ON THE BAYESIAN MODELING OF ROAD ACCIDENTS DUE TO VEHICLE TYPE IN OYO STATE NIGERIA

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Abstract

Transportation plays an important role in the day to day activities of human race. Road, rail, water and air are the four major forms of transportation in Nigeria. Road transportation is the most common means of movement in Oyo State and this has raise the likelihood of the occurrence of road traffic accident even posing a serious problem that needs serious attention. Road traffic accidents would Continually increase if tangible efforts are not made to tackle is problem. In Oyo state, the epicenter of the western Nigeria, road transportation is the most popular means of transportation. Of concern is the accidents recorded daily on the roads. This study takes into account the series of accidents caused on the state roads due to vehicle types. Seven vehicle types were considered due to the data available. Bayesian Model Averaging (BMA), a variable selection approach, was used to handle uncertainty in the model selection process. Several classical approach like time series have been used in analysing road accidents but few had explored the Bayesian approach via BMA route. A uniform model prior was used with a numeric g-prior to improve the predictive performance. The trend of accidents were observed for a period of 15 years from (2006 - 2020). 78% of the models were visited and using the Posterior Inclusion Probability results (99.546%), it was seen that the accidents that occurred via private cars was the predominant. It is the most important in modeling vehicle type accidents in Oyo State Nigeria. Also, accidents for 2023 and 2024 were predicted using the posterior predictive distribution. It is imperative for concerned authorities (Federal Road Safety Corps amongst others) in the state to look into the issue of private car owners in the state.

Keywords: Bayesian Model Averaging, Posterior Inclusion Probability, Predictive, Trend, Transportation, Private Cars

1. Introduction

Transport plays a significant role in the day to day activities of man. The four main modes of transportation are air travel, road travel, river travel, and rail travel. Of these forms of transport, the most popular is road transport. As a country develops in economy, it proportionally becomes more motorized, as a result, more persons are expected to use road transport. This increase in the usage of road transport raises the probability of road traffic accident occurrence to a significant amount. Road traffic accidents are serious problems facing mankind today.

According to a 2018 World Health Organization publication on the state of global road safety (WHO), there have been increase in fatalities emanating from road traffic accident to 1.3 million annually (WHO [1]).

Nigeria is ranked as a lower middle-income economy, over the last decade an increase in Road transport accidents has been experienced. This is as a result of growing motorization and increase in urbanization in the country. As a low-income economy, road infrastructure development is still lagging, as are policy challenges in meeting international safety standards. According to Ogbodo and Nduoma [2], the death rate from road traffic accidents is 162 per 100,000 people. This data compares to the global average of 22 deaths per 100,000 people (Sukhai *et al.* [3]).

Road traffic accident has become one of the issues of great concern in Nigeria. A road traffic accident occurs almost every day, resulting in an overall increase in morbidity and mortality rates, as well as financial costs to both society and the individual involved. It is disheartening that road accident is becoming a daily occurrence due to the fact that road traffic integration is treated as secondary issue in Nigeria.

According to Sanusi, *et al.* [4], road traffic accident has been classified using the International Statistical Classification of Diseases and Related Health Problems, as one of the leading causes of death worldwide. Road traffic accident was defined by Odugbemi [5] as anything that occur by chance, anything happening unexpectedly and undersigned. It has been noticed that there is an overall increase in the incidence, morbidity, and mortality rates of road traffic accidents around the world, with the majority of these fatalities and morbidities occurring in developing nations such as Nigeria. (Eze [6]; Agbonkhese *et al.* [7]).

Road traffic accidents are caused by one or more of three basic variables: environmental factors, mechanical factors, and human factors. Human factors are considered to be responsible for around 80% of all traffic accidents since drivers' operating ability is critical to the causes and prevention of traffic accidents Afolabi and Gbadamosi [8]. Agbonkhese, *et al.* [7] opined that on many Nigerian roads, deterioration often begins with the production of cracks or potholes on the road tarmacs, which vary depending on their configuration, traffic flow, forms, amplitude of stress, and rate of deformation. Aside from human and vehicle factors, the existence of these potholes is known to be one of the leading causes of road traffic accidents in Nigeria.

