricing is to accurately evaluate individual risk and charge premiums that align with the frequency and severity of potential claims.

Coming from the risk assessment perspective for BMS modelling, three categories of datasets were needed for operation of this model which include primary, assessment, and secondary datasets. The primary dataset identifies with the insured or potential insured who needs to be insured, the assessment dataset is a list of the risked based data collected from the insurance regulator (NAICOM) and the secondary dataset are system generated using some computation mapping algorithm model which would be explained later in the section.

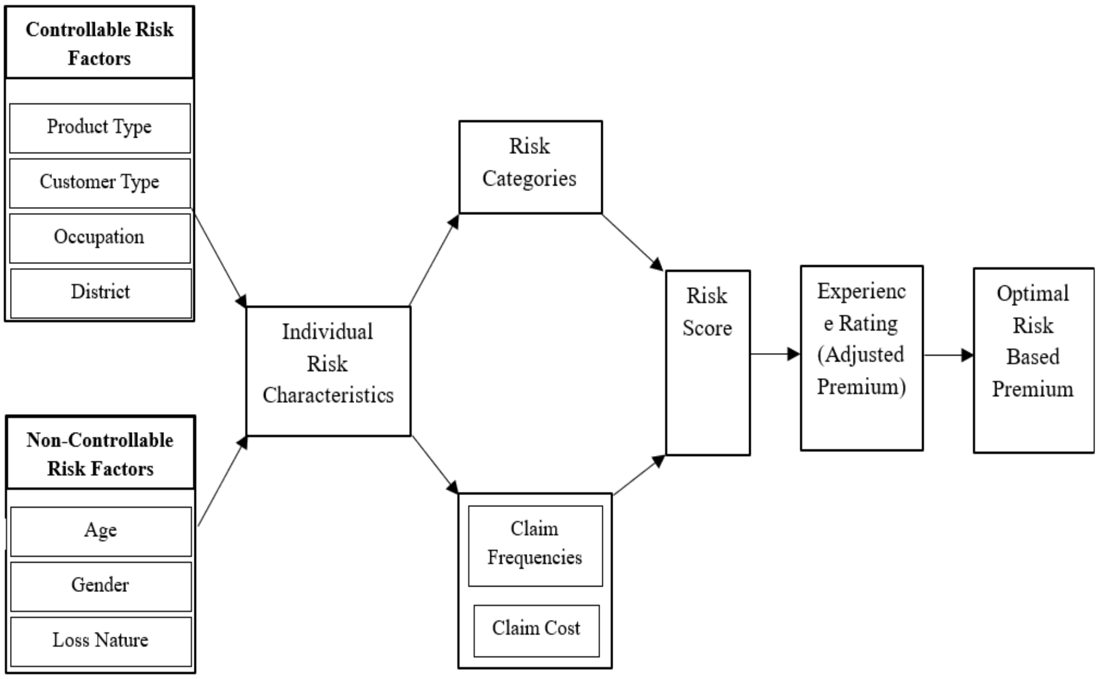

Fig.2. Conceptual framework for BMS with respect to risk criteria and claims frequency. Source: Mesike &Adeleke [25]

3.1 Data Sources

Primary dataset is collected per insured for the assessment procedure. Many a times, it comes from the KYC (Know-Your-Customer) of the insurer usually in a form manually or digitally. This dataset also aids in determining if it's an assessment is a new or existing policy.

i. Name of the user,
ii. Product Type,
iii. Category
iv. Sum-Insured
v. Premium
vi. Claims Ratio

The assessment dataset serves as the controller for the entire risk assessment evaluation. It uses the following dataset:

i. Risk Criteria
ii. Frequency of Occurrence (FOO)
iii. Severity of Impact (SOI)

The secondary dataset would be the system generated output and would be discussed at the next section of this work.

3.1 System Analysis

Analysing existing system using the approach were the implementation of a 3-by-3 model construct for assessment. The matrix is rated as High, Medium and Low. High is denoted as H; Medium is denoted as M while Low is denoted as L. These symbols are assigned corresponding values of 3, 2 and 1 respectively.

	H – 3	M – 2	L – 1
H – 3	9	6	3
M – 2	6	4	2
L - 1	3	2	1

The frequency of occurrence (FOO) and severity of impact (SOI) for each of these criteria are to be selected with respect to the denotations (H, M or L). The model gets the values assigned to each denotation and computes the products of FOO and SOI i.e.

$$F(y) = foo * soi \quad (1)$$

This gives the score for a criterion in an evaluation and runs through each of the criteria iteratively as shown below:

$$Ts = \sum F(y) \quad - \quad (2)$$

where Ts is the total score for the risk evaluation

$$Av = Ts / n_i \quad (3)$$

where i = 1, 2, 3, ..., n (number of criteria)

The Average Score (Av) gets the resultants which are represented as HH, HM, HL, MH, MM, ML, LM, LM, LL.

Where:

HH = High-High, HM = High-Medium,
HL = High-Low, MH = Medium-High,
MM = Medium-Medium,
ML = Medium-Low, LH = Low-High,

LM = Low-Medium, LL = Low-Low

Some of the shortcomings of the 3-by-3 matrix model are that the boundary of probabilities are lower which could aid a smaller business portfolio to achieve their risk management in terms of decision making but would have critical challenges when the business entity decides to increase their scale of business frontlines. Also, the 3-by-3 risk matrix for assessment is not comprehensive tool to aid a high-level decision-making standpoint.

