A STUDY OF FACTORS AFFECTING HIGHWAY ACCIDENT RATES IN JORDAN

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Abstract: - Traffic accidents are one of the problems that all countries around the world face. One of the countries that face this problem is Jordan which witnesses continuous growth in population in addition to the development that Jordan passes through.

This study has adopted descriptive and statistical analysis of the data and information concerning traffic accidents. The study aims at illustrating the factors and the causes that lead to traffic accidents. It also compares the data concerning accidents during the period (2008-2017).

This research work discusses the factors that affect the rate of accidents in Jordan, this factors include: number of accidents in (peak hour, off peak hour), day or night conditions, weather conditions, road surface conditions and speed limit.

The Multiple linear Regression Model in this study has been developed to recognize the factors that affect the rate of accidents in Jordan. One of the results was fair weather is one of the most effective factors that affect the rate of accidents in Jordan.

Key-Words: traffic engineering, traffic accidents, traffic safety, traffic risk rate, vehicle crashes, crash-injury severity.

1 Introduction

Road traffic accidents represent a large ratio of total fatalities. Traffic fatality rates in many countries increase over time. This has led to road accidents and their resulting fatalities being regarded as a growing social and economic problem especially in developing countries where resources are limited.

Population and vehicle ownership are increasing rapidly in developing countries while many features necessary to reduce accidents and fatality rates are not being introduced effectively such as enforcing Laws, training drivers, and improving roads design standards and vehicle safety.

An accident occurs due a sequence of events or circumstances which lead to the incident that causes injuries, loss of lives or property damages. Although traffic on roads is a mixed combination of different types of vehicles such as cars, trucks, and buses, an accident is still considered a single event even when it involves more than one vehicle.

Traffic accidents have increased in Jordan to reach 280 accidents per day. The Kingdom is considered one of the countries of which accidents are the main reason of death even though the population is doubled since 1989, up to 2017 (3,011 million – more than 5,850 million), but the number of vehicles increased three times (251287-905592) vehicle and the number of accidents increased to five and a half times (18336 -101066) accident.

1.1 Study Problem:

Traffic accidents are a major cause of increasing fatalities in Jordan. Traffic fatality rates in Jordan have increase over time. This has led to a growing social and economic problem especially in Jordan which is considered as a developing country in which resources are limited.

This study aims to identify the most effective factors that affect the accident rates and to develop a prediction model involves two stages: the first stage includes the selection of the factors that are significant effect on accident rates and for which sufficient reliable data is available. Second stage will include the development of the model incorporating the selected parameters.

The study will also focus on comparing rates of accidents between different governorates in Jordan.

2 Literature review:

(Panagiotis Ch. Anastasopoulos et al., 2012) studied the factors affecting highway accident rates using the random-parameters tobit model.Past research has appropriately applied a tobit regression model to address this censoring problem, but this research has been limited in accounting for unobserved heterogeneity because it has been assumed that the parameter estimates are fixed over roadway-segment observations [1].

(Panagiotis Ch. Anastasopoulos et al., 2012) studied a multivariate tobit analysis of highway accident-injury-severity rates. Tobit regression has been used because accident rates on specific roadway segments are continuous data that are left-censored at zero (they are censored because accidents may not be observed on all roadway segments during the period over which data are collected). The issue of censoring by the severity of crashes has not been addressed. However, a tobit-regression approach that considers accident rates by injury-severity level, such as the rate of no-injury, possible injury and injury accidents per distance traveled (as opposed to all accidents regardless of injury-severity), can potentially provide new insights, and address the possibility that censoring may vary by crash-injury severity [2].

(Rui Fu et al., 2011) studied the correlation between gradients of descending roads and accident rates. The traffic accident rate on descending roads on mountainous highways is quite high. The findings indicate that a steep gradient alone is not the reason for an accident, also the presence of "continuous long" descent prior to it should be taken in consideration [3].