Deaths from reckless driving are the third biggest cause of mortality in Nigeria as a whole. According to Agbonkhese *et al.* [7], 473 people died in a total of 1,115 automotive accidents in Nigeria in 2012, while more people perished in vehicular accidents in 2013. They advocated for treating road traffic accidents as a serious issue that requires immediate attention in order to prevent early deaths and reduce the health, social, and economic consequences for the typical Nigerian.

Despite the scale of the problem and the loss of life, Oyo state has failed to receive the necessary attention. It is past time for the government to prioritize road traffic accidents in order to reduce their health, social, and economic consequences. In this project, an analysis of a 15-year (2006-2020) publically accessible data set will be sought to reveal patterns and traffic conditions on Oyo state's highways. The primary goal is to analyze the prevalence of accidents in Oyo state based on deaths, causative agent, and kind of vehicle involved.

Many safety strategies have been put in place by the Nigerian Government to check the menace of road traffic accidents through its agencies. For these policies to be effective continuous researches on the Road Traffic Accident (RTA) cases as well as on the implementation of the policies need to be carried out. Therefore, considering the importance of the road and the increased level of road traffic accidents in recent years, there is the need for this study which aimed at obtaining a model which would show the pattern of road traffic accidents. This would provide a parameter for assessing the effectiveness of current strategies for reducing accidents on our roads and for the development of new strategies where necessary by those responsible for maintaining safety on our local

2. Nigerian Road Traffic Accidents

A crash is an unexpected event that causes damage, injuries, and, in extreme cases, death. A crash might be single (just one vehicle involved) or multiple (two or more vehicles involved). Accidents are classified as fatal, serious, or minor. A crash is considered fatal when there is a loss of human life. A serious crash occurs when someone is critically hurt and hospitalized, whereas a minor crash occurs when no injuries occur or when the victim is treated for minor injuries and immediately dismissed from the hospital. According to Chun *et al.* [9] and Abayomi [10], the causes of road traffic accidents can be divided into three categories: human factors, mechanical factors, and environmental factors.

According to Oyenuga *et al.* [11], human factors account for approximately 80% of the causes of road traffic accidents, with the following being the leading causes: drunk driving, illiteracy, psychological factors, reliance, poor vision, temperaments, overconfidence, poor driving culture, economic factors, and underage drivers. Mechanical issues include the usage of motorized vehicles such as cars, trucks, buses, and motorcycles without adequate maintenance. Iwok [12] concurs that, while the driver (human factor) accounts for roughly 80% of the causal index of road crashes in Nigeria, vehicle conditions are a component that cannot be overlooked in this type of analysis. The geography of most of Nigeria's road network presents significant challenges to road development. Mountains, valleys, and rivers lead to acute bends, steep bills, and sharp slopes, all of which are potentially dangerous aspects for inexperienced highway motorists. Our tropical climate also presents difficulties for drivers. Heavy rainfall in the south and abnormally hot weather conditions, along with harmattan dust in northern Nigeria, have an impact on our road network. Potholes are easily formed, and deadly black's pots all pose obstacles to reading users.

In his study titled "Time Series Analysis of Road Accident in Osun State," Iwok [12] suggested that in order to better the work of the FRSC, there should be an emergency line for the commission to contact in case of an accident. Aluko [13] used multiple correlation coefficients to analyze her data and came to the conclusion that if the government improves the measures against motor vehicle accidents, the total number of accidents and adverse socioeconomic effects would be greatly reduced, allowing the country to move forward positively into an advanced or developing country. Trivedi and Rawal [14], evaluated the frequency of major and minor road traffic accidents among young drivers, as well as its relationship with driving practices. The study employed a cross-sectional design with young drivers drawn from tuition programs in Ahmedabad and Vadodara. The findings revealed that the prevalence of road traffic accidents is high among young drivers and is associated to driving at high speeds, using mobile phones, and failing to observe safety measures while driving.

