THE IMPACT OF PAVEMENT CONDITIONS ON ACCIDENT SEVERITIES

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Abstract

This paper focuses on the aspect of road safety based on the impact of pavement conditions on accident severities. Four models of binomial and multinomial logistic regression were produced using the R software and utilizing two years of accident and pavement conditions data on Malaysian highways. The surface characteristics analyzed included the International Roughness Index (IRI), rut depth (RD) and mean texture depth (MTD). The accident severity assessed ranged from damage to death. Results indicated that IRI has the highest tendency to affect accident severity for all models. At the thresholds identified for all independent variables, the chances of death had increased significantly. As such, efforts must be driven to ensure the thresholds are not reached in the maintenance of pavements for better road safety.

Keywords: **Accident severity, Pavement condition, Binomial logistic regression model, Multinomial logistic regression model**

Introduction

Road accident is a common occurrence in many countries. Malaysia is no exception. The efforts to curb rising road accident rate have so far focused on physical measures such as the implementation of Automated Enforcement System (AES), the Variable Message System (VMS), signboards, alert signals, improved road infrastructure and facilities, better driver training programmes, improved vehicles quality, and better enforcements through appointed bodies such as the Jabatan Pengangkutan Jalan (JPJ). Despite all these safety measures in place, the death rate remains at an alarming figure of approximately 6,000 cases yearly (MOT, 2019). This has prompted the Malaysian Institute of Road Safety Research (MIROS) to implement the Road Safety Plan 2014-2020 to reduce 50% of the predicted deaths from 10,716 to 5,358 deaths by the year 2020 (MOT, 2014). Needless to say, the plan

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can only be effective when the factors contributing to the rising accident rate are correctly identified and addressed.

The factors contributing to road accidents are multi-dimensional. These include driver awareness, driver behavior, maneuvering, speeding, pavement conditions, weather, environmental influences, and vehicle conditions (Andriejauskas *et al*., 2014). According to Gicquel *et al*. (2017), the main factor is human error, but the pavement condition is another important factor that should not be overlooked. Li *et al*. (2013) have also stated that poor pavement conditions are often linked to severe accidents. Researchers such as Karlaftis and Golias (2002) and Han *et al*. (2011) have identified poor pavement condition as the leading factor of road accidents on the highway. Al-Masaeid (1997) found about 45% of rural road accidents captured by his study were caused by poor pavement conditions. This was estimated at 31% in the study of Smith and Larson (2010). In the study of Darma *et al*. (2017), 11.25% of the total road deaths are related to road defects. These figures attest to the importance of avoiding or improving poor pavement conditions to reduce road accidents.

In Malaysia, Hosseinpour *et al*. (2013) examined the effects of roadway characteristics on pedestrian-vehicle accidents. Shahid *et al*. (2015) studied the spatial and temporal variation of accidents in Peninsula Malaysia. Abdul Manan *et al*. (2018) studied factors contributing to motorcycle accidents in the nation. Darma *et al*. (2017) analyzed accidents related to death caused by various road environments in Malaysia. Hamsan *et al*. (2018) assessed pavement conditions on state roads in the Petaling district in Selangor for maintenance forecasting. Khalifa *et al*. (2020) studied the impact of heavy vehicle damage on local roads in Ampang Jaya at Kuala Lumpur. Musa *et al*. (2020) investigated accident severities on federal roads in Malaysia. However, investigation on the impact of pavement conditions on accident severities on Malaysian highways has not been the main research topic thus far.

Table 1 below depicts the findings by Darma *et al*. (2017) on Malaysian roads which indicated that the highest accident deaths are at state and municipal roads. However, when quantified according to death per kilometer, expressways have a shorter length compared to state and municipal roads, and thus making expressways having the highest rate of death per kilometer.

Contradict to the above-mentioned, Chen *et al*. (2017) discovered that the likelihood of an accident increases when pavement quality improves since some drivers tend to speed when the pavement condition is good. Nevertheless, a high level of pavement roughness is in general an unfavourable condition for road users. The Jabatan Kerja Raya (JKR) recommended the IRI value of 1.6 m/km for four-lane highways, 2.5 m/km for two-way highways, and 8 m/km for minor roads (JKR, 2008). The Malaysian Highway Authority (MHA) proposed IRI below 3 m/km as good and fair IRI levels. The most stringent has been the Federal Highway Administration (FHWA), which suggested that a threshold of 2.7 m/km is recommended for acceptable ride quality (Arhin *et al*., 2015).

