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Performance of Traffic Accidents' Prediction Models

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ABSTRACT

Modeling traffic-accident frequency is a critical issue to better understand the accident trends and the effectiveness of current traffic policies and practices in different countries. The main objectives of this study are to model traffic road accidents, fatalities and injuries in Jordan, using different modeling techniques, including regression, artificial neural network (ANN) and autoregressive integrated moving average (ARIMA) models and to evaluate the safety impact of travel-restriction strategies during Covid-19 pandemic on traffic-accident statistics for the year 2020. To accomplish these objectives, data of traffic accidents, registered vehicles (REGV), population (POP) and economic gross domestic product (GDP) from 1995 through 2020 were obtained from related sources in Jordan. The analysis revealed that accidents, fatalities and injuries have an increasing trend in Jordan. Root mean of square error (RMSE), mean absolute error (MAE) and coefficient of multiple determination (R^2) were sued to evaluate the performance of the developed prediction models. Based on model performance, the ANN models are the best, followed by the ARIMA models and then the regression models. Finally, it was concluded that the strategies undertaken by the government of Jordan to combat Covid-19, including complete and partial banning of travel, resulted in a considerable reduction of accidents, injuries and fatalities by about 35%, 37% and 50%, respectively.

KEYWORDS: Traffic accidents, Artificial neural network, Covid-19 pandemic, Regression, Time-series analysis, Prediction models.

INTRODUCTION

Traffic accidents have resulted in 1.35 million deaths and in 20 to 50 million injuries, therefore being considered the main cause of death of children and young people between the ages of 5 and 29 years (WHO, 2018). In addition to economic losses, these accidents created social, emotional and psychological damages to the casualties and their relatives. However, traffic accidents have not received the same attention from the international community nor the strict preventive and proactive measures, as is the case of the COVID-19 pandemic (Sekadakis et al., 2021).

Jordan, as a lower-middle income developing country, exacerbates the global traffic situation and worsens it (Mujalli et al., 2015). Jordanian traffic accidents accounted for 4.5% of deaths in 2007 and ranked as the third cause of death in 2010 (Al-Omary et al., 2013). According to the latest reports and statistics provided by the Jordan Traffic Institute, there was a significant increase in the number of accidents in 2019, as 161511 traffic accidents were recorded, including 10857 causality accidents, leading to 643 deaths, at a financial cost estimated at US$ 456 million. Different policies and actions have been implemented to combat this problem, including the intensification of police enforcement, new traffic laws, the installation of speed cameras, among other related measures (JTI, 2020). In evaluating these policies and measures at the country level, however, different *ad hoc* procedures are used. Thus, it is vital to develop traffic accident prediction models that are able to figure out future traffic accident trend and use the appropriate ones to evaluate the

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effectiveness of the implemented policies and measures (Al-Masaeid, 2009).

The objectives of this study are two-fold; first, to develop accident-prediction models using multiple linear regression, artificial neural networks and time-series analysis. The performance of the developed models will be investigated and the best one will be identified for future use. Second, to evaluate the safety impact of strategies undertaken by the government of Jordan to combat Covid-19, including complete and partial banning on vehicle travel. Traffic accidents' data for the period 1995-2020 was used in model development, validation and evaluation of Covid-19 strategies. Population, number of registered vehicles and gross domestic product were used in developing the models of the numbers of accidents, injuries and fatalities.

LITERATURE REVIEW

Several studies analyzed accidents, their causes and trends, as first steps in achieving road sustainability at the national and international levels and several accident-prediction models (APMs) have been developed. The development of APMs has become essential to traffic-safety management, road planning and design (Hmaid and Imam, 2019). These models estimate expected accident frequency as a function of different factors, including road-infrastructure features, traffic volume, geometric characteristics, socio-economic characteristics, pavement conditions and weather conditions, in a way that enables highway and traffic engineers to understand the traffic and engineering conditions of different sections of roads. They effectively identify problems faced by road-safety engineers (Lakshmipriya, 2018).

Previous works done on the development of APMs concentrated on different types of modeling techniques. The most used models were based on conventional regression modeling techniques (Al-Masaeid et al., 2020; Khasawneh et al., 2018). This type of APMs is one of the earliest modeling techniques and is characterized by high application flexibility. Those models can be applied to all types of roads or parts of them, such as divided urban highways, arteries, collectors, intersections or any traffic mixture of these parts. This type of modeling is not able to explain all variabilities in traffic accidents, especially for temporal data.

However, due to the nature of traffic-accident data of being non-negative, random and discrete integers, unlike the assumptions of regression models, time-series modeling technique has become more used in modeling traffic accidents over the past twenty years. Several researchers used the Box-Jenkins method, often called ARIMA models (a term that refers to an auto-regression integrated moving average) (Avuglah et al., 2014; Ihueze and Onwurah, 2018; Hassouna et al., 2020). The data of these models is characterized in comparison to the conventional regression models' data by being temporally arranged, in addition to being based on the analysis of annual data for periods of more than fifteen years, without reservation, which led to a new and unique style in modeling and statistical inference (Hassouna and Tubaileh, 2020).