According to Agbonkhese *et al.* [7], reckless driving deaths are the third biggest cause of death in Nigeria. According to Agbonkhese *et al.* [7], at least 473 people died in a total of 1,115 automobile incidents in Nigeria in 2012. More people perished in automotive accidents in 2013. They advocated for treating road traffic accidents as a serious issue that requires immediate attention in order to prevent early deaths and reduce the health, social, and economic consequences for the typical Nigerian. Using bus priority measures in Melbourne and analyzing resultant road safety performance and bus-involved accidents, Chun *et al.* [9], summarized their findings. An empirical investigation of accident types found a considerable reduction in the proportion of accidents involving buses colliding with stationary objects and cars, indicating the influence of bus priority in addressing bus maneuverability concerns. A main result of this study is that bus priority improves road safety in Melbourne and should be a major concern for road management organizations when implementing bus priority and road plans. Abdulkabir and Edem [15], investigated the pattern of accident occurrence in Ibadan, Nigeria. Their research revealed an increase tendency.

According to Sanusi *et al.* [4], vehicle traffic accidents in Nigeria have been increasing at an alarming rate. They examined road traffic accidents in Nigeria from 1960 to 2013 using time series analysis. They provided appropriate Autoregressive Integrated Moving Average (ARIMA) models for several kinds of road accidents, including minor cases, major cases, fatal cases, and total cases. They discovered that the ARIMA (1,1,1) model works best for minor and total cases, the ARIMA (1,1,0) model works best for serious instances, and the ARIMA (0,1,1) model works best for fatal cases. The forecast based on the various models suggests an average increase in the data for all scenarios. Iwok [12], utilized the ARIMA model to fit data from road traffic accidents in Port Harcourt. The seasonal-ARIMA model was found to fit the data in the study. Oyenuga *et al.* [11], also analyzed the pattern of monthly road accidents data along Oyo-Ibadan express road between 2004 to 2014. They employed moving average method to decompose the time series using additive model approach. From the result they observed that accidents and deaths were higher at festive periods. Emenike and Kanu [18], examined how road traffic accidents can be caused by drivers distraction in Port Harcourt. The study also publicized that the use of mobile phones and gadgets in vehicles were blamable for most accidents involving commercial drivers.

Aluko [13], investigated the characteristics of road accident victims in Ado-Ekiti, Nigeria. According to the report, a bigger proportion of those involved in vehicle accidents were of working age. Macharia *et al.* [19] examined monthly road accident data for eight years, beginning in January 2010 and ending in December 2017. They used the Box-Jekins method for the analysis and Eviews as the statistical software. The study found no seasonality in the data, contradicting popular notion that accidents in this region of the world are seasonal, with increased incidence in September, October, November, and December. This implies that road accidents occur throughout the year, not just during specific seasons, within the research area. Feldkircher and Zeugner [20], utilized the ARIMA model to anticipate accidents up to ten years later (2030) and characterize the frequency of road traffic incidents that result in harm. A total of 70039 road traffic accidents were recorded during the 9-year observation period (from 2013 to 2021). The time plot shows a systematic shift, indicating a trend in the data. Furthermore, the trend exhibits an exponential decrease. This analysis concluded that traffic accidents are falling exponentially at a rate of 0.360 per year. The number of road accidents was predicted to fall to 47 (97%) by 2030, which is higher than the current objective of 50%, and that the time series for the yearly number of road traffic accidents did not exhibit substantial seasonality or moving average components.

The significance of this study is that it provides a method of minimizing the number of road traffic accidents/collisions in Oyo state and throughout Nigeria. It will assist road users and management of the Federal Road Safety Corps and the Nigeria police in determining the rate and working toward the reduction of accidents in Oyo state, particularly in the always busy and congested areas that have the highest reported cases and casualties of road traffic crash/accidents.