The research on the impact of pavement roughness on road accidents is not a new topic. For instance, Chan *et al*. (2010) has reported that higher IRI considerably increases the risk of all types of accidents. Similarly, Ihs (2004) discovered that, as the IRI rises, the accident rate rises as well. IRI, according to Anastasopoulos *et al*. (2012), increases the rate of accidents by 95.72% of the road section. In the study of Mamlouk *et al*. (2018), the accident rate had increased significantly when the IRI value was above 3.16 m/km. Kassu and Anderson (2019) found that increasing IRI increases the likelihood of non-severe dry pavement accidents and severe wet pavement accidents. Nevertheless, smoother roads may increase road accidents in certain cases, as reported by Buddhavarapu *et al*. (2013). In Iowa, Alhasan *et al*. (2018) stated the increase in IRI value has contributed in decreasing the number of road accidents. Some other authors such as Anastasopoulos and Mannering (2011) opined that IRI is not a significant factor in causing road accidents.

In addition, there are also research conducted on accidents involving rutting. According to Cenek *et al*. (2014), the accident rate is lower when the rut depth is lesser than 10 mm but remains constant for rut depths up to 30 mm. A similar conclusion was reached in Mamlouk *et al*. (2018). Rutting has also been linked to a high number of road accidents in Turkey (Tortum *et al*., 2012). High rutting,

Table 1. Rate of fatal accidents on Malaysian road year 2012 (Darma *et al.*, 2017)

Road category	Number of drivers/ rider fatalities	Road length (km)	Rate of driver/ rider fatalities per kilometer
Expressways	704	1,742	0.404
Federal roads	2,252	17,474	0.129
State and municipal roads	2,860	108,301	0.026

according to Anastasopoulos *et al*. (2012), increased accident rates by 94.27% due to hydroplaning and vehicle loss of control in the presence of excessive rut. Cairney and Bennet (2008); Cenek *et al*. (2014) and Mamlouk *et al*. (2018) found that rut depths up to 10 mm did not increase the accident rate significantly, whereas Alhasan *et al*. (2018) did not discover any consistent relationship between the total number of accidents and rut depth.

Another interesting correlation that has been consistently studied is between mean texture depth and accidents. Fernandes and Neves (2011) found a substantial link between accidents and low macrotexture, particularly in urban areas compared to rural areas. In Jordan, wet pavement accidents account for 20% of all accidents, indicating that insufficient skid resistance causes road accidents (Ramadan and Muslih, 2013). Kassu and Anderson (2019) researched on a dry pavement surface and concluded that the chances of road accident increases as mean texture depth increases, but not on a wet pavement surface. According to Anastasopoulos and Mannering (2011), increased pavement friction leads to an increase in the number of accidents resulting in injuries.

This research has adopted the binomial logistic regression and multinomial logistic regression models to determine the probability of accident severity in relation to pavement conditions on Malaysian highways. The binomial logistic regression model provides a relationship between the identified independent variables on accident severity as the dependent variable to make predictions and assess the resultant probabilities (Al-Jabri, 2015). This binomial logistic regression has been implemented with the following assumptions - there is a relationship between the dependent and independent variables; the relationship is linear between the log-odds (logit) of the outcome and the predictor variable; there is no outlier in the continuous independent variable(s); and there is no multicollinearity problem.

Equation (1) to Equation (3) defines the mathematical forms of the binomial logistic regression model. In this study, four severity levels have been defined, which are Y=1 (Damage), Y=2 (Minor Injury), Y=3 (Serious Injury) and Y=4 (Death). Equation (1) determines the probability of death against all other accident severities based on the pavement conditions, defined using the three parameters IRI, RD and MTD. Equation (2) determines the probability between severe accidents and non-severe accidents based on pavement conditions. Death and serious injury are categorised as severe accidents while minor injury and damage are grouped as non-severe accidents. Equation 3 determines the probability of all other accident severities against damage on pavement conditions.