ARIMA, if fitted well, can forecast small ups and downs much better than other models, but given that the overall trend has not changed. If there is an unusual growth or slowdown in the series, ARIMA might not perform well. This is because ARIMA is only looking into the back data of the variable. Accordingly, another more advanced type of models has been recently utilized in analyzing and predicting traffic accidents, which is the artificial neural network (ANN) (Akgngor and Dogan, 2009). What distinguishes the ANN modeling technique and made it more widely used is its ability to provide rich, robust and powerful models in transportation engineering and road-safety applications. ANN models are very convenient for approximating unknown nonlinear functions that rely on many variables, since the use of ANNs eliminates the need to define these functions (Kim et al., 2004).

Accordingly, it can be concluded that many international and local studies have analyzed traffic accidents, their trends and characteristics using different accident-prediction models, whether being time-series models, regression models or ANN models, and that these models differ in their accuracy, strengths, weaknesses and effectiveness in predicting traffic accidents in the region. Up to the authors' knowledge, there is no local or international study that compares the performance of these techniques and identifies the best one in predicting accidents and causalities.

DATA SOURCES

In this study, the required data has been acquired from different sources (Khaled, 2020). The annual data of traffic road accidents, injuries and fatalities for the period 1995-2020 and the number of registered vehicles in Jordan have been acquired from the annual reports prepared by the JTI (2020). Data on the population of Jordan for the period 1995- 2020 has been acquired from the estimates provided by the Jordanian Department of Statistics (DOS, 2020). Finally, the economic data related to the Jordanian GDP for the period 1995-2020 was obtained from the World Bank website (World Bank, 2020).

All types of accidents, including fatal, injury and property damage which occurred during the study period (1995-2018) were included in developing the traffic accident models. Furthermore, it was decided to use the 2019-related data for verification purposes; so it was kept aside from developing the trend analysis and modeling. Moreover, the models have been applied to predict accidents, fatalities and injuries in 2020, which will show us the impact of the Corona “Covid-19” pandemic and the closures that the Jordanian sectors witnessed on the rates of traffic accidents.

Table 1 presents a summary of descriptive statistical measures for traffic data (number of accidents (NOA), number of injuries (NOI) and number of fatalities (NOF)) used in the modeling for specific years during the indicated period.

Table 1. Summary of descriptive data statistics during 1995-2019

Variable	Number of Years	Min. Value	Max. Value	Mean	St. Dev.
POP (thousands)	25	4264	10554	6400.59	1973.44
REGV (thousands)	25	312	1677	902.32	452.88
GDP (million USD)	25	6727	44503	21778.35	13633.89
NOA	25	28970	161511	93011.76	41898.54
NOI	25	13184	19015	16830.00	1488.11
NOF	25	469	992	710.12	116.07

METHODOLOGY

Regression Models

Regression analysis is one of the methods used to obtain a relationship of a dependent variable to one or more independent variables (IVs). SPSS, v.24 software was used to develop regression models for accidents, fatalities and injuries in this study. The development of the regression models was done by experimenting with a subset of significant independent variables; namely, GDP, POP, REGV, motorization level (REGV/1000 POP) and the ratio of POP/REGV. In this procedure, all the possible regression models were fitted and the best one with a high R^2 value, a minimum standard error as well as a low p-value for the coefficients of independent variables and y intercept was chosen.

Artificial Neural Network Models

Three different ANN models were developed in this study using WEKA 3.8.5 software. The models were formulated using 24 data points of accidents and a feed-forward back-propagation training algorithm through a supervised multi-layer perceptron (MLP) (type of ANN) to classify instances and develop the prediction models. In this study, the sigmoid function produced the least error from the networks. Therefore, the sigmoid function was employed in the hidden and output layers of the models’ networks. This function performs regression instead of just classification. The output layer will output continuous values instead of binary ones. This function is unlike other step functions, where it introduces non-linearity into the neural network model, hence enabling each neuron in a multi-layer neural network to produce a new representation of the original data (Lippmann, 1987).

Accordingly, NOA, NOI and NOF were calculated using the sigmoid function represented in Equation 1 and the final model was developed using Equation 2.

$$y = \frac{1}{1+e^{-x}} \quad (1)$$

$$NOA' = \sum_{i=1}^{n} (\omega_i * sig(\alpha)_i) + \vartheta \quad (2)$$

where:

NOA': The normalized value of predicted NOA.

n : Number of nodes in the hidden layer.

ω_i: Weight of node from the hidden layer to the output.

$sig(\alpha)_i$: Sigmoid value for the weighted sum of the parameter which can be calculated by ($x_1 * w_1 + x_2 * w_2 + x_3 * w_3$ +node bias), where each x represents the normalized value of the parameter.

ϑ: The output bias.

