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Article

Developing Artificial Neural Networks and Highway Safety Manual Models for Predicting Accidents at Intersections in Bahrain

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Abstract: Intersections are among the places where the highest number of accidents occur, thus, studying their safety and considering countermeasures to increase their safety should improve the overall safety of a traffic system. Prediction models, such as Artificial Neural Networks, have not been used for planning purposes in terms of providing countermeasures for accidents. This shortcoming forces the practitioners to employ traditional statistical methods which may be less accurate and have restricted applications. Hence, the Artificial Neural Networks models of this study were developed with the application of suggested countermeasures. Their performance was also compared with the traditional method given in the Highway Safety Manual after calibrating the procedure for local conditions. In this study, the intersections with the highest reported accidents isn the Kingdom of Bahrain were analyzed. The data was taken for the years 2013–2016, courtesy of the data provided by the Bahrain General Directorate of Traffic. Using this data, two predictive Artificial Neural Networks models were developed and used to forecast the accident number and severity in these selected intersections. Four intersections were selected to showcase the findings and to study the potential countermeasures that can be applied to reduce the occurrence of accidents. The comparison between Artificial Neural Networks and Highway Safety Manual procedures showed that Artificial Neural Networks models were more convenient to use with generic applications to different types of intersections. Moreover, they also provided higher accuracy while the Highway Safety Manual model was found to be heavily dependent upon traffic demand, which greatly affected its accuracy. The countermeasures suggested in this study were shown to reduce the accidents at the selected locations.

Keywords: traffic; car accidents; artificial neural network; accident prediction

1. Introduction

Machine learning techniques are being utilized on a wide scale for various applications [1]. Their ability for pattern recognition can be used to interpret big datasets [2]. An example of this can be seen in shopping websites which provide recommendations based on patterns of the user's shopping history [3]. Based upon the acclaimed success of machine learning techniques in several fields, their use in the field of road safety is expected to be effective. In this research, one of the machine learning techniques is used to predict the number of accidents that can potentially occur, along with recognizing the factors that are more likely to contribute to said accident.

The increase in motorization around the world has resulted in a subsequent increase in traffic accidents [4]. These accidents cost 1.2 million lives per year and render 20–50 million people disabled. Other serious issues related to traffic accident include the involvement of kids and young people (5–25 years) in these accidents and their frequent occurrence in low- and middle-income countries which constitute major population of the world [5]. However, there is less attention given to small countries such as Bahrain which may show different patterns than the high population countries. Bahrain has a population of approximately 1.6 million with more than 50% expatriate residing in it [6]. Bahraini travelers mainly rely on private modes of road transport for their trips with the public transport mode being non-existent. It has a population growth rate of 4.6%, density of 1936 people per sq. km., with majority of population living in the urban areas [7]. Traffic crashes are a major problem in Bahrain due to their frequency and the involvement of young drivers. It was estimated that a crash is reported every 5 minutes in Bahrain, with more than 40% victims being under the age of 25 years [8]. As per the data from General Directorate of Traffic, there has been a reported increase of more than 20% in the crashes involving injuries and fatalities.

In this study, we have chosen to utilize Artificial Neural Networks (ANNs) for predicting number and severity of accidents occurring on intersections in Bahrain. ANNs have gained popularity in the field of predicting accidents and their severity [9,10]. With the advancement in computational abilities and techniques, deep learning has also been utilized widely in different fields including Intelligent Transportation Systems (ITS). Haghighat et al. [11] has discussed these applications extensively in their review. The application of this technique is also found in the field of crash prediction in many studies [12]. The main challenges related to the application of machine learning techniques include imbalanced data, incorporation of non-crash events, issues with forecasting of crash frequencies and inconsistencies in injury classes [13]. It was also noticed that there is a lack of studies which deal with the incorporation and measuring the impact of countermeasures with the use ANNs. These countermeasures refer to the changes which are made to the crash sites to reduce the number and severity of crashes. They are linked with the causes of the crashes and can result in changes in policy for implementation at the regional level [14].