(Saffet Erdogan, 2009) studied Explorative spatial analysis of traffic accident statistics and road mortality among the provinces of Turkey. The aim of the study is to describe the inter-province differences in traffic accidents and mortality on roads of Turkey. Accident and death rates were also modelled with some independent variables such as number of motor vehicles, length of roads, and so forth using geographically weighted regression analysis with forward step-wise elimination. The level of statistical significance was taken as $P < 0.05$. Large differences were found between the rates of deaths and accidents according to denominators in the provinces. The geographically weighted regression analyses did significantly better predictions for both accident rates and death rates than did ordinary least regressions, as indicated by adjusted R2 values. Geographically weighted regression provided values of 0.89–0.99 adjusted R2 for death and accident rates, compared with 0.88–0.95, respectively, by ordinary least regressions [4].

(Ming-Chih Tsai et al., 2004) studied Scenario analysis of freight vehicle accident risks in Taiwan. This study develops a quantitative risk model by utilizing Generalized Linear Interactive Model (GLIM) to analyze the major freight vehicle accidents in Taiwan. Eight scenarios are established by interacting three categorical variables of driver ages, vehicle types and road types, each of which contains two levels. The database that consists of 2043 major accidents occurring between 1994 and 1998 in Taiwan is utilized to fit and calibrate the model parameters. The empirical results indicate that accident rates of freight vehicles in Taiwan were high in the scenarios involving trucks and non-freeway systems, while; accident consequences were severe in the scenarios involving mature drivers or non-freeway systems. Finally, the study recommends using number of vehicle as an alternative of traffic exposure in commercial vehicle risk analysis. The merits of this would be that it is simple and thus reliable; meanwhile, the resulted risk that is termed as fatalities per vehicle could provide clear and direct policy implications for insurance practices and safety regulations [5].

(David Navon, 2003) described the paradox of driving speed: two adverse effects on highway accident rate. Whereas speeding is known to be a substantial risk factor in driving, there is no unequivocal evidence that accident rate on limited-access motor highways is considerably affected by average speed or by speed limits meant to regulate it. It is suggested here that the seeming puzzle actually may have a straightforward explanation: accident–prone interactions (APIs) between cars occur when they pass each other—mostly moving in the same directions or in opposite ones. Such interactions are shown here to happen more frequently, the lower average speed is. To the extent that high speed limits contribute to increase in average speed, they serve to reduce the number of such interactions, thereby to moderate at least part of the negative effect of speed on the driver's ability to avoid an impending accident [6].

(Michael A Gebers et al., 2003) studied using traffic conviction correlates to identify high accident-risk drivers. One of the primary missions of the California Department of Motor Vehicles is to protect the public from drivers who represent unacceptably high accident risks. Predicted models identify drivers at increased risk of future accident involvement would increase the number of accidents prevented through post license control actions. Although the results did not support prior findings that equations keyed to citations do as well as or better than equations keyed to accidents in predicting subsequent accident involvement, a canonical correlation approach considering subsequent accident and citation rates simultaneously produced a 14.9% improvement in the classification accuracy or "hit rate" for identifying accident-involved drivers [7].

(Liisa Hakamies-Blomqvist et al., 2002) concluded Driver ageing does not cause higher accident rates per km. Based on Finnish survey data, older ($\mathbf{65+, n = 1559}$) and younger (26–40, n=310) driver's accident rates were compared. In accordance with earlier studies, the rates were similar per driver (0.1) but there was a non-significant trend towards older drivers having more accidents per distance driven (10.8 vs. 8.3 per 1 million km) [8].

(Matthew G Karlaftis et al., 2002) studied Effects of road geometry and traffic volumes on rural roadway accident rates. The results show that although the importance of isolated variables differs between two-lane and multilane roads, 'geometric design' variables and 'pavement condition' variables are the two most important factors affecting accident rates. Further, the methodology used in this study allows for the explicit prediction of accident rates for given highway sections, as soon as the profile of a road section is given [9].