$$In\left[\frac{p(Y=4)}{1-p(Y=4)}\right] = \beta_1 + \sum \beta_i X_i \quad (1)$$

$$In\left[\frac{p(Y=4,Y=3)}{1-p(Y=4,Y=3)}\right] = \beta_2 + \sum \beta_i X_i \quad (2)$$

$$In\left[\frac{p(Y=4,Y=3,Y=2)}{1-p(Y=4,Y=3,Y=2)}\right] = \beta_3 + \sum \beta_i X_i \quad (3)$$

where

p represents the probability of severity levels (1, 2, 3 or 4);
β is a model coefficient to be estimated;
X represents a set of explanatory variables at the individual level
i represents number of observations

A multinomial logistic regression model is suited to assess categorical data (Islam and Mannering, 2006) without assuming normality, linearity or homoscedasticity (Malyshkina and Mannering, 2009; Abdulhafedh, 2017). For this reason, it has been adopted in this study to model accident severities and improve the fitted model with only the significant variables in comparison to the full model. This means that the assumption of independence of irrelevant alternatives (IIAs) was investigated in the multinomial logistic regression to ensure that the addition or removal of alternative outcome categories would not affect the prediction of the remaining outcomes (Yasmin and Eluru, 2013).

The mathematical equations pertaining to the multinomial logistic regression model are shown in Equation (4) to Equation (6). The four severity levels are defined by Y=1 (Damage), Y=2 (Minor Injury), Y=3 (Serious Injury) and Y=4 (Death) with Y=1 as the reference category.

$$In\left[\frac{p(Y=2)}{p(Y=1)}\right] = \beta_{21} + \sum \beta_i X_i \quad (4)$$

$$In\left[\frac{p(Y=3)}{p(Y=1)}\right] = \beta_{31} + \sum \beta_i X_i \quad (5)$$

$$In\left[\frac{p(Y=4)}{p(Y=1)}\right] = \beta_{41} + \sum \beta_i X_i \quad (6)$$

where

p represents the probability of severity level (1, 2, 3 or 4);
β is a model coefficient to be estimated;
X represents a set of explanatory variables at the individual level
i represents number of observations

Table 2. Data categorization

Attributes	Data Type	Levels	Description
Fatalities	Binary	0	Serious Injury, Minor Injury and Damage
		1	Death
Injuries	Binary	0	Minor injury and Damage
		1	Death and Serious injury
Damages	Binary	0	Damage
		1	Death, Serious Injury and Minor injury
Severities	Multiple	1	Damage
		2	Minor Injury
		3	Serious Injury
		4	Death
IRI	Continuous	-	0.76 m/km - 5.83 m/km
RD	Continuous	-	0.90 mm - 12.40 mm
MTD	Continuous	-	0.30 mm - 2.00 mm

Within the existing literature, Haadi (2014) had applied binomial logistic regression on accident severities in Ghana. Yau *et al*. (2006) modelled the binomial logistic regression model by categorizing two-year accident severities data into two categories which are fatal/serious and slight. Sze and Wong (2007) investigated the probability of deaths and the probability of severe injury of a pedestrian using binomial logistic regression. Al-Ghamdi (2002) used two binary variables (fatal and non-fatal) as the dependent variables. Jung *et al*. (2014) employed a multinomial logistic regression model to examine impact factors on highway safety on Wisconsin highway. Bham *et al*. (2012) used a multinomial logistic regression model to predict the severity of injuries on Arkansas' urban highways. Usman *et al*. (2016) evaluated 31 highway routes across Ontario, Canada, using sequential binary logistic regression models, ordered logistic regression models, and multinomial logistic regression models which found the best overall fit to the data was the multinomial logistic regression model. This is also supported by Bham *et al*. (2012).

Materials and Methods

This study was conducted to identify the probability of accident severities based on the pavement conditions (IRI, RD and MTD) on Malaysian highways using logistic regression models. The road accident data were collected from PDRM. The pavement condition data were provided by the Malaysia Highway Authority (MHA). The pavement conditions used in this study were limited to roughness (IRI), rut depth (RD) and texture depth (MTD), which cover the general surface characteristics of a road.

The accident data and pavement condition data were merged based on the accident location. The data collected spanned over two years, totalling up to 1,789 data points. The data were analysed using the R statistical software. Table 2 shows the data categorized according to the fatalities, injuries, damages and severities as the dependent variables. Binary levels of 0 and 1 were assigned for fatalities, injuries and damages attributes for binomial logistic regression. The attribute of severities includes four severity levels with the level of 4 for death, level 3 for serious injury, level 2 for minor injury and level 1 for damage which were used for multinomial logistic regression. The continuous variables (IRI, RD and MTD) were the independent variables for the statistical model.