3. Methodology

3.1. Averaging in the Bayesian Model (BMA)

Canonical regression problems including model uncertainty are addressed with Bayesian Model Averaging (BMA) Akanbi and Oladoja, [21], (Akanbi and Oladoja [22], Obisesan and Oladoja [23]). Given a linear model, y is the response variable, μ_i is the intercept, and φ_j are the predictors,

$$y = \mu_i + X_j\varphi_j + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I) \tag{1}$$

where ε is independently and identically distributed with mean zero and variance σ^2 The problem arises if matrix X has a large number of explanatory variables. It is inefficient or even impossible to draw conclusions from a single linear model that includes all variables when the sample size is small. An alternative strategy is to estimate models for all possible combinations of [X] and then construct a weighted average of those models. The estimate of 2^K models is required if X consists of K potential variables. As a result of Bayes' theorem, posterior model probabilities are used for weighting the models.

$$p(B_j|y, X) = \frac{p(y|B_j, X)p(B_j)}{p(y|X)} = \frac{p(y|B_j, X)p(B_j)}{\sum_{s=1}^{2^K} p(y|B_s, X)p(B_s)} \tag{2}$$

The integrated likelihood over all models is denoted by the multiplicative term $p(y|X)$. In other words, the posterior model probability (PMP) $(p(B_j|y, X))$ can be determined as a function of the model's marginal likelihood (MLM) $(p(y|B_j, X)$, the probability of the data given the model) multiplied by a prior model probability $(p(B_j)$ - a researcher's belief before looking at data is the likelihood of the model being accurate. For any statistic, renormalization yields the model weighted posterior distribution (MWPD) π.

$$p(\pi|y, X) = \sum_{j=1}^{2^K} p(\pi|B_j, X)p(B_j|X, y) \tag{3}$$

Priors on the model parameters must be specified in order to obtain posterior distributions. The constant variance and error variance here have 'improper' priors, which means their distribution is equal. The researcher constructs a normal distribution based on her prior beliefs on coefficients before analyzing the data. Often, it is assumed that the coefficients have zero prior means because little is known about them. Their variance structure is

$$\varphi_j|g \sim N\left(0, \sigma^2 \left(\frac{1}{g} X_j' X_j\right)^{-1}\right) \tag{4}$$

Essentially, the researcher believes coefficients are zero and their variance-covariance structure closely matches the data's. In relation to g, a researcher's level of certainty is expressed by the degree to which he or she believes that coefficients are indeed zero. It implies that the researcher is confident (or conservative) that there are no prior coefficient variances. An increase in g, in contrast, indicates a researcher's uncertainty about the coefficients.

3.2. Predictive Performance of Priors in BMA

Forecasting is a primary goal of statistical analysis. Similarly, there is always the argument that, everything else being equal, when comparing rival modeling systems, we are more impressed with a modeling strategy that consistently assigns greater probabilities to the events that really occur. Thus, one way to assess the efficacy of a BMA strategy is to measure how effectively a model predicts future data. The logarithmic scoring rule, which is based on the conditional predictive ordinate, is one measure of predicting ability. The Log Prediction Score (LPS) specifically gauges an individual model's predictive skill by summing the logarithms of the observed ordinates of the predictive density for each observation in the test set.

$$-\sum_{d \in D^{test}} logP(d|B, D^{train}) \tag{5}$$

The LPS is considered by splitting the data into two halves: training set, D^{train} (which will use the observation to estimate the BMA predictive distribution by obtaining the parameter posterior distributions, $P(\pi_j|y^*, B_j)$ and testing set, D^{test} (this formula forms the weights over the space of the model to measure its predictive ability). In order to find the posterior predictive density, you have to take the predictive likelihood and the posterior distribution of the parameters and multiply them.

$$p(\tilde{y}|y^*, B_j) = \int_{\pi_j} p(\tilde{y}|\pi_j, y^*, B_j)p(\pi_j|y^*, B_j)d\pi_j \tag{6}$$

It indicates how likely it is that the future observations $\tilde{y}$ have been generated under model B_j given data y^*.

$$-\sum_{d \in D^{test}} log\left[\sum_{B \in A} P(d|Z, D^{train})P(B|D^{train}\right] \tag{7}$$

The better the prediction performance, the smaller the log predictive score for a specific model or model average. We can see that the logarithmic scoring rule is correct. There are two kinds of disparities between observed and expected values in probabilistic predictions: the predictor tends to overestimate or underestimate their predictive accuracy because of predictive biases (synthetically predicting on either side) and lack of calibration (synthetically underestimating or overestimating). The predicted log score is a bias and calibration metric.