(Mohamed A. Abdel-Aty et al., 2000) estimated Modeling traffic accident occurrence and involvement. The Negative Binomial modeling technique was used to model the frequency of accident occurrence and involvement. The results showed that heavy traffic volume, speeding, narrow lane width, larger number of lanes, urban roadway sections, narrow shoulder width and reduced median width increase the likelihood for accident involvement. Subsequent elasticity computations identified the relative importance of the variables included in the models. Female drivers experience more accidents than male drivers in heavy traffic volume, reduced median width, narrow lane width, and larger number of lanes. Male drivers have greater tendency to be involved in traffic accidents while speeding. The models also indicated that young and older drivers experience more accidents than middle aged drivers in heavy traffic volume, and reduced shoulder and median widths. Younger drivers have a greater tendency of being involved in accidents on roadway curves and while speeding [10].

3 Data collection

The following data items were collected:
1. Number of accidents, number of slight injuries, number of serious injuries and number of fatalities over the period (2008 – 2017) the data were taken from Greater Amman Municipality (GAM).
2. Number of accidents, number of injuries and number of fatalities according to governorate over the period (2008 – 2017) were obtained from the Central Traffic department.

These data are shown in tables (1), (2), (3), (4), (5), (6) and (7) (in appendix A).

- Number of accidents in (peak hour, off peak hour) denoted by X1
- Day or night condition denoted by X2
- Weather conditions denoted by X3
- Road surface conditions denoted by X4
- Speed limit denoted by X5.

4 Results and analysis

4.1 Accident trends in Jordan:

One of the approaches used to forecast future events worldwide is the trend analysis. Trend analysis is based on the assumption that the contributing factors will still be dominant at the point of estimation and will stay valid. Thus, the next future events will be easily expected by simple extrapolation. Table (8) (in appendix A) shows Traffic accidents, their results and risk rates over the period 2008-2017.The number of accidents over the period 2008-2017are presented in figure(1).It can be seen that the average annual increase in traffic accidents around (10.7%) over the period 2008-2017. Fatalities over the period 2008-2017 in figure (2). Fatalities have increased with time until reached their maximum in 2014, then declined. Serious Injuries over the period 2008-2017 are presented in figure (3). It can be seen that the highest number of slight injuries in 2008 and the highest number of serious injuries in 2017. Risk rate of traffic accidents over the period 2008-2017 in figure (4). It can be seen that risk rate of accidents during the period 2008 -2017decline "continuous".

Figure (1): Number of accidents over the period 2008-2017

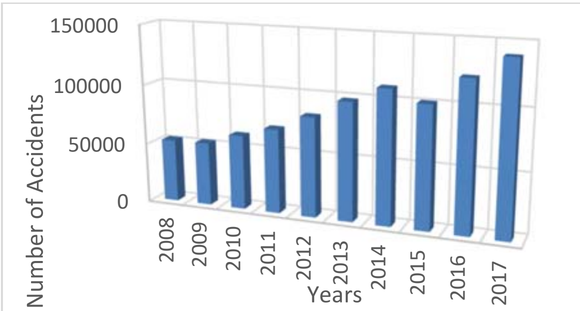


Figure (2): Number of fatalities over the period 2008-2017

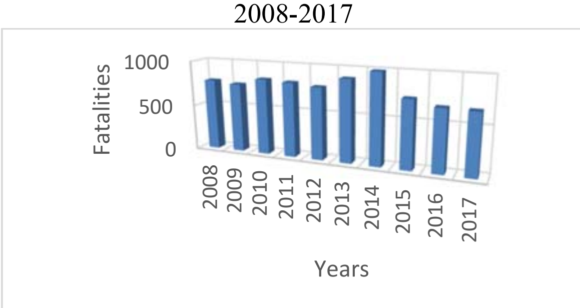
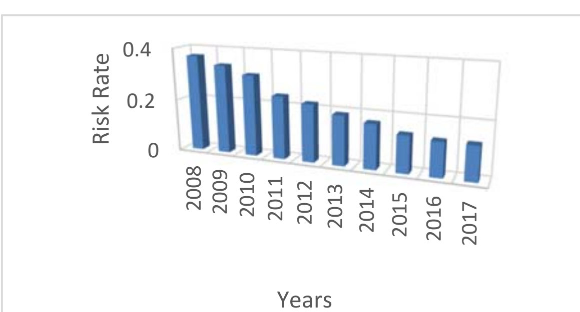