Three binomial logistic regression models were developed based on the attributes in Table 2 as shown from Equation (7) to Equation (9).

$$\textit{Model 1: Logit (Fatalities)} = \beta_0 + \beta_1 IRI + \beta_2 RD + \beta_3 MTD \quad (7)$$

$$\textit{Model 2: Logit (Injuries)} = \beta_0 + \beta_1 IRI + \beta_2 RD + \beta_3 MTD \quad (8)$$

$$\textit{Model 3: Logit (Damages)} = \beta_0 + \beta_1 IRI + \beta_2 RD + \beta_3 MTD \quad (9)$$

For accident severity, a probability of 0.50 to 1.00 indicated a death outcome for Model 1. In Model 2, a probability of 0.50 and above indicated serious injury and damage. In Model 3, a probability of 0.50 and above indicated death, serious injury and minor injury. For all three models, a probability of 0.49 and below indicated the less severe categories.

The fourth model was the multinomial logistic regression model, expressed mathematically in Equation (10) below to determine the probability of multiple accident severity outcomes. Damage was set as the reference level for comparison with other severity levels.

$$\textit{Model 4: Logit (Severities (Nominal))} = \beta_0 + \beta_1 IRI + \beta_2 RD + \beta_3 MTD \quad (10)$$

Table 3. Likelihood Ratio Test

Condition	Log-Likelihood	Chi-Squared	p-value
Null	-182.530		
Model 1	-175.610	13.826	0.003
Null	-704.560		
Model 2	-694.120	20.876	0.000
Null	-940.010		
Model 3	-936.570	6.883	0.076
Null	-1415.700		
Model 4	-1402.200	26.988	0.001

Table 4. Independence of irrelevant alternative (IIA) test results

Omitted Severity Level	Chi-Squared	p-value	Null Hypothesis	IIA Property
Death	-1.435	1	Fail To Reject	Holds
Serious Injury	-1.968	1	Fail To Reject	Holds
Minor Injury	-0.207	1	Fail To Reject	Holds

The multinomial logistic regression model probability outcomes were assessed independently. Since there are four severity outcomes, the probability threshold was divided equally into four parts. Any probability above 0.25 indicated a high severity outcome.

The odds ratio in the binomial logistic regression refers to the ratio between the probability of accident severity and a unit increase in the pavement condition. Odds greater than 1 means that the probability of accident severity is greater than 0.5 for a unit increase in pavement condition and vice versa. Similarly, in the multinomial logistic regression model, the odds ratio indicates the ratio between the probability of accident severity by a unit increase in the odds of pavement condition. Odds greater than 1 means that the probability of either death, serious injury or minor injury is high when there is a unit increase in pavement condition. If lesser than 1, it shows that the probability of damage is much higher.

Testing of the Binomial and Multinomial Logistic Regression Assumptions

The binomial and multinomial logistic regression assumptions were tested and confirmed not violated. There was a linear relationship between log odds of accident severity and each of the pavement conditions. There were also no influential points since Cook's distance result was less than 1.0 for all data. The standardized residuals for all data were within the limit between -3.0 and 3.0, implying that there was no outlier. Lastly, the variable inflation factor (VIF) result was below 10, indicating that there was no multicollinearity among the pavement condition variables.

Likelihood Ratio Test

Table 3 shows the likelihood ratio test of all models based on Equation (7) to (10). The full models were compared with the null model (without any of the independent variables). If the independent variables (IRI, RD and MTD) were significant, the p-value would be less than 0.05 and the full model would be adopted for further analysis. Otherwise, the model would be dropped. In this study, all models had a p-value less than 0.05 except for Model 3. As such, Model 3 was not considered for further analysis.

Independent of Irrelevant Alternative (IIA) Test

Table 4 shows the Independent of Irrelevant Alternative (IIA) test results for each omitted accident severity. The null hypothesis assumes that IIA exists while the alternative hypothesis assumes that IIA does not exist. The test was conducted at a 5% significance level. Based on the results, since the p-value was greater than 0.05 for all omitted accident severity levels, the null hypothesis could not be rejected. As such, it was concluded that all groups were independent of each other. Similar results were noted in the findings of Abrari Vajari *et al*. (2020) on crash severity at intersections using multinomial logistic regression analysis.