Alternatively, Highway Safety Manual (HSM), published by AASHTO, provides many tools and recourses for quantifying and evaluating the safety performance of a highway system [15]. The components of the highway system covered by the manual include highway segments, control devices, and intersections. HSM models have been found useful for evaluating highway safety inside, as well as outside, USA [16,17]. There are extensive requirements for data collection and computation for applying these tools outside USA. HSM methods mainly depend upon traffic volumes in the prediction of crashes. They have safety performance functions developed to predict the number of crashes for specific types of sites (segments, intersections, etc.). The geometric configurations of the sites are incorporated as crash modification factors which provide average reduction/increase in crashes due to the presence of a feature. Moreover, calibration factors are required to apply the functions to specific areas for inclusion of any unexplained variation in the crashes.

Due to this reason, there have been studies which have focused on empirical methods to provide safety impacts of different countermeasures. Gupta [18] used Empirical Bayes method to study the safety impacts of speed limits. Spatial analysis has also been utilized for this purpose by Pusuluri et al. [19]. These studies have not focused on intersections which are found to be the hot spots for crashes in most of the cases.

It was found that the studies found in this field do not focus on application of prediction models, such as ANN, for developing improvement measures for the accident locations. This is the main concern of traffic management authorities which leads them to use other models (such as HSM), rendering the application of ANNs less effective. This study attempts to cover this aspect of modeling with ANNs by providing ANN models equipped to evaluate the effects of countermeasures on intersection safety. There are various advantages associated with ANN which merit their use in this study. These include the ability to capture complex nonlinear relationships in data, adapt to changing conditions without any priori information, and handle large datasets effectively [20].

In this context, transferability of HSM models, for application in different countries and situations, is another major issue which has been an active area of research in the current literature [21,22]. The current study addressed the challenge of transferability of HSM models with their appropriate calibration. Moreover, no such study has been found in the context of Gulf Cooperation Council (GCC) countries. Therefore, predictive models given by HSM for intersections were recalibrated, for conditions in Bahrain, and their performance was compared with ANN models in terms of accuracy. It is expected that the calibrated HSM models, from this study, could also be applied to other countries of this region as they have similar driving and road conditions. The calibrated HSM models and ANN models were utilized to investigate the effects of countermeasures on the number and severity of accidents. The models from this study can also be used to develop crash modification factors.

In light of the above discussion, the present research addresses the following research gaps:

- Incorporation of countermeasures in the ANN-based prediction models.
- Recommending a methodology for the recalibration of HSM models for Bahrain. The applied methodology is generic while the recalibrated model could be applied to other countries in the region.

2. Methods and Data Acquisition and Preparation

The research methodology is depicted in Figure 1. The detailed accident data for intersections were obtained from the General Directorate of Traffic [23–26]. The data included the time of accident, type of accident, severity of the accident, age of the driver, sobriety, and other relevant information. Based upon the available data, locations with the highest accident frequencies were selected which are shown in Figure 2. More details about the accidents on these sites are shown in Table 1. After acquiring the data, the first task was to format the data to be used as an input vector. This is done by removing the data points with incomplete information. Furthermore, the text variables were converted to numerical representations, for example: presence of rumble strips was converted to a dichotomous variable of 0 or 1. The details of all the input variables can be seen in Tables 2 and 3. After arranging the available dataset, it was divided into two sets: one for training the ANN models and the other for validating them. It was followed by the calibration HSM model for predicting number and severity of accidents on the same locations for which ANN was developed. In the end, the results from both datasets were compared in terms of their accuracy for the available dataset.