Risk Assessment Matrix played a significant role in Enterprise Risk Framework, as if served as a tool for assessment with respect to risk tolerance and appetite. It has a 3-level of probability and 3-level of severity.
Some of its limitations of our current are:

i. It is a basic design when compared to the global risk assessment tools used in insurance business space for risk assessment.
ii. It is open to errors which could make some rejection in businesses due to its lower bound probability occurrence.
iii. It is not effectively scrutinized at the decision level. For that reason, it might become difficult to truly determine where the true boundary between acceptable and unacceptable lies.
iv. Its risk categories of risks are only bound to - Low, Medium and High.

3.3 Proposed Model

Like the 3-by-3 risk assessment matrix being used, the proposed risk matrix is 5-by-5. This tends to pose a higher advantage over the former which is a basic design and the latter having a higher probability occurrence scope and serve as a comprehensive tool used by organizations during the risk assessment stage of project planning, operations management, or job hazard analysis. It also provides a more thorough way of rating risks using a 5-point scale which has 25 possibilities compared to the former which was 9. It gives a wider range of probability occurrence for effective decision-making to mitigate or eliminate businesses loss but rather effective scrutiny consideration. Hence, provides platform for business expansion

i. Makes risk planning more effective and balance etc.

4. Results and Discussion

The interpretation of the results is given as follows based on probability:

i. Rare: Unlikely to happen and/or have minor negligible consequence
ii. Unlikely – Possible to happen and/or to have moderate consequences
iii. Moderate – Likely to happen and/or to have serious consequences
iv. Likely – Almost sure to happen and/or to have major consequences
v. Almost certain – Sure to happen and/or have major consequences

Impact:

i. Insignificant – Would not cause serious injuries or illnesses or damage
ii. Minor – Can cause injuries or illnesses or damage, only to a mild extent
iii. Significant – Can cause injuries or illnesses or damage that may require medical attention but limited treatment
iv. Major – Can cause irreversible injuries or illnesses or damage that require constant medical attention
v. Severe – Can result in fatality

Using the Risk Level Calculation Model

Risk Level = Probability x Impact

$$Rl = Pr \times Im \qquad (4)$$

4.1 Results

i. 1-4: Acceptable – No further action may be needed and maintaining control measures is encouraged
ii. 5-9: Adequate –May be considered for further analysis
iii. 10-16: Tolerable – Must be reviewed in a timely manner to carry out improvement strategies
iv. 17-25: Unacceptable –Must implement cease in activities and endorse for immediate action.

a. Discussion

With these, business entities can improve their Risk Control Measures (RCM) and Quality of Decisions (QoD) tied to the computational results which would impact on the overall risk portfolio.

Table 2: Risk Level Calculation Model. Source: https://safetyculture.com/topics/risk-assessment/5x5-risk-matrix/

Impact

How severe would the outcomes be if the risk occurred?

Probability — *What is the probability the risk will happen?*

	Insignificant 1	Minor 2	Significant 3	Major 4	Severe 5
5 Almost Certain	Medium 5	High 10	Very high 15	Extreme 20	Extreme 25
4 Likely	Medium 4	Medium 8	High 12	Very high 16	Extreme 20
3 Moderate	Low 3	Medium 6	Medium 9	High 12	Very high 15
2 Unlikely	Very low 2	Low 4	Medium 6	Medium 8	High 10
1 Rare	Very low 1	Very low 2	Low 3	Medium 4	Medium 5

5. Conclusion

Risk selection problems in the Nigerian insurance market can negatively impact insurers, regulators, and society. Unprincipled underwriting practices, where premiums are not based on sufficient data, can lead to increased motor claim costs and threaten the solvency of insurance companies. Previous studies suggest that traditional regression models may not be suitable for risk adjustment in both pre-loss and post-loss scenarios. Risk assessment-based models offer a more effective approach to pricing and risk management. These models can help determine fair premiums, mitigate adverse selection, and stabilize premiums for individual and aggregate portfolios. By adopting risk assessment-based models, Nigerian insurance companies can improve their profitability and better manage their risk exposure.

5.1 Recommendation

i. Accurate risk assessment is crucial for setting appropriate motor insurance premiums. Risk-based pricing helps calculate expected losses and ensure profitability.

ii. Insurance companies should conduct more regional research on claim amounts. Claim frequency and amounts are influenced by various factors experienced by policyholders, not just computational analysis.

iii. A sustainable motor liability insurance framework requires accurate pricing. Insurers must conduct thorough research and analysis, considering a multitude of factors, to develop intelligent pricing structures.

iv. Insurance companies should improve data collection to establish a sound tariff system. Better data can help refine rate calculations, integrate nuanced risk assessments, and encourage responsible driving behaviours.

By implementing these components, insurance companies can build a strong foundation for actuarial analysis and sustainable motor insurance risk pricing. This will help manage motor risks, improve responses to motoring challenges, and promote road safety in developing nations.

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