According to Lippmann (1987), a simple network structure of one or two hidden layers is preferred over a complicated one. Also, Goodfellow et al. (2016) found and proved that MLP with one hidden layer can approximate any function that is required if given enough hidden units (nodes) in the layer. Therefore, a network with a structure of an input layer, one hidden layer and an output layer was considered an acceptable starting point for the modeling process.

Developing the ANN models for accidents, fatalities and injuries prediction involved a sequence of steps, including data pre-processing, rescaling and determining the node number. In data pre-processing, the 24 data points are divided into training and testing points at the ratio of 80:20 (Hegazy and Ayed, 1998). Rescaling is used to give all the variables in the model the same attention and importance (Lepikhin et al., 2020; Bhandari, 2020). The optimization process was used to select the optimum number of nodes in the hidden layer. This method is an iteration process that starts with zero or one node in the hidden layer and increases this number as long as there is an improvement in the performance of the network model. Figure 1 shows the methodology flowchart for developing ANN models.

Different performance measures were used to evaluate the performance of the developed ANN models and to determine the optimal ANN parameters. These measures are RMSE, MAE and R^2. RMSE is considered a performance metric to evaluate the loss in the ANN model. Also, it is used to measure the standard deviation in the model residual. However, MAE is used to calculate the average error between the predicted values from the model and the actual values. The lowest value of this metric measures the highest model accuracy. On the other hand, R^2 is a scaled term that measures the goodness-of-fit of the models (0-1). The higher the value, the better the model (Garcia et al., 2018).

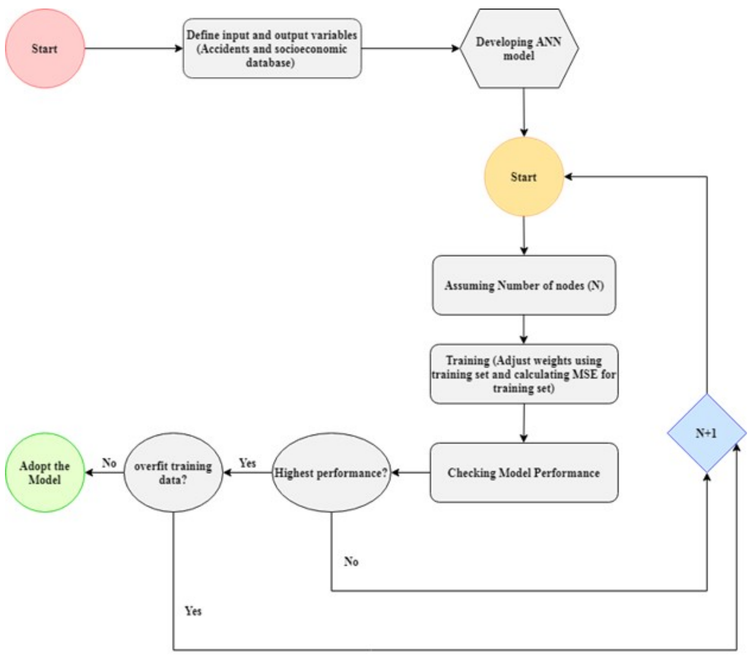


Figure (1): Flowchart for developing ANN models to predict accidents, fatalities and injuries

ARIMA Models

In this study, the Box-Jenkins development strategy of three stages was followed, as presented by Avuglah et al. (2014). These stages include identification, estimation and diagnostics checking. Identification can be reached through several steps, including the investigation of stationary Augmented Dickey–Fuller (ADF) test as well as time, ACF and PACF plots (Avuglah et al., 2014). The estimation phase is to detect the parameter estimates (p,d,q.) that limit the mean square error (Hyndman and Athanaopoulos, 2018). The goal of diagnostics checking is to test the goodness-of-fit of the specified model. If the fit is poor, appropriate modifications will be conducted (Sekadakis et al., 2021).

Moreover, to obtain the best-fit model with the highest validity using the time-series methodology, several tests are required, represented as follows: RMSE and MAE are often determined to choose the best-fit model. The lowest values of RMSE and MAE represent an indicator for the best-fit model, as indicated by Mwenda et al. (2014). Also, the model with the lowest value of BIC is considered the best-fit model, as indicated by Din (2016). Ljung–Box test is lastly implemented to verify the normality of the selected model's residuals (Hassouna et al., 2020).

RESULTS and DISCUSSION

Descriptive Statistics of the Variables

In general, the Jordanian population is increasing with time with a steady state for the citizens during the study period (1995-2018), as shown in Figure (2-b). However, there were some sudden increases due to forced migration that happened two times during the study period: in 2003 from Iraq due to the Gulf war and from Syria from 2012 to 2014 due to the Syrian civil war. Regarding the GDP, it was also increasing during the study period, because Jordan's economy is classified as an emerging market, trying to improve the investment environment in a way that improves the economic situation, see Figure (2-c). This contributed to the increase in banking facilities the impact of which is noted in increasing the number of vehicles in Jordan, as shown in Figure (2-a). This relationship between population increase, economic increase and increase in the number of vehicles has been explained by many studies (Garcia-Ferrer et al., 2007; Yannis et al., 2014).