Binomial Logistic Regression

Tables 5 and 6 show the binomial logistic regression analysis for Model 1 and Model 2 respectively. The IRI and MTD are significant variables for Model 1 based on the results in Table 5. Therefore,

Table 5. Binomial logistic regression results for Model 1

Model 1	Estimate	Std. Error	z value	p-value
Intercept	-5.088	0.476	-10.695	0.000
IRI	0.679	0.204	3.322	0.000
MTD	0.152	0.065	2.337	0.019

Table 6. Binomial logistic regression results for Model 2

Model 2	Estimate	Std. Error	z value	p-value
Intercept	-1.614	0.240	-6.736	0.000
IRI	0.366	0.115	3.175	0.001
RD	-0.148	0.046	-3.313	0.000

Table 7. Multinomial logistic regression results for Model 4

Model 4	Estimate	Std. Error	z value	p-value
Death:(Intercept)	-4.328	0.496	-8.725	0.000
Minor Injury:(Intercept)	-1.231	0.266	-4.619	0.000
Serious Injury:(Intercept)	-0.974	0.278	-3.500	0.000
Death:IRI	0.808	0.199	4.045	0.000
Minor Injury:IRI	-0.061	0.138	-0.443	0.657
Serious Injury:IRI	0.072	0.141	0.512	0.608
Death:RD	-0.108	0.099	-1.084	0.278
Minor Injury:RD	0.013	0.042	0.324	0.745
Serious Injury:RD	-0.159	0.051	-3.126	0.001

Model 1 was fitted as in Equation (11). The results in Table 6 showed that IRI and RD are significant variables for Model 2, so the model was fitted as in Equation (12).

$$Logit\ (Fatalities) = -5.008 + 0.679*IRI + 0.152*MTD \quad (11)$$

$$Logit\ (Injuries) = -1.614 + 0.366*IRI - 0.148*RD \quad (12)$$

Multinomial Logistic Regression

Table 7 showed that IRI and RD were significant pavement condition variables for at least one of the accident severities in the multinomial logistic regression model. MTD was insignificant for all the accident severity categories, hence MTD was omitted from the analysis. The multinomial logistic regression estimation for each of the accident severity categories is shown from Equation (13) to (15).

$$Logit\ (Death\ /\ Damage) = -\ 4.328 + 0.808\ IRI - 0.108\ RD \quad (13)$$

$$Logit\ (Serious\ Injury\ /\ Damage) = -\ 0.974 + 0.072\ IRI - 0.159\ RD \quad (14)$$

$$Logit\ (Minor\ Injury\ /\ Damage) = -\ 1.231 - 0.061\ IRI + 0.013\ RD \quad (15)$$

Table 8. Odds ratio for Model 1

Model 1	Odds Ratio
IRI	1.972 (97.2%)
MTD	1.164 (16.4%)

Odds Ratio and Accident Severity Probabilities of Model 1

The odds ratio values for IRI and MTD of Model 1 are shown in Table 8. The odds of resulting in death is greater than the odds of getting major injury, minor injury, and damage by 1.972 for IRI. This means, that a unit increase in IRI increases the probability of death by 97.2% compared to major injury, minor injury, and damage. The MTD coefficient suggested that the odds of death are greater than the odds of major injury, minor injury, and damages by 1.164. This means that a unit increase in MTD increases the probability of death by 16.4% in comparison to major injury, minor injury, and damage.

The probability graph based on IRI and MTD is shown in Figure 1. The graph showed that both the IRI and the MTD had a direct impact on the probability of accidents severities. As the IRI value increased, the probability of accident severities increased. If the probability of accident severities is below 0.5 (50%), the chances of major injuries, minor injuries, and property damage are considered. It was found that the probability of