Figure (3): Number of slight and serious Injuries over the period 2008-2017

Figure (4): Risk rate of traffic accidents over the period 2008-2017



4.2 Accident Rates

Rates are used to compare the safety performance of different location and to prioritize safety improvements. Many accident rates are used to describe the magnitude of the problem and its consequences. These include the rates that relate the number of accidents, injuries or fatalities to safety parameters such as population, number of registered vehicles, and distances travelled expressed in vehicle-km. Some of the common rates related to road traffic fatalities include the number of fatalities per 10,000 persons, per 10,000 vehicles, or per million vehicle mile or kilometer traveled. Simple counts are almost never used since they are not representative because of the vastly different population sizes and degrees of motorization in the various countries. However, it should be noticed that the definition of a road-traffic fatality varies from country to country, and may change with time in the same country. The changes in fatality rates in Jordan during the period (2008-2017) are shown in table (9) (in Appendix A).

It can be seen that during the10-year period, there has been an increase of almost 200 percent in vehicle ownership accompanied by 50 percent reduction in fatality rate (per 10,000 vehicles) as compared to the growth of population and almost the same fatality rate per 10,000 persons. The letter may be attributed to the larger increase in the number of vehicles over the study period.

4.3 Analysis of traffic accidents according to Governorates:

The results of comparison according to governorates during the period (2008-2017) are depicted on table (10) (in appendix A). It can be seen that:

- The accidents in Amman recorded (65.85%) of the total accidents, and the highest mortality rate was (33.97%) in Amman, (38.7%) in the rest of the Kingdom; that is because of the number of population in the capital Amman which cause traffic rush, that leads to a growing number of accidents and deaths.
- Injuries in the capital Amman was (13.2%) of the total accidents.
- Maa’n province recorded the highest rate of severe traffic accidents during the period (2008-2017) while the lowest rate was in Amman.

4.4 Statistical analysis:

The reliability of data will be tested by normality tests. After that regression analyses will be applied to test the effect of selected parameters.

4.4.1 Normality test:

Two normality tests are used to ensure that the data are free of outliers and distributed normally, as we noted below.

Table (11): Tests of Normality

	Kolmogorov-mirnov(a)		Shapiro-Wilk	
	Degree of freedom	Significance level	Degree of freedom	Significance level
Peak hour	10	0.087	10	0.181
Off peak hour	10	0.200	10	0.624
Daytime	10	0.200	10	0.461
Night	10	0.054	10	0.057
Fair	10	0.200	10	0.609
Unfair	10	0.076	10	0.286
Dry	10	0.200	10	0.638
Wet	10	0.200	10	0.292
Speed limit at 40km/hr	10	0.200	10	0.538
Speed limit at 60km/hr	10	0.112	10	0.116
Number of accidents	10	0.200	10	0.615

As known, the tests of normality overlay a normal curve on actual data to assess the fit. A significant test means the fit is poor. For the standard alloy, the test is not significant; they fit the normal curve well. However, for the premium alloy the test is significant; they fit the normal curve poorly.

The above Table (11) shows that the test of normality is not significant for all variables. This means that the collected data fit the normal curve well. According to Kolmogorov-Smirnov test the significant level for all variables is greater than the test significant level $\alpha = 0.05$. Therefore, all the values of study's variables fit the normal curve. Similar results are obtained by Shapiro-Wilk test.

4.4.2 Predictors Selection and Model Construction:

A simple linear regression analysis applied to all variables individually, in order to determine the highest effect of independent variables in the annual number of accidents, the following table summarize the results.