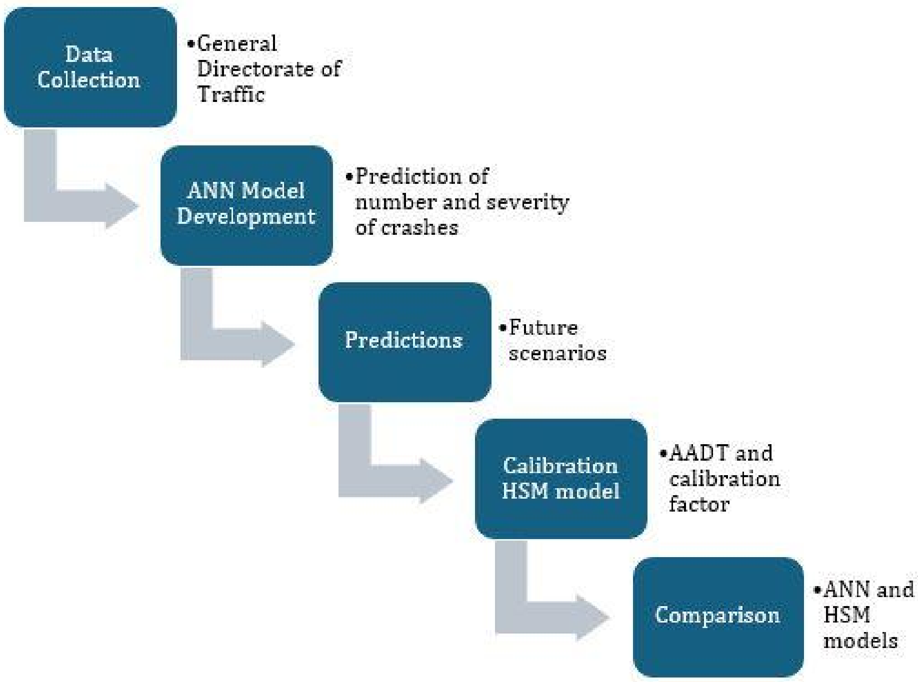

Figure 1. Research methodology.

Table 1. Details of accidents on selected sites.

Number [Figure 2]	Intersection Region	Traffic Control	Number of Approaches	Urban/ Rural	Crash Total			
					Year 2013	Year 2014	Year 2015	Year 2016
1	MANAMA	SIGNALIZED	4	Urban	-	-	7	10
2	BAHRAIN BAY	SIGNALIZED	3	Urban	9	10	8	12
3	SITRA	SIGNALIZED	4	Urban	-	-	-	6
4	AL RIFFA	SIGNALIZED	4	Urban	-	-	-	5
5	NORTHERN	SIGNALIZED	4	Urban	-	-	-	8
6	MUHARRAQ	SIGNALIZED	4	Urban	-	-	6	9
7	AL JANABIYAH	SIGNALIZED	4	Urban	-	-	-	6
8	MANAMA	SIGNALIZED	4	Urban	-	6	6	-
9	MANAMA	SIGNALIZED	4	Urban	9	-	6	-
10	RIFFA	SIGNALIZED	4	Urban	-	-	6	-
11	ISA TOWN	SIGNALIZED	4	Urban	7	-	6	-
12	MANAMA	SIGNALIZED	4	Urban	9	10	7	-
13	ISA TOWN	SIGNALIZED	4	Urban	-	6	8	-
14	DIPLOMATIC AREA	SIGNALIZED	4	Urban	-	8	-	-
15	MUHARRAQ	SIGNALIZED	4	Urban	-	8	-	-
16	MUHARRAQ	SIGNALIZED	4	Urban	-	7	-	-
17	SITRA	SIGNALIZED	2	Urban	8	-	-	-
18	ISA TOWN	SIGNALIZED	4	Urban	7	-	-	-
19	MANAMA	SIGNALIZED	4	Urban	7	-	-	-
20	ALBA ROUNDABOUT	ROUNDABOUT	5	Urban	12	8	10	7
21	NUWAIDRAT ROUNDABOUT	ROUNDABOUT	4	Urban	7	5	10	5
22	RIFFA ROUNDABOUT	ROUNDABOUT	4	Urban	-	5	-	-

(a)

(b)

Figure 2. Study Area.(**a**) Bahrain (Courtesy: Google maps); (**b**) Locations (Courtesy: https://www.nationsonline.org/oneworld/map/bahrain_map.htm).

2.1. ANNs

ANNs are data-driven machine learning algorithms designed to recognize patterns in data after being trained on a set of data. Once that is done, the trained network can take new data that was never shown to it and the network will output the best prediction based on its training [27]. Some notable applications of ANNs include predicting stock prices [28], language and speech recognition [29], and pattern recognition [30]. One of the major benefits of using an ANN is its ability to adapt to any given data, whether the data are linear or nonlinear [31]. Considering the success of ANNs in accurate prediction for the above-mentioned problems, they were used in this study to predict crash frequency and severity with the inclusion of possible countermeasures. This will aid in studying the impacts of these countermeasures on road safety. It should be noted that there are more advanced versions of ANNs available such as Convolutional and Deep learning, which have been utilized for image, and text detection with the latest Artificial Intelligence (AI) applications. However, their successful development and implementation requires large amounts of data which was not available for this study.

Table 2. Input vector prepared for accidents prediction network.