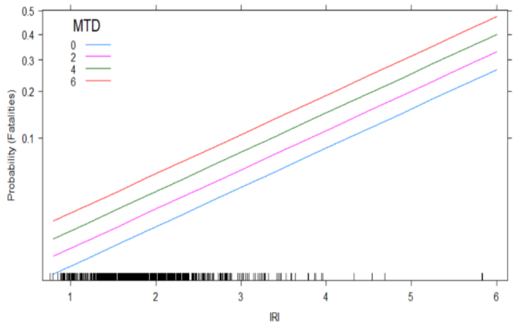

Figure 1. **Probability of fatalities outcome versus IRI at intervals of MTD for Model 1**

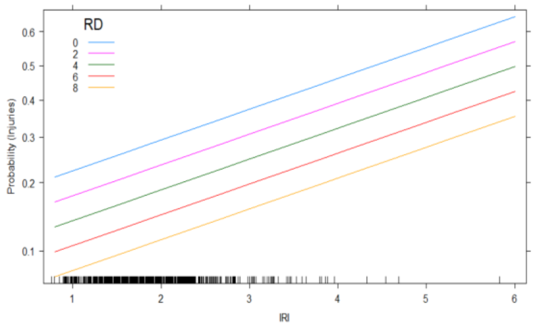

Figure 2. **Probability of injuries outcome versus IRI at intervals of RD for Model 2**

Table 9. Odds Ratio for Model 2

Model 2	Odds Ratio
IRI	1.442 (44.2%)
RD	0.863 (-13.7%)

Table 10. Odds ratio for Model 4

Model	Odds Ratio
Death:IRI	2.245 (124.5%)
Serious Injury:IRI	1.075 (7.5%)
Minor Injury:IRI	0.940 (-6.0%)
Death:RD	0.897 (-10.3%)
Serious Injury:RD	0.852 (-14.8%)
Minor Injury:RD	1.013 (1.3%)

getting death was lower for IRI up to 6 m/km. The IRI was projected to observe the probability of getting death and it was found that IRI beyond 7.5 m/km would increase the chances of death. Meanwhile, the increase in MTD value increased the probability of accident severities. However, the accident severity probabilities at MTD up to 6 mm were less than 0.5 (50%), indicating that death was unlikely due to MTD.

Odds Ratio and Accident Severity Probabilities of Model 2

The odds ratio for IRI and RD are shown in Table 9 for Model 2. The findings showed that IRI had an odds ratio of 1.442 and RD had an odds ratio of 0.863. The odds of death and serious injury over the odds of minor injury and damages was 1.442 for IRI. For every unit increase in IRI value, the probability of death and serious injury increased by 44.2%. The impact of RD on injury outcomes was investigated. According to the odds ratio of 0.863, each unit increase in RD value had reduced the chances of death and serious injury by 0.137 (13.7%) but increased the possibility of damage and minor injury by 15.9% (1/0.863 = 1.159).

The probability graph for Model 2 based on IRI and RD values is shown in Figure 2. Both the IRI and RD had an inverse relationship with accident severities. Increased IRI values were associated with higher accident severity probability while higher RD values were associated with lower accident severity probability. As the IRI value increased, the chances of death and serious injury increased. IRI value exceeding 4.5 m/km with RD value remained constantly at zero resulted in higher death and serious injury occurrence. The probability of death and serious injury was negligible for IRI values lesser than 4.5 m/km. Higher RD, on the other hand, increased the probability of minor injury and damage. In general, increased RD value indicated a high likelihood of minor injury and damage.

Odds Ratio and Accident Severity Probabilities of Model 4

Table 10 shows the odds ratio of the independent variables that were significant for Model 4 with damage being the reference level. From the result, death and serious injury showed odds of more than one for IRI while for RD, the minor injury resulted in odds of more than one. The results implied that a unit increase in IRI would increase the probability of death and serious injury more than mere damage and minor injury. The odds for death was 124.5% higher than the odds for damage. For serious injury, the IRI coefficient showed that, by keeping RD at a fixed value, the probability of serious injury would increase by 7.5% with every unit increase in IRI. For minor injury, the IRI coefficient showed that the odds had decreased by 5.9% with every unit increase.

Meanwhile, a unit in RD would increase the probability of damage more than death and serious injury, but not for minor injury. By keeping IRI constant, the probability of death had decreased by 10.3% for every increase in the RD value. The RD coefficient showed that the chances of getting serious injury had decreased by 14.8% with every increase in the RD value. The probability of minor injury increased by 1.3% with every increase in RD.