4. Results and Discussion

4.1. Exploratory Data Analysis

The data for this study is road accident data sourced from Oyo State Bureau of Statistics. It includes the types of vehicle (taxi, private car, bus, motor lorry, motor cycle, pedal cycle and hand manual) plying the road in the state. It is an annual data that spans from 2006 to 2020. Nigeria's inland state of Oyo is located in the southwest. According to the 2016 estimate, Oyo State's population is estimated at 7,840,864. Road is a major means of travelling in the state with, the state capital and previously the continent's second most populous city, Ibadan a commercial hub linking the west to the northern axis of the country. On the average, the number of accidents caused by private car outweighs that of the other vehicle types while accidents caused by pedal cycle has the least number of accidents as displayed in Table 1 below in the state.

Table 1: *Five-Figure Summary of Road Accidents Due to Vehicle Types in Oyo State from 2006 to 2020*

Vehicle	Minimum	1^{st} Quartile	Median	Mean	3^{rd} Quartile	Maximum
Taxi	8.0	36.5	60.0	97.3	147.5	323.0
Private Car	14.0	152.5	192.0	218.9	250.0	677.0
Bus	13.0	119.5	163.0	197.1	193.5	695.0
Motor Lorry	3.0	100.0	130.0	160.1	189.0	426.0
Motor Cycle	10.0	98.0	129.0	179.3	242.0	473.0
Pedal Cycle	0.0	5.0	16.0	22.6	39.0	63.0
Hand Manual	0.0	13.0	50.0	53.53	65.0	152.0

The trend for accident due to vehicle types is displayed in Figure 1 below.The trend shows that the highest number of road accidents in the state occurred in 2013 and the number of road accidents begins to reduce in 2020 due to the COVID'19 outbreak.

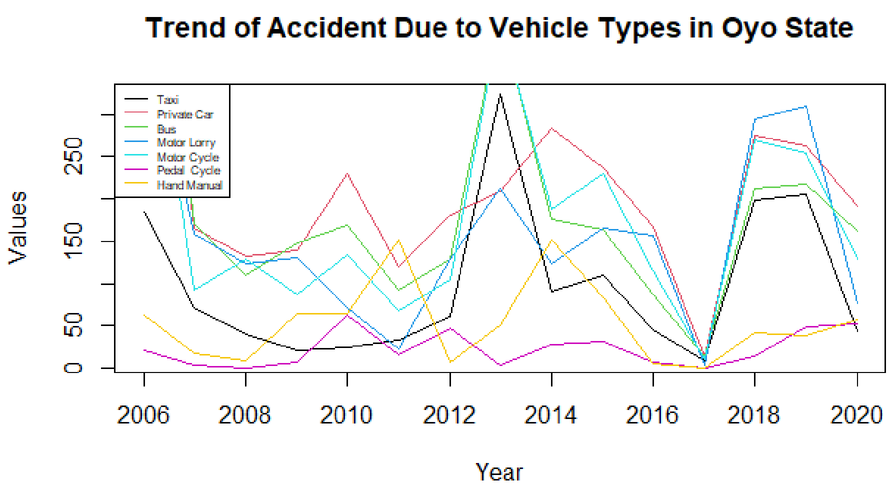

Figure 1: *Time Plots for Vehicle Types of Road Accidents in Oyo State*

4.2. Bayesian Model Averaging of Road Accidents

The study variable is the serious occurrences of accidents in the state from 2006 to 2020 and the predictor are the accidents caused by different type of vehicles namely taxis (TAXI), private cars (PRIVATE.CAR), bus (BUS), motor lorry (MOTOR.LORRY), motor cycle (MOTOR.CYCLE), pedal cycle (PEDAL.CYCLE) hand manual (HAND.MANUAL). The Markov Chain Monte Carlo sampler uses 100,000 draws after the burn ins of 25,000 with uniform distribution as the prior model and the numeric modified g-priors for the parameters. Therefore the accident model due to vehicle types is given as

$$Accidents = \theta_0 + \theta_1 TAXI + \theta_2 PRIVATE.CAR + \theta_3 BUS + \theta_4 MOTOR.LORRY$$
$$+\theta_5 MOTOR.CYCLE + \theta_6 PEDAL.CYCLE + \theta_7 HAND.MANUAL + \epsilon$$

where, ϵ is a stochastic error term, independent and identically distributed as $N(0, \sigma^2)$.