It can be noticed that there has been a noticeable and continuous increase in NOA for the period (1995-2018), with a total increase of 419.2% as a result of the rise in POP, REGV and level of motorization. It should be noted that 2008 witnessed a decrease in NOA (it seems to contradict the prevailing trend) compared to 2007, as a result of intensifying the traffic control laws and speed-violation penalties in Jordan.

As for NOI and NOF, it is noted that there is an upward trend and this upward trend is fluctuating compared to NOA, which can be explained by the fact that the Jordanian traffic laws have succeeded in reducing the severity of accidents more than their success in reducing the number of accidents. This fluctuation makes it more difficult to develop the models than in the case of NOA.

Regression Models' Results

Based on regression analysis carried out using 24 data points and by trying different types of curve-estimation models, the power regression model was the best to predict NOA using motorization level as an IV. For NOI and NOF, the polynomial (quadratic) model was the best and using (POP/REGV) as the most suitable predictor.

Based on regression analysis, the following equations were obtained:

$$NOA = 64.636\, M^{1.471} \qquad (3)$$

$$NOI = 188.664\, X_i^2 - 13.190\, X_i + 12537.112 \qquad (4)$$

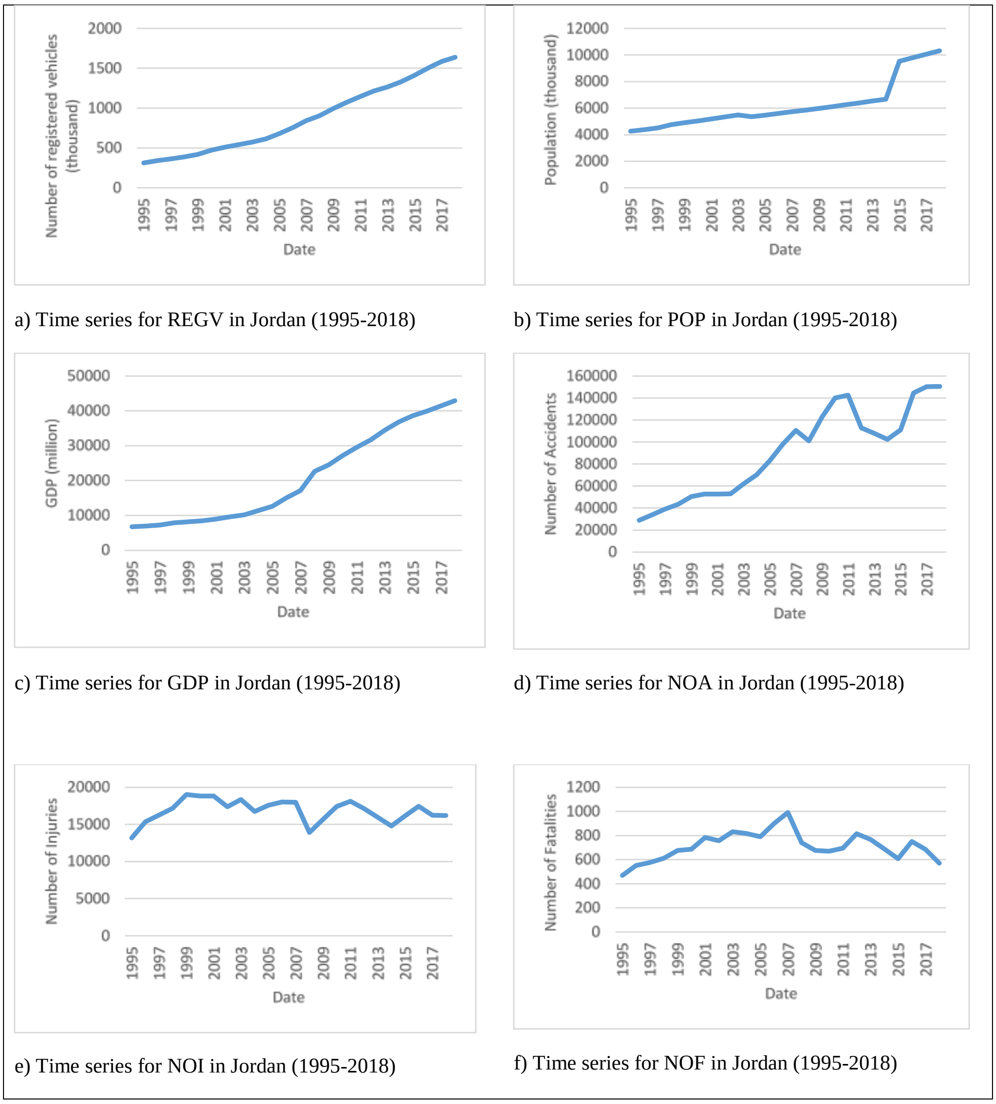
$$NOF = 10.255\, X_i^2 - 0.790\, X_i + 535.809 \qquad (5)$$

where:

X_i = Population per number of registered vehicles per year (POP/REGV).