Table (12): Model summary

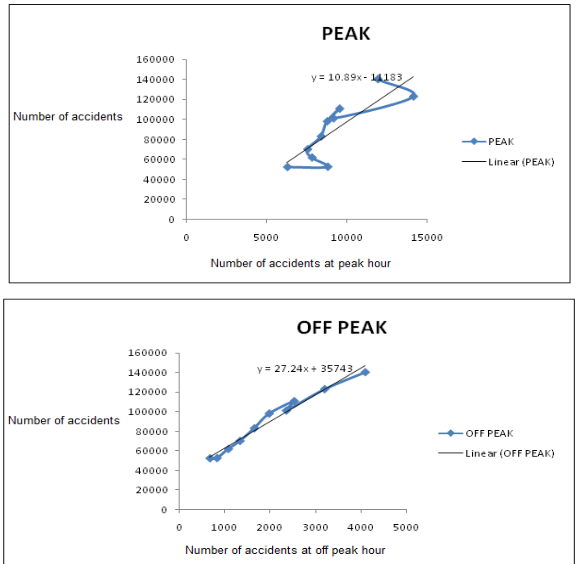
Independent Variable	R correlation coefficient	R^2 determination coefficient	F calculated	P- value	Decision
Peak	0.818	0.669	16.163	0.004	Significant
Off peak	0.987	0.974	303.186	0.000	Significant
Day	0.977	0.954	166.493	0.000	Significant
Night	0.441	0.194	1.930	0.202	Not Significant
Fair	0.887	0.787	28.021	0.001	Significant
Unfair	0.879	0.773	27.232	0.002	Significant
Dry	0.999	0.998	66001	0.000	Significant
Wet	0.194	0.038	0.314	0.591	Not Significant
Speed limit at 40km/hr	0.994	0.988	664.319	0.000	Significant
Speed limit at 60km/hr	0.824	0.679	16.942	0.003	Significant

The Table (12) shows that the effect of all variable (taken individually) in determining the annual number of accidents is significant, except the annual number of accident occurred at night time, and at wet roads. The methodology applied here is to select the variable that has the significant effect in determining number of accidents, so the accident occurred at day time, and at dry roads were selected. Moreover, number of accidents occurred at off peak instead of at peak was selected, since at off peak accidents had more significant effect than at peak accidents. In spite of the significant effect of the accidents occurred at fair and unfair weather, accidents at fair weather was selected, since it had high significant level than unfair weather.

Finally, by applying the same methodology the number of accidents occurred at speed 40km/hr was selected, based on significant level.

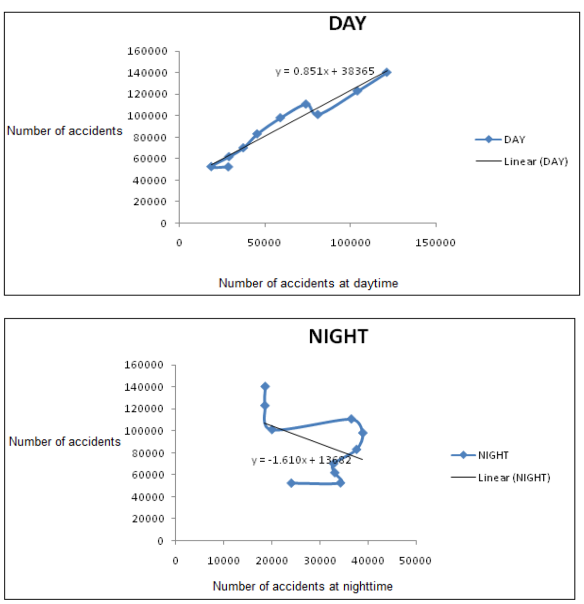
We supported the above results by plotting the relationship between the predictors and number of accident separately.

Figure (5): Comparing the graphs of peak and off peak accidents



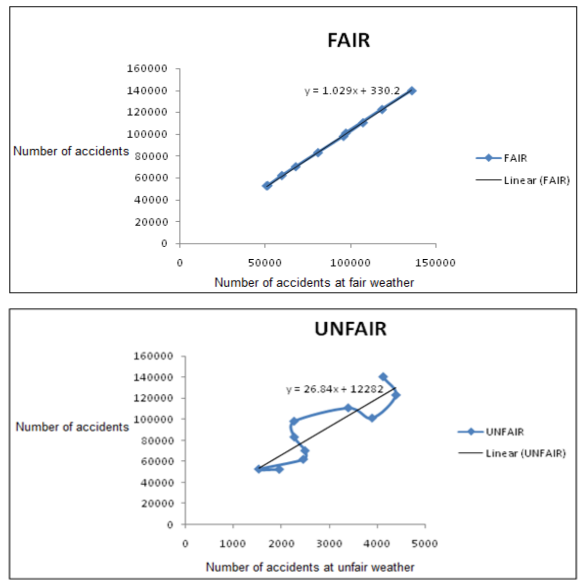
The above figure (5) shows that the scatter plot of the relationship between annual number of accidents and accidents occurred at off peak time fitted the line more than the other scatter plot that represented the peak accidents relationship with number of accidents.