The posterior probabilities of incorporating each of the regressors are shown in Table 2. It can be seen that there are 7 explanatory factors and 15 years of observations of relevance. The model space is 128 and the number of models visited is 100, indicating that 78% of the models were visited. The modified g-prior employed for the application to significant accidents caused by vehicle types in Oyo State, Nigeria, established that the shrinkage factor was close to one, indicating overfitting. The averages and standard deviations of the Posterior Inclusion

Table 2: *Summary of the Posterior Probabilities of Including each of the Regressors*

Variables	7
Observations	15
Mean no. regressors	0.9973
Draw	100000
Burnings	25000
No. models visited	100
Model Space 2^K	128
% Visited	78
% Top Models	100
Corr PMP	1.000
Model Prior g-prior	Uniform/3.5 numeric
Shrinkage-Stats (Average)	1.0

Probabilities (PIP) of each regressor in the vehicle type accident model are shown in Table 3. Post Mean represents the coefficients averaged over all models, even those in which the variable was not present (implying that the coefficient is zero in this case). The covariate private automobiles with a PIP of 99% and a relatively big coefficient band appears to be the most relevant in modeling Nigeria vehicle type accidents in Oyo state. This demonstrates that private cars play an important part in the selection of any vehicle type accident model in Oyo state. Table 4 displays the posterior

Table 3: *Posterior Probabilities of including the Regressors in the Accident Model*

Regressors	PIP	Post Mean	Post SD	Cond.Pos.Sign	Index
PRIVATE.CAR	0.99546	1.4382	0.1462	1.0000	2
BUS	0.00147	0.10216	0.2980	0.96599	3
PEDAL.CYCLE	0.00033	-1.4630	0.9392	0.00000	6
TAXI	0.00002	-0.19399	0.2613	0.00000	1
MOTOR.CYCLE	0.00001	0.1553	0.2797	0.00000	5
MOTOR.LORRY	0.00000	0.00000	0.00000	0.00000	4
HAND.MANUAL	0.00000	0.00000	0.00000	0.00000	7

probability of the top five models out of the 128 visited for both the MCMC and precise samplers. This table shows that the best model, with a probability of 99.5%, depicts vehicle type accidents in Oyo State, with private automobile as the predictor. The chart shows that the genuine vehicle type accident model (20) is always preferred over any other model. Figure 2 depicts the prior

Table 4: *Best 5 models of 128 models visited*

Model	PMP (Exact)	PMP (MCMC)	Predictors
20	0.99492	0.99505	PRIVATE.CAR
00	0.00350	0.00312	
10	0.00118	0.00058	BUS
22	0.000204	0.000060	PRIVATE.CAR, PEDAL.CYCLE
28	0.000078	0.00026	PRIVATE.CAR, MOTOR.LORRY

and posterior distribution of model sizes, which helps to demonstrate the impact of the model prior assumption on the estimation outcomes. In accordance with the literature (Ley and Steel, 2009; Eicher *et al.*, 2011), the plot created allows for visual clarity of the choice of model prior on posterior outcomes.