M= Motorization level (number of registered vehicles per one thousand of population).

All developed models and their parameter estimates were found to be significant at the 95% confidence level. The NOA power regression model's coefficient of determination (R^2) was 0.872, which means that the model explained 87.2% of the variations in NOA. This model is similar to that suggested by Al-Masaeid (2009), as it was found that the power model suits the nature of traffic-accident data.



a) Time series for REGV in Jordan (1995-2018)

b) Time series for POP in Jordan (1995-2018)

c) Time series for GDP in Jordan (1995-2018)

d) Time series for NOA in Jordan (1995-2018)

e) Time series for NOI in Jordan (1995-2018)

f) Time series for NOF in Jordan (1995-2018)

Figure (2): Descriptive statistics for the study variables (REGV, POP, GDP, NOA, NOI and NOF) during 1995-2018

For NOI and NOF, coefficients of determination (R^2) were (0.556) and (0.594), respectively, which indicates the moderate degree of fit of the quadratic model to predict NOI and NOF. The residuals' analysis, normality and homoscedasticity were also considered and achieved for the developed models.

It is worth mentioning that the developed regression models employed a limited number of variables. Addition of more related variables, such as length of paved roads or vehicle-kilometer of travel, may improve their prediction power. However, accurate values for these variables are not available.

ANN Models' Results

Table 2 presents the final performance measures for the developed NOA model, using the WEKA software. Table 2 indicates that the most accurate model for predicting NOA is model No. 3, which has a 3-3-1 model structure. The model has 3 input variables, 3 nodes and 1 output. Figure 3 shows the model structure as well as the weights and bias. The (3-3-1) structure was the most appropriate one to predict NOA having the least RMSE and MAE and the highest R^2 of 0.984. Furthermore, the (3-4-1) structure was found to be the most appropriate one to predict NOI and NOF having the least RMSE and MAE and the highest R^2 of 0.912 and 0.960, respectively.

It is worth mentioning that the ANN developed models are better than the regression models. This was clearly noticed for NOI and NOF models, where R^2 has improved from 0.594 to 0.960 for NOF and from 0.556 to 0.912 for NOI. This is in agreement with previous studies (Garcia et al., 2018; Yu et al., 2016), which showed that neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques.

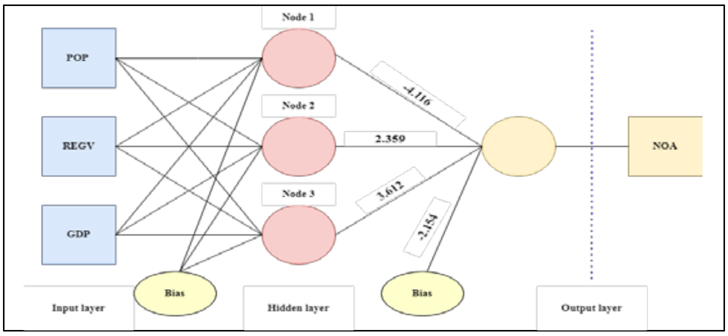


Figure (3): Number of accidents (NOA) model structure

Table 2. ANN architecture and performance measures for NOA model

ANN Models for NOA								
Model No.	**Model Variables**	**No. of Nodes**	**ANN Model Structure**	**Dataset**	**R**	**R^2**	**RMSE**	**MAE**
1	POP, GDP, REGV	1	3-1-1	Training	0.958	0.918	13091.7	10509.3
				Validation	0.949	0.901	12917.4	10359.2
2	POP, GDP, REGV	2	3-2-1	Training	0.989	0.978	7643.6	6338.1
				Validation	0.956	0.914	11718.3	8482.3
3	POP, GDP, REGV	3	3-3-1	Training	0.992	0.984	5193.8	3930.5
				Validation	0.988	0.976	6339.3	5052.8
4	POP, GDP, REGV	4	3-4-1	Training	0.945	0.893	14631.7	11096.3
				Validation	0.952	0.906	12089.9	9235.5

ARIMA Models' Results

The Box-Jenkins (Box, 1976) approach of model identification, parameter estimation and diagnostics check was followed in the analysis of accidents data. The stationarity of the time series of NOA, NOI and NOF was investigated. The ADF test indicated that the series of NOA, NOI and NOF were non-stationary. To remove the non-stationary trend, the data was differenced. After differencing the data (d = 1), the time plot and the ACF and PACF plots showed stationary trends for NOA, NOI and NOF. This is confirmed by the ADF test, where ADF= -0.2577, -4.1337 and -4.1118 with p-value < 0.05 for NOA, NOI and NOF, respectively; thus, the series of NOA, NOF and NOI were stationary. Consequently, the stage of identifying other parameters in the ARIMA model started. The model parameters were estimated using the maximum likelihood estimation method (Wei, 2006) and using idealized patterns represented by Dixon (Dixon, 1992). All probable models were diagnosed to determine the best-fit model among the estimated potential models with varying parameters. RMSE, MAE, BIC and R^2 were used to select the best-fit model.