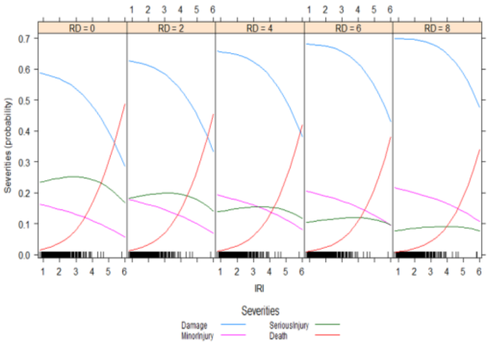

Figure 3. Probability of accident severities based on IRI at intervals of RD for Model 4

Figure 3 illustrates the accident severity probabilities graph of the multinomial logistic regression model. Four accident severity lines were plotted independently based on IRI values with five RD intervals. The results showed that, in general, an increase in IRI had increased the probability of death and serious injury and decreased the probability of minor injury and damage. The probabilities of death and damage deviated significantly beyond an IRI value of 3 m/km whereby the death outcome rose steeply reaching 124.5% for each unit increase in IRI. A similar trend was noted in the research carried out by Mamlouk *et al*. (2018) on accident rates due to IRI for five accident severity levels in Arizona and Maryland. The accident rate did not display a significant increase for all accident severity rates until an IRI value of 210 inches/mile or 3.31 m/km. Beyond this level, the accident rate had increased drastically, especially for the Arizona state in 2013.

The proven relationship between IRI and all accident severity levels was attested in the study of Popoola *et al*. (2020) on the Sagamu-Ore expressway and the Ilesha-Owo-Akure road, albeit a different outcome was achieved. The study concluded that the accident rate increased when the IRI value was up to 4 m/km, above which the accident rate began to decrease. Bad pavement roughness on the Sagamu-Ore expressway did not necessarily increase the accident probability. The researcher discovered that the decrease in accident severity was attributable to undesirable pavement roughness, which slowed down driving speed and reduced accident risk.

The probability of serious injury and minor injury did not significantly change over the IRI values. Increasing IRI showed only a significant probability increase in death beyond 3 m/km. Above 4.5 m/km, the probability was consistently below 0.25. This means that the probability of death is only considered high for IRI above 4.5 m/km. The damage severity level significantly decreased when the IRI increased, but it remained high at up to 6 m/km.

There was no significant change in all severity levels with an increase in RD, particularly in relation to death as shown in Figure 3. Nevertheless, the most significant decline was observed in serious injury cases. An increase in RD would generally increase the chance of damages and minor injury and decrease the chance of serious injury and death. The probabilities of death, serious injury and minor injury were lower than 25% for RD up to 12 mm. Meanwhile, the probability of damage was above 25%.

To conclude, the influence of IRI is greater than RD, as demonstrated in the results. In all cases, the chance of suffering from damage remained higher than death, serious injury and minor injury.

Conclusions

This study has reached the conclusions stated hereafter based on the outcome. The logistic regression has met all the assumptions relevant to the statistical model. Based on the likelihood ratio test, for the binomial logistic regression model, only Model 1 and Model 2 supported the existence of a relationship among IRI, RD and MTD with accident severities. Model 3 was omitted since a significant relationship was not supported. For the multinomial logistic regression model, the likelihood ratio test supported the existence of a relationship among IRI, RD and MTD with accident severities.

Based on the odds ratio for Model 1, IRI had a greater impact than MTD in predicting the probabilities of accident severities. Accident severity probability increased gradually with increasing IRI and MTD. The probability of death for Model 1 was lower for IRI lesser than 7.4 m/km. The impact of IRI was higher than RD in predicting accident severity probabilities for Model 2. The accident severity probability increased with an increasing IRI and reducing RD. The probability of death and serious injury was lower for IRI up to 4.5 m/km. In Model 4, the probability of death, serious injury, minor injury was below 25% except for the probability of damage. IRI has a higher impact on accident severities compared to RD, especially on deaths. This study concludes that, during an accident, it is more likely for damages to happen rather than any kind of injury or even death.

This study recommends the inclusion of the entire pavement condition variables such as pavement cracking, skid resistance value and pavement condition index for projection on the probability outcomes. Similar research is suggested to be implemented on federal roads, state roads and rural roads so that the impact of pavement conditions on other pavement categories related to accident severities are analysed.

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