Factor	Description	Input Style
AADT Major	Average annual daily traffic for major road	Numeric value (based on target year)
AADT Minor	Average annual daily traffic for minor road	Numeric value (based on target year)
Pedestrian crossing volume	Number of pedestrian crossing the intersection for the peak/design hour	Numeric value (based on target year)
Approaches w/ left turn Lanes	Number of approaches at the intersection with exclusive left turn lanes	Numeric value (based on the intersection, value between 0 and 4)
Approaches w/ right turn Lanes	Number of approaches at the intersection with exclusive right turn lanes	Numeric value (based on the intersection, value between 0 and 4)
Number of approaches w/ left-turn signal phasing	Number of approaches at the intersection with exclusive left turn phase	Numeric value (based on the intersection, value between 0 and 4)
Red light camera	Presence of a camera at the intersection to capture drivers committing signal violations	0 if not present, 1 if present
Rumble strips	Presence of rumble strips near the intersection	0 if not present, 1 if present

Table 3. Input vector for training accident severity network.

Factor	Input Style
Drunk	0 if false, 1 if true
Crossing red light	0 if false, 1 if true
Careless lane change	0 if false, 1 if true
Collision w/pedestrian	0 if false, 1 if true
Time of day	0 if night, 1 if day
Turning	0 if false, 1 if true
Right angle	0 if false, 1 if true
Rear end	0 if false, 1 if true
Control type	0 if signalized, 1 if unsignalized
Location type	0 if rural, 1 if urban
Speed limit	Numeric value of posted speed limit

2.2. Prediction of the Number of Accidents

The first prediction model that we developed in this research was designed to take the intersection features as its input (as shown in Table 2) and give its best approximation of the number of predicted accidents on that intersection for a particular year. The input data were acquired courtesy of the directorate of traffic and the ministry of works in Bahrain. Acquisition of data is explained in Section 2. MATLAB, by MathWorks Inc., was used to develop and test ANN models for this research. The program was used due to its widespread use among researchers and the familiarity of the authors with the interface. 522 data points were available to train this model, out of which 70% were used to train the network. The remaining 30% of the data was used for validation. The Bayesian Regularization algorithm was used as the training algorithm; this algorithm was used for its generalization and stable numeric performance abilities with relatively small datasets [32]. Figure 3 shows more details about the training process while Figure 4 shows the typical structure of this network. Mean squared error was used for optimizing the number of neurons in the hidden layer and it was found that 10 neurons provided the least mean squared error. Network accuracy was found to be approximately 97% for the training as well as validation dataset.

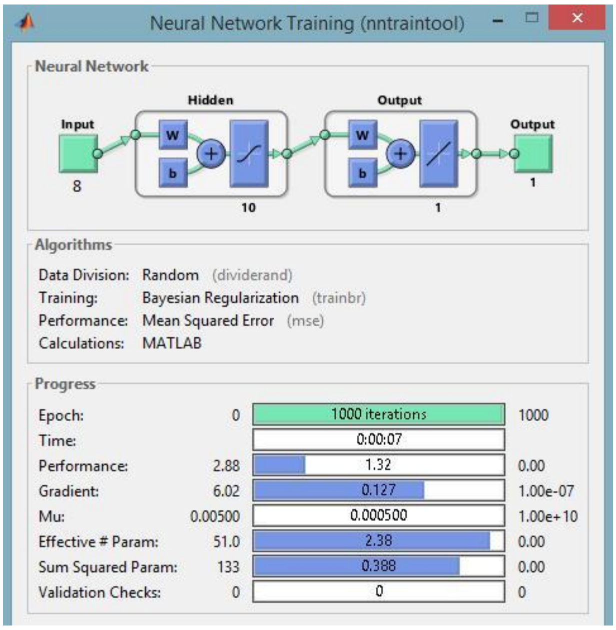

Figure 3. Training specifications for accident prediction ANN.