The ARIMA (8,1,0), ARIMA (7, 1,4) and ARIMA (8,1,2) were found to be the best-fit models for predicting NOA, NOI and NOF, respectively, because they have the lowest values of RMSE, MAE and BIC and the highest values for R-squared and stationary R-squared. R^2 values for NOA, NOI and NOF models were 0.96, 0.67 and 0.76, respectively. To examine the validity of the selected models, the Ljung-Box test was used to determine the independency of the residuals. The results showed that the significant *p*-values were > 0.05 for the three models; therefore, the null hypothesis cannot be rejected and thus, the residuals are independent and not correlated.

Clearly, there are considerable variations in the R^2 values for NOA, NOI and NOF ARIMA models. Both NOI and NOF trends are less predictable when compared with NOA trend, as shown in Figure 2. The low values of R^2 in NOI and NOF models may be explained by the fact that ARIMA may not perform well if there is an uncommon slowdown or growth in the series, because ARIMA is only looking at the back data of the variable.

Validation and Application of Models

Using the accidents' data of 2019, the prediction performance of the three types of models (Regression, ANN and ARIMA) was validated, as shown in Table 3. The accuracy of the models was compared through computing the percentage errors of prediction for the NOA, NOI and NOF in the year 2019. Figure 4 shows the validation results for the number of fatalities during the period (1995-2019).

According to the previous conducted comparison and validation shown in Table 3 and Figure 4, it can be inferred that the developed ANN models provided higher accuracy compared with ARIMA models regarding the performance measures (RMSE, MAE, R^2 and % Error). Clearly, ANN models provide very accurate estimates of the number of accidents, injuries and fatalities, with a maximum error of about 1%. ARIMA was also better than regression that comes in the last place in terms of the prediction power; however, the developed regression models were much simpler in terms of models' structure and analysis than the developed ARIMA and ANN models. Although it is preferred to use more than one-year data for validation purposes, the use of one-year data is not unreasonable.

Finally, the developed models were used to predict NOA, NOI and NOF for the year 2020 to show the difference between observed and forecast values; i.e., to show the impact of strategies undertaken to combat Covid-19 on road traffic-accident statistics. The implemented strategies included a complete ban on travel and a quarantine, except for emergency, from 17th of March 2020 to 15th of June 2020, followed by a partial ban on travel at night, except for emergency cases, until 15th of August 2020, as well as the implementation of odd and even system for vehicles allowed to travel (Al-Tammemi, 2020).

Table 3. Comparison between actual and predicted NOA, NOI and NOF for regression, ANN and ARIMA models

NOA models comparison results					
Year	Actual NOA	Regression-predicted NOA	ANN-predicted NOA	ARIMA-predicted NOA
2019	161511	111774	159489	156501
% Error		-30.7%	-1.2%	-3.1%
Goodness of Fit (R^2)		0.872	0.984	0.960
NOI models' comparison results				
Year	Actual NOI	Regression-predicted NOI	ANN-predicted NOI	ARIMA-predicted NOI
2019	17013	19926	16992	16862
% Error		17.12%	-0.12%	-0.89%
Goodness of Fit (R^2)		0.556	0.912	0.674
NOF models' comparison results				
Year	Actual NOF	Regression-predicted NOF	ANN-predicted NOF	ARIMA-predicted NOF
2019	643	937	652	618
% Error		45.7%	1.4%	-3.9%
Goodness of Fit (R^2)		0.594	0.960	0.764