Figure (6): Comparing the graphs of day and night accidents



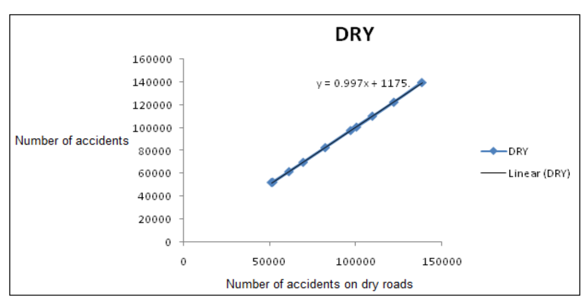
The above figure (6) shows that the scatter plot of the relationship between annual number of accidents and accidents occurred at day time fitted the line more than the other scatter plot that represented the night time accidents relationship with number of accidents.

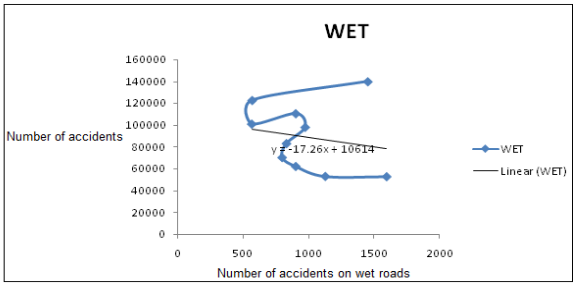
Figure (7): Comparing the graphs of fair weather and unfair weather accidents



Above figure (7) shows that the scatter plot of the relationship between annual number of accidents and accidents occurred at fair weather fitted the line more than the other scatter plot that represented the unfair weather accidents relationship with number of accidents.

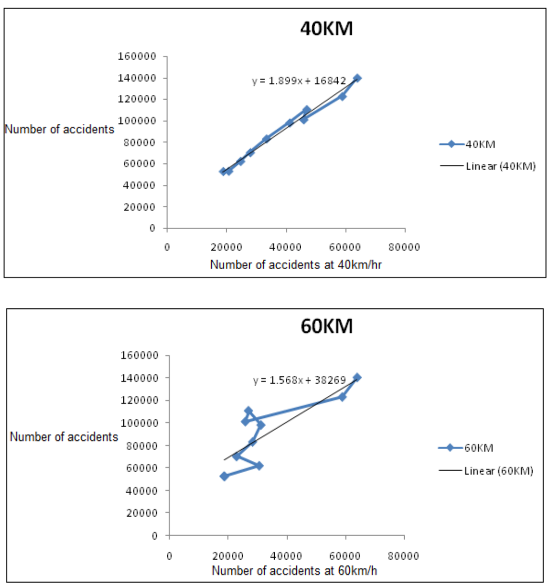
Figure (8): Comparing the graphs of dry roads and wet roads accidents





The above figure (8) shows that the scatter plot of the relationship between annual number of accidents and accidents occurred at dry roads fitted the line more than the other scatter plot that represented the wet roads accidents relationship with number of accidents.

Figure (9): Comparing the graphs of accidents at 40km/hr and 60km/hr



The above figure (9) shows that the scatter plot of the relationship between annual number of accidents and accidents occurred at 40km/hr fitted the line more than the other scatter plot that represented at 60km/hr accidents relationship with number of accidents.

4.4.3 Testing the effect of five factors aggregated on the annual number of accidents:

In this stage of analysis a multiple linear regression was developed, where the dependent variable is the annual number of accidents, whereas the independent variables are the number of accident at off peak (X1), at day time (X2), at fair weather (X3), on dry roads (X4), and at 40km/hr (X5), the following table summarize the results.