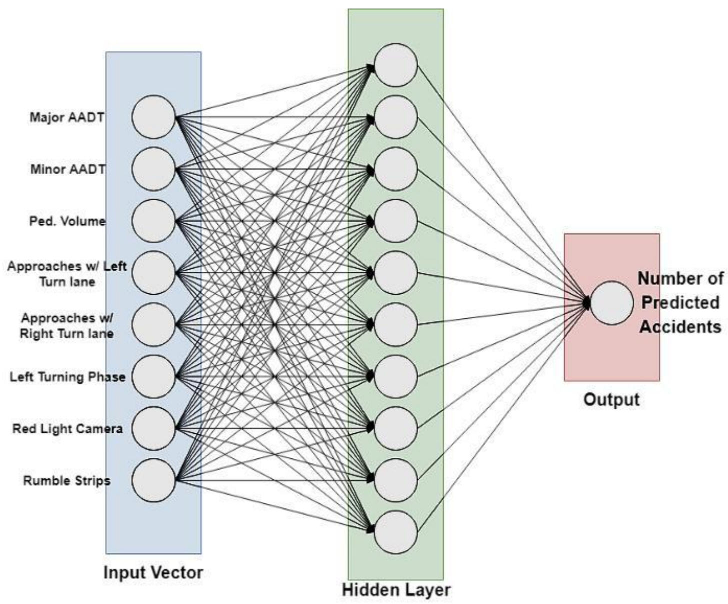

Figure 4. Typical structure of accident prediction ANN.

Once the training and performance validation are done, we can acquire the trained model in the form of a MATLAB function. The function we designed for predicting the number of accidents takes an input matrix of size

8 × n, as per Table 2, and gives the number of predicted accidents as "n" number of values, where "n" represents the number of intersections for which the accidents are to be predicted. A simple MATLAB code was generated, as shown in Figure 4, to facilitate this task. Note that ANN models work through simultaneous processing across all their neurons, which cannot be represented in the form of an equation. Therefore, the associated details, structure, and MATLAB code are provided in Figure 3 and Algorithms 1 and 2, respectively.

Algorithm 1: Pseudocode for predicting accidents

```
%ModBays() is the trained network function
%The input can be modified down below
%The purpose of this code is to have easy control over the inputs,
%in addition to formatting the output in a desired fashion
AADTMaj=106928.64;
AADTMin=4728.64;
Ped=113;
LTL=4;
RTL=4;
LTP=2;
camera=0;
rumble=0;
for i=1:12;
x(1,i)=AADTMaj;
x(2,i)=AADTMin;
x(3,i)=Ped;
x(4,i)=LTL;
x(5,i)=RTL;
x(6,i)=LTP;
x(7,i)=camera;
x(8,i)=rumble;
end
sum(ModBays(x))
```

As a practical application of this research, the trained ANN model was used on four intersections in Bahrain, which have been identified as blackspots for several years by Bahrain General Directorate of Traffic. Two of them are signalized intersections (i.e., M049, M007). M049 is located in the city of Manama where King Faisal Highway and Bahrain Bay Highway cross through it. M007 is also located in Manama and has King Faisal Highway and Al Furtha Avenue crossing through it. The other two intersections (5071, 6058) are roundabouts. 5071 being Alba roundabout and 6058 being Nuwaidrat Roundabout. Both are located in Sitra. Stop-controlled intersections were not found to be hazardous for accidents, hence this study only applies to signalized intersections and roundabouts. The countermeasures were selected using results from previous studies done at intersections [33–37]. Table 4 shows a comparison of model predicted values with and without the countermeasures for the years 2017 and 2018 from the ANN model. It should be noted that the actual number of accidents at these intersections was not known at the time the model was developed. Moreover, the models treat the number of accidents as a continuous variable, as there are no defined limits for this variable. Hence, outputs with fractional values can be observed which is the same for established models given by HSM as well. It is very clear from Table 3 that the suggested countermeasures could be effective in reducing accidents in all the cases. Such analysis also demonstrates the usefulness of the models developed in this study which were helpful in determining the effects of these countermeasures.

Table 4. Predicted number of accidents from ANN model.

Intersection	Countermeasure	Predicated for 2017		Predicted for 2018	
		With Countermeasure	Without Countermeasure	With Countermeasure	Without Countermeasure
M049	Red light camera	10.3	11.5	10.9	12.1
M007	Rumble strips	8.8	10.4	9.3	11.0
5071	Rumble strips	7.6	8.4	6.7	8.0
6051	Rumble strips	4.4	5.1	5.6	6.6

2.3. Prediction of Accident Severity

Following the same steps as before, another neural network was trained and used to predict the severity of an accident, given the conditions. Using the same 522 data points, the data is sorted and prepared with the appropriate inputs for training. However, for the purpose of finding the severity, the network will use the input vector (as per Table 3) to output the severity in an output vector of length 3 [0 0 0], where the first element indicates a slight injury, the second a serious injury, and the third a fatal injury. For example, a serious injury will be represented as [0 1 0]. One of the shortcomings of the current model is that it does not consider the use of a seatbelt nor the type of vehicle as an input. These factors were not available to us at the time of study. Future studies should investigate the role of these factors.