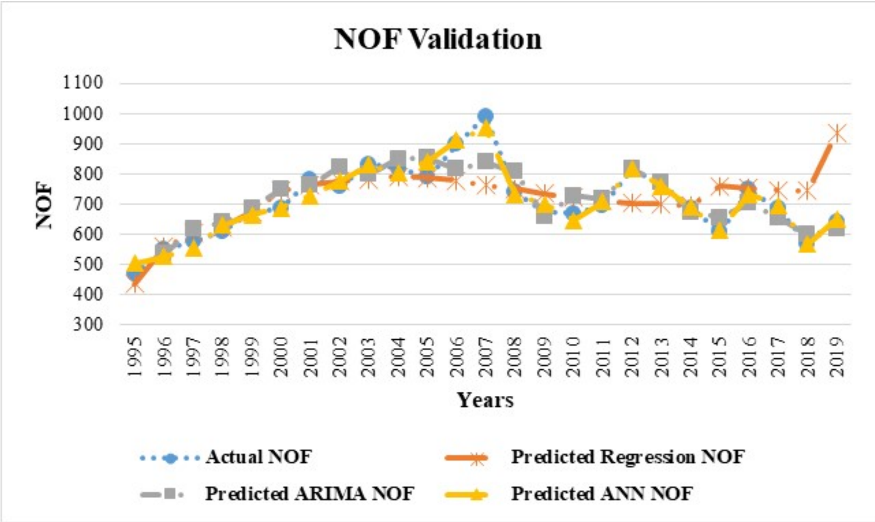


Figure (4): Actual *vs.* predicted NOF for regression, ANN and ARIMA models

In 2020, the observed numbers of accidents, injuries and fatalities were 122970, 12690 and 461, respectively. Since the performance of ANN models was very accurate, they were used in accident statistic estimates for 2020. According to the ANN models, the estimated numbers of accidents, injuries and fatalities were 166965, 17496 and 690, respectively. Thus, the implemented strategies had reduced the numbers of accidents, injuries and fatalities by approximately 35%, 37% and 50%, respectively. This result is in agreement with many international studies, including Yasin et al. (2021) and Saladié et al. (2020), which indicated that during the COVID-19 pandemic, travel restrictions led to a significant reduction in vehicle traffic that was reduced by more than 50% worldwide, which in turn led to a reduction in the numbers of traffic fatalities and injuries globally.

CONCLUSIONS

This study investigated the possibility of using different modeling techniques; namely, regression, ARIMA and ANN, to predict traffic NOA, NOI and NOF in Jordan and compared the performance of these models to find out the best of them in predicting future statistics. The study also explores the impact of the Covid-19 pandemic and subsequent closures and restricted-travel strategies on traffic accidents in Jordan in 2020.

The results of this study indicated that all three modeling techniques can be used to predict the numbers of traffic accidents, fatalities and injuries in the future. Based on the model performance, the ANN models are the best, followed by the ARIMA models and then the regression models. Compared with regression and ARIMA models, ANN models provided more accurate estimates of traffic accidents and casualties. For the developed ANN models, the obtained R^2 values of the NOA, NOI and NOF models were 0.984, 0.912 and 0.96, respectively. In the validation analysis, these models provided estimates of NOA, NOI and NOF with a maximum error of estimate of about 1 %.

Also, analysis revealed that population, number of registered vehicles and gross domestic product have significant effects on the number of accidents and their consequences. This implies that the inclusion of a broad spectrum of human-, vehicle- and economy-related factors in road traffic accident modeling and forecasting is necessary rather than solely aggregated accident counts. Probably, incorporating more independent variables, such as length of paved roads and vehicle-kilometer of travel, may improve some models' prediction power.

Finally, it was concluded that complete and partial banning of vehicle travel undertaken by the government to prevent the spread of Covid-19 resulted in a significant reduction of traffic accidents and casualties. In 2020, the estimated reductions in traffic accidents, injuries and fatalities were approximately 35%, 37% and 50%, respectively.

Recommendations

For future studies, the researchers recommend incorporating more related independent variables that may affect accident occurrences or consequences. Probably, the use of variables, such as vehicle-kilometer of travel and length of paved roads, may improve some models' prediction power or ranking.

Conflicting Interests

The authors have to declare no potential conflicting interests with respect to the research authorship and/or publication of this article.

REFERENCES

Akğngör, A.P., and Doğan, E. (2009). "An artificial-intelligent approach to traffic accident estimation: Model development and application". Transport, 24 (2), 135-142.

Al-Masaeid, H.R. (2009). "Traffic accidents in Jordan". Jordan Journal of Civil Engineering, 3, 331-343.

Al-Masaeid, H.R., Mujalli, R.O., and Al-Haj, E.H. (2020). "Impact of fixed cameras on traffic crashes". Saudi Journal of Civil Engineering, 4 (10), 192-198.

Al-Omari, B., Ghuzlan, K., and Hasan, H. (2013). "Traffic-accident trends and characteristics in Jordan". International Journal of Civil Engineering, 13, 9-16.

Al-Tammemi, A.B. (2020). "The battle against COVID-19 in Jordan: An early overview of the Jordanian experience". Frontiers in Public Health, 8. https://doi.org/10.3389/fpubh.2020.00188.

Avuglah, R. K., Adu-Poku, K.A., and Harris, E. (2014). "Application of ARIMA models to road traffic accident cases in Ghana". International Journal of Statistics and Applications, 4 (5), 233-239.

Bhandari, A. (2020). "Feature scaling for machine learning: Understanding the difference between normalization and standardization-introduction to feature scaling: Why should we use feature scaling?" https://www.analyticsvidhya.com/blog/2020/04/feature-scaling-machine-learning-normalization-standardization/.

Box, G., and Jenkins, G. (1976). "Time-series analysis: forecasting and control". Holden-Day, San Francisco, 1976.

Din, M. A. (2016). "ARIMA by Box-Jenkins methodology for estimation and forecasting models in higher education". ATINER's Conf. Pap. Ser., Athens, Greece.

DOS, Department of Statistics. (2020). "Jordan statistical yearbook 2020". http://dosweb.dos.gov.jo/products/jordan-statistical-yearbook-2020/.

García de Soto, B., Bumbacher, A., Deublein, M., and Adey, B.T. (2018). "Predicting road traffic accidents using artificial neural network models". Infrastructure Asset Management, 5 (4),132-144.