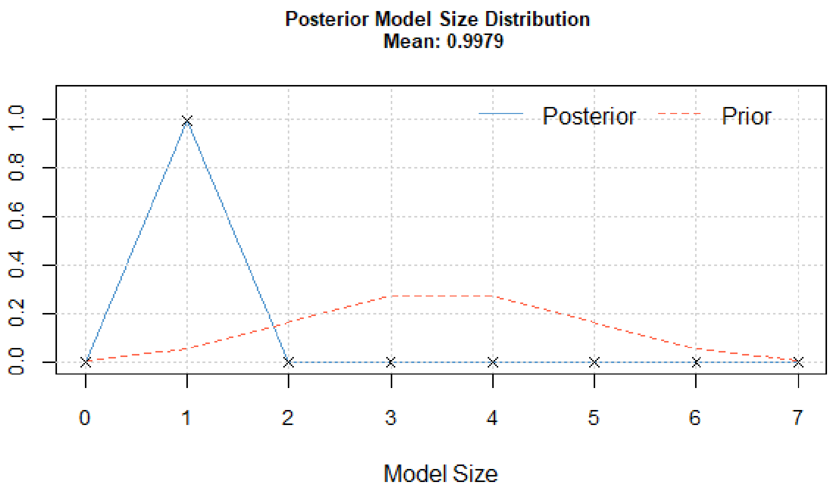

Figure 2: *Posterior Model Size Distribution with Uniform Model Priors*

Figure 3 depicts the mixed marginal posterior density for the significant regression coefficients. The red dotted vertical lines represent the equivalent standard deviation bounds from the MCMC technique, while the red and green vertical lines represent the conditional expected value and median, respectively. The charts show that the values of the conditional expected value and the median are very close to each other. Given that the related variable is included in the regression, the density in the graphs describes the posterior distribution of the regression coefficient.

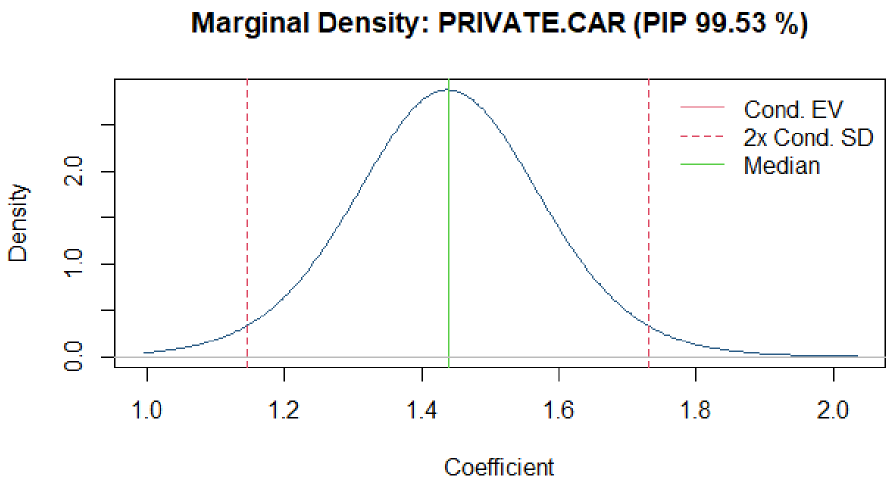

Figure 3: *Posterior Density of Private Cars Accidents in Oyo State*

Bayesian Model Averaging lends itself not only to inference, but also to prediction. The employed Bayesian regression models naturally give rise to predictive densities, whose mixtures yields the BMA predictive density. The predictive density represents the likelihood of future accidents based on our fitted model. Using the information from the first 15 years (2006-2020) to forecast vehicle type accidents for the next two years, namely 2023 and 2024 as displayed in Table 5 below. The 95% credible intervals were also estimated.

5. Conclusion

Because BMA provides researchers with a thorough framework for measuring model uncertainty, the theoretical and empirical evidence presented in this paper demonstrates the vital role of previous assumptions in BMA. In Oyo state, Nigeria, road accidents were on the high side in 2013. Series of vehicle types accident were monitored from 2006 to 2020 namely Taxi, Private Cars, Bus, Motor Lorry, Motor Cycle, Pedal Cycle and Hand Manuals. Using model averaging approach, the posterior probabilities of the explanatory variables was able to visit the 78% of the model space. Private Cars with a Posterior Inclusion Probability of 99% is important in modelling vehicle type accidents in Oyo state Nigeria. There is need for concerned authorities (Federal Road Safety Corps amongst others) in the state to look into the issue of private car owners in the state.

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Conflict of Interest

The authors declare no conflict of interest.

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