For predicting the severity of an accident, we focused on the factors that we suspected were more likely to be significant in determining the severity of the crash. The training was conducted using the same parameters used for ANN for predicting the number of accidents. The training process resulted in three neurons in the hidden layer.

Once the training process is complete, we can start using the network to make predictions about the severity of accidents. The MATLAB function produced by the toolbox takes a matrix of 11xn parameters (as shown in Table 3) and gives output in the form a matrix size 3xn that contains the severity for each of the "n" intersections. Algorithm 2 shows the script written for using this ANN with any given input data. The network achieves the validation accuracy of approximately 80% for training and validation datasets with a standard deviation of less than 1 accident in both cases.

Algorithm 2: Pseudocode for predicting accidents severity

```
%input must be loaded in the memory before running
%SeverityPrediction() is the trained network function
%The purpose of this code is to have easy control over the inputs,
%in addition to formatting the output in a desired fashion
SP=SeverityPrediction(x);
len=size(SP);
len=len(2);
for i=1:len;
  check=SP(1,i);
    k=1;
  for j=1:2;
    if check<SP(j+1,i)
      check=SP(j+1,i);
      k=j+1;
    end
  end
    for m=1:3;
   SP(m,i)=0;
  end
```

```
    SP(k,i)=1;
end
SP
```

2.4. HSM Prediction Model

In order to assess the accuracy of the predicted values of the ANNs, a traditional prediction approach is also used to compare numbers obtained from the ANNs. The steps of the HSM prediction model are detailed in the manual published by AASHTO. This section will explain how the major variables were calculated. The basic formula, as per HSM, for predicting the average crash frequency is shown in Equation (1):

$$N_{predicted\ int} = C_i \times (N_{bi} + N_{pedi} + N_{bikie}), \tag{1}$$

where,

$N_{predicted\ int}$ = predicted average crash frequency for an intersection for selected year.

C_i = calibration factor for intersections developed for use in geographical area.

N_{bi} = predicted average crash frequency for an intersection for selected year (excluding vehicle-pedestrian and vehicle- bicycle collision).

N_{pedi} = predicted average crash frequency for vehicle-pedestrian collision.

N_{bikie} = predicted average crash frequency for vehicle-bicycle collision.

Each part of this formula requires its own share of detailed calculation to find the relevant Crash Modification Factors (CMFs). Details of which can be found in HSM (AASHTO 2010 and 2014). We focused on the blackspot intersections which were mentioned previously, because taking up all the intersections would require a lot of field work and computations. To simplify the calculation, a spreadsheet program was used. Once the spreadsheet is prepared following the HSM, only 3 major inputs are required for the calculation:

The Annual Average Daily Traffic (AADT) of the Target year.

The calibration factor for local data.

The type of modification to the facility.

The 12-hour flow count for the four intersections of interest was acquired from the Ministry of Works. Using this data, the value for AADT was approximated for the major and minor highway at each intersection. To do that, the formula for directional design hour volume (DDHV) will be used (shown in Equation (2)) [38]. Calculation of AADT using DDHV is detailed in Table 5.

$$DDHV = AADT \times K \times D, \tag{2}$$

where,

K= proportion of daily traffic occurring during the peak hour.

D= proportion of peak hour traffic traveling in the peak direction.

According to the data from ministry of works, the annual growth rate for Bahrain will be 2%, so if we want to estimate the AADT for the future years, we can use the growth rate to do that.

Table 5. AADT calculation.