Table (13): The SPSS output for the multiple regression analysis

Y Dependent variable	R Correlation Coefficient	R^2 Determinant Coefficient	F Calculated	F Table	Significance Level
Number-of accidents	0.956	0.914	11.304	5.19	0.012

The above table (13) shows that the strength of the relationship between the model and the dependent variable. R, the multiple correlation coefficients is the linear correlation between the observed and model-predicted values of the dependent variable. Its large value indicates a strong relationship. In this model (R=0.956) which indicates a perfect positive linear relationship between number of accidents and independents variables.

R Square, the coefficient of determination, is the squared value of the multiple correlation coefficients. It shows that about (91.4%) of the variation in number of accidents (Y) is explained by the model.

While the ANOVA (F-test) tests the acceptability of the model from a statistical perspective, and it is a useful test of the model's ability to explain any variation in the dependent variable number of accidents, it does not directly address the strength of that relationship. The significance value of the F statistic (F= 11.304) is less than 0.05, (Sig=0.012) which means that the variation explained by the model is not due to chance.

Table (14): The coefficient of regression (model parameter)

Independent Variable	β	T calculated	p-value
Constant	847.218	0.165	0.877
X1 (off peak)	-6.354	-4.374	0.012
X2 (day)	-0.292	-0.959	0.392
X3 (fair)	1.129	4.723	0.009
X4 (dry)	0.457	2.630	0.058
X5 (40km/hr)	-0.252	-1.355	0.247

The above table (14) shows that the coefficient of the regression line, it states that X1 (off peak) has a significant effect on decreasing the number of accidents, where β equals (-6.354) is significant with p-value (0.012) less than 0.05, and X3(fair) has a significant effect on increasing the number of accidents, where β equals (1.129) is significant with p-value (0.009) less than 0.05. But the effect of other variable depending on the acceptability of model given by ANOVA test cannot be ignored. This leads to conclusion that off peak hours and fair weather has the largest contribution in explaining the variation in number of accident.

To support the above results apply stepwise regression to determine the variables that have the most effect to determine the annual number of accidents, the following table summarize the results.

Table (15): Model resulted by stepwise regression

Y Dependent variable	X3 Independent variable	R Correlation Coefficient	R^2 Determinant Coefficient	F Calculated	F Table	P value
Number of accidents	X3	0.887	0.787	28.021	5.32	0.001

The table (15) shows that the annual number of accidents at fair weather (X3) has the most effect in determining the annual number of accidents, where (F=28.021) is significant with level (p-value = 0.001) less than 0.05. Moreover, the value of correlation coefficient (R = 0.887) refers to a strong positive relationship between dependent and independent variables, and almost (78.7%) of the variation occurred in the annual number of accident can be explained by the variation in the annual number of accident at fair weather when taking the entire variable in a stepwise matter.

In addition, the stepwise regression analysis explores that the other variables excluded from the model, where the effects of excluded variables were not significant.

4.5 The developed model:

Based on the above discussion a model using the identified predictors under local condition and available data as following may be developed as:

$$\boldsymbol{Y = 847.218 - 6.354X1 - 0.292X2 + 1.129X3 + 0.457X4 - 0.252X5}$$

Where,
Y: annual number of accident
X1: annual number of accidents at off peak time.
X2: annual number of accidents at daytime.
X3: annual number of accidents at fair weather.
X4: annual number of accidents on dry roads.
X5: annual number of accidents at 40km/hr.
The coefficient of determination being R-square = 0.914.

The regression model is found to be statistically significant. The high value of R2 indicates that 91.4% of number of recorded accidents can be explained by the developed model through the mentioned variables.

4.6 Testing the prediction power of the model:

Table (16): Prediction power of the model

Actual number of accidents	Predicted number of accidents	Residuals
52662	64087	11425
52913	66649	13736
62115	74674	12559
70266	82712	12446
83129	97598	14469
98055	113191	15136
110630	122593	11963
101066	106331	5265
122793	124849	2056
140014	140080	66

We notice that the value of residuals were decreasing during the time, which give a reasonable indicator about the prediction power of the model, so we expect that the residual will approach to zero if the sample enlarge enough.