García-Ferrer, A., De Juan, A., and Poncela, P. (2007). "The relationship between road traffic accidents and real economic activity in Spain: Common cycles and health issues". Health Economics, 16 (6), 603-626.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). "Deep learning (adaptive computation and machine learning series), illustrated edition". The MIT Press, Cambridge, Massachusetts.

Hassouna, F.M.A., Abu-Eisheh, S., and Al-Sahili, K. (2020). "Analysis and modeling of road crash trends in Palestine". Arabian Journal for Science and Engineering, 45 (10), 8515-8527.

Hassouna, F.M.A., and Tubaileh, M. (2020). "Road traffic casualties in the West Bank: Trends' analysis and modeling". International Review of Civil Engineering, 12, 1-8.

Hegazy, T., and Ayed, A. (1998). "Neural-network model for parametric cost estimation of highway projects". Journal of Construction Engineering and Management, 124, 210-218.

Hmaid, T., and Imam, R. (2019). "Development of crash-prediction models for roadway segments in Jordan". Proc., of the Second Balqa'a International Engineering Conference, Dead Sea, Jordan, 1-12.

Hyndman, G., and Athanasopoulos, R.J. (2018). "Forecasting: Principles and practice". Heathmont, Melbourne.

JTI, Jordan Traffic Institute. (2020). "Yearly report of traffic accidents in Jordan 2020". https://www.psd.gov.jo/images/jti/images/002.pdf.

Khaled, F.J. (2020). "Analysis of traffic accidents in Jordan for two decades". MSc Thesis, Civil Engineering Dept., Jordan University of Science and Technology, Irbid, Jordan.

Khasawneh, M.A., Al-Omari, A.A., and Ganam, B. (2018). "Forecasting traffic accidents in Jordan using regression techniques". Jordan Journal of Civil Engineering, 12 (4), 570-579.

Kim, G.H., An, S.H., and Kang, K.I. (2004). "Comparison of construction-cost estimating models based on regression analysis, neural networks and case-based reasoning". Building and Environment, 39 (10), 1235-1242.

Lakshmipriya, C. P. (2018). "Development of crash-prediction models for uncontrolled intersections". International Journal of Engineering Science, 5, 104-110.

Lepikhin, D., Lee, H., Xu, Y., Chen, D., Firat, O., Huang, Y., Krikun,M., Shazeer, N., and Chen, Z. (2020). "GShard: Scaling giant models with conditional computation and automatic sharding". Proceedings of the International Conference on Learning Representations, Vienna, Austria. http://arxiv.org/abs/2006.16668. 2020.

Lippmann, R.P. (1987). "An introduction to computing with neural nets". IEEE ASSP Magazine, 4, 4-22.

Mujalli, R.O., López, G., and Garach, L. (2016). "Bayes classifiers for imbalanced traffic accidents' datasets". Accident Analysis and Prevention, 88, 37-51.

Mwenda, A., Kuznetsov, D., and Mirau, S. (2014). "Time-series forecasting of solid-waste generation in Arusha city Tanzania". Mathematical Modeling and Analysis, 4 (8), 29-39.

Saladié, Ò., Bustamante, E., and Gutiérrez, A. (2020). "COVID-19 lockdown and reduction of traffic accidents in Tarragona province, Spain". Transportation Research Interdisciplinary Perspectives, 8, 2020. https://doi.org/10.1016/j.trip.2020.100218

Sekadakis, M., Katrakazas, C., Michelaraki, E., Kehagia, F., and Yannis, G. (2021). "Analysis of the impact of COVID-19 on collisions, fatalities and injuries using time-series forecasting: The case of Greece". Accident Analysis and Prevention, 162, 2021. https://doi.org/10.1016/j.aap.2021.106391.

Towards Data Science. (2009). "Multi-layer neural networks with sigmoid function: Deep learning for rookies (2)". https://towardsdatascience.com/multi-layer-neural-networks-with-sigmoid-function-deep-learning-for-rookies-2-bf464f09eb7f.

WHO, World Health Organization. (2018). "Road-safety report: Global-status report on road safety". https://www.who.int/violence_injury_prevention/road_safety_status/2018/en/.

World Bank. (2020). "GDP (present value in US dollars) – Jordan". https://data.albankaldawli.org/indicator/NY.GDP.MKTP.CD?locations=JO.

Yannis, G., Papadimitriou, E., and Folla, K. (2014). "Effect of GDP changes on road-traffic fatalities". Safety Science, 63, 42-49.

Yasin, Y.J., Grivna, M., and Abu-Zidan, F.M. (2021). "Global impact of COVID-19 pandemic on road traffic collisions". World Journal of Emergency Surgery, 16, 1-14.

Yu, B., Wang, Y.T., Yao, J.B., and Wang, J.Y. (2016). "A comparison of the performance of ANN and SVM for the prediction of traffic-accident duration". Neural Network World, 26 (3), 271-287.