4.7 Testing the effect of five factors aggregated on the annual number of accidents applying exponential model:

For the completeness of the subject and to achieve the objective of the current study the exponential regression analysis had been applied where the dependent variable is the natural logarithm of annual number of accidents, whereas the independent variables are the number of accident at off peak (X1), at day time (X2), at fair weather (X3), on dry roads (X4), and at 40km/hr (X5), the following table summarize the results.

Table (17): The SPSS output for the exponential model

Y Dependent variable	R Correlation Coefficient	R^2 Determinant Coefficient	F Calculated	F Table	Significance Level
Ln(Number of accidents)	0.987	0.974	303.186	5.19	0.000

The table (17) shows that the strength of the relationship between the model and the dependent variable. R, the multiple correlation coefficient is the linear correlation between the observed and model-predicted values of the dependent variable ln (number of accidents). Its large value indicates a strong relationship. In this model (R=0.987) which indicates a perfect positive linear relationship between ln (number of accidents) and independents variables. R Square, the coefficient of determination, is the squared value of the multiple correlation coefficient. It shows that about (97.4%) of the variation in number of accidents (Y) is explained by the model. While the ANOVA (F-test) tests the acceptability of the model from a statistical perspective, and it is a useful test of the model's ability to explain any variation in the dependent variable ln (number of accidents), it does not directly address the strength of that relationship. The significance value of the F statistic (F= 303.186) is less than 0.05, (Sig=0.000) which means that the variation explained by the model is not due to chance.

Table (18): Model parameter

Independent Variable	β	T calculated	p-value
Constant	10.095	155.43	0.000
X1(off peak)	-0.370	-1.728	0.159
X2(day)	-0.176	-0.921	0.409
X3(fair)	-0.230	-2.152	0.098
X4(dry)	5.132	3.056	0.038
X5(40km/hr)	-0.377	-0.931	0.405

The above table (18) shows that the coefficients of the regression line, it states that X4 (dry road) has a significant effect on increasing the number of accidents, where β equals (5.132) is significant with p-value (0.038) less than 0.05, other variable had no significant effect, but effect of other variable depending on the acceptability of model given by ANOVA test cannot be ignored.

4.8 The exponential developed model:

Based on the above discussion a model using the identified predictors under local condition and available data as following may be developed as:

$$\boldsymbol{Ln\,(Y) = 10.095 - 0.370X1 - 0.176X - 0.230X3 - 5.132X4 - 0.377X5}$$

Where,

Y: annual number of accident
X1: annual number of accidents at off peak time.
X2: annual number of accidents at daytime.
X3: annual number of accidents at fair weather.
X4: annual number of accidents on dry roads.
X5: annual number of accidents at 40km/hr.
The coefficient of determination being R-square = 0.974.

The regression model is found to be statistically significant. The high value of R2 indicates that 97.4% of number of recorded accidents can be explained by the developed model through the mentioned variables.

5 Conclusions and Recommendations

5.1 Conclusions:

1. Fatalities have increased with time until reached their maximum in 2014, then declined. This may be related to the implementation of the Strategic Plan in the Public Security Directorate (2015-2020) and the improvement of the emergency rescue and emergency medical services that play a significant role in treatment for victims of traffic accidents.
2. The effective factors that affect the rate of accidents in Jordan were:

X1: annual number of accidents at off peak time.
X2: annual number of accidents at daytime.
X3: annual number of accidents at fair weather.
X4: annual number of accidents on dry roads.
X5: annual number of accidents at 40km/hr.

3. The study showed that the capital of the province experienced the highest rate of accidents and the province of Maa'n highest rate in the severity of accidents during the period (2008-2017).

4. The study concluded that the areas in which speed is controlled by (40 km / hr) have registered the highest rate of accidents.

5. The most effective factors in determining the annual number of accidents which appear in a multiple regression model was fair weather (X3).

6. The most effective factors in determining the annual number of accidents which appear in exponential model was dry road (X4).

5.2 Recommendations:

1. The explanatory power of the model can be increased by increasing the period of data if available.

2. To execute more studies about the effect of other variables such as the gradients, number of registered vehicles, distance travelled expressed in vehicle-km, roadway geometrics, driver's sex, driver's age, and level of education.

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