INTER.	DDHV Major	DDHV Minor	Year	K	D	AADT Major	AADT Minor
M049	6874	304	2014	0.12	0.6	95472	4222
M007	6874	1383	2014	0.12	0.6	95472	19208
5071	36110	2731	2015	0.12	0.6	50152	37925
6051	5523	1043	2015	0.12	0.6	76708	14486

One major input to be entered is the calibration factor. In order to find the calibration factor, an iterative approach was employed using The bisection method. This method is based on narrowing the search space by centering on the middle point of the available set. It is a very convenient method and can be performed without the use of any sophisticated algorithms or tools, especially for a relatively small search space which was the case in this research. The procedure is shown below in Figure 5, and it was performed using MS Excel. The findings along with the predictions can be found in Table 6. Utilizing the script editor in conjunction with the spreadsheet, an algorithm was developed following the procedure of bisection method. The script targets the cell of the calibration factor and modifies its value. Next, it checks the cell that has the value of predicted accidents and takes the appropriate action based on the value. The process is repeated until the desired error is reached. Table 6 shows the calibration factors for each intersection attained through this process. More details about the calibration procedure can be found in Gazder et al. [39].

Table 6. HSM prediction method results without countermeasures.

Intersection	Calibration Factor	Predicted for 2017	Predicted for 2018
M049	1.69	11.1	11.4
M007	2.35	10.7	10.9
5071	1.48	9.8	10.1
6051	1.34	9.5	9.8

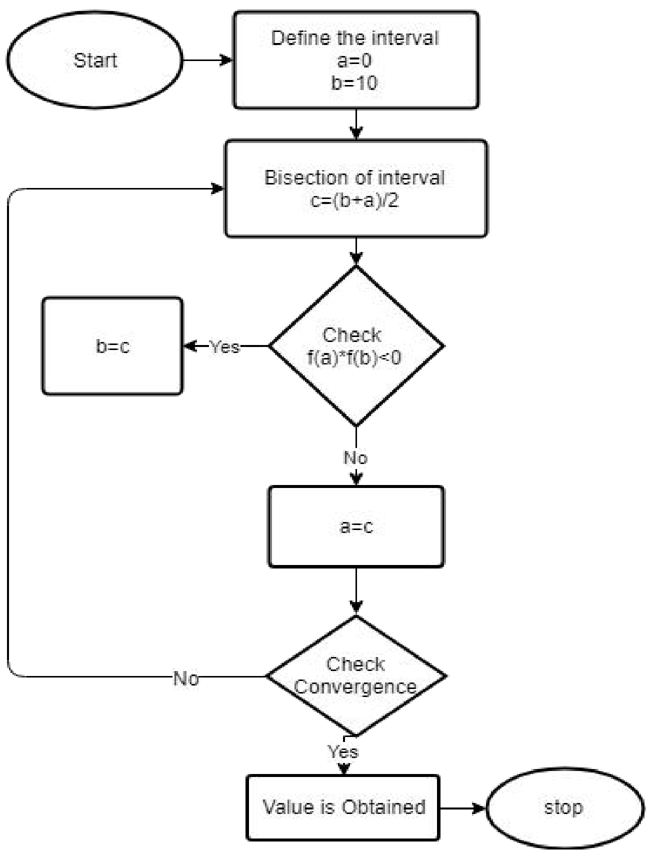

Figure 5. Flow chart for calibration code.

Once all the required inputs are obtained, the calculation of predicted crashes can be done easily. The accuracy of the prediction model was checked by using it to predict the accidents for a known year (2016). The model was able to predict the number of accidents for 2016 with an average accuracy of approximately 90% with a standard deviation of approximately 1. The calibration factors were then used to calculate the number of accidents in 2017 and 2018. By comparing these numbers with those by ANN (in Table 7), HSM model predictions are generally higher than those by ANN. The main reason could be the effect of AADT which is increasing in all cases, consequently, increasing the predictions by HSM model since it is linearly correlated in the model.

Table 7. Comparison of predictions.

Intersection	HSM Model		ANN Model	
	Predicted for 2017	**Predicted for 2018**	**Predicted for 2017**	**Predicted for 2018**
M049	11.1	11.4	10.3	10.9
M007	10.7	10.9	8.8	9.3
5071	9.8	10.1	7.6	6.7
6051	9.5	9.8	4.4	5.6

3. Discussion of Results

This study was aimed at providing practical models for prediction of road accidents using ANN technique and HSM procedures. Moreover, it also outlines a strategy to calibrate the HSM model which can be applied to other conditions similar to the study area. The results of this study prove that ANNs can be used successfully for two of the most critical aspects of road safety, which are predicting number and severity of accidents at intersections. The major advantage of ANNs comes from their ability to learn and recognize trends and patterns from the dataset. We have also shown the application of ANN model in suggesting/evaluating different countermeasures which may be applied to a site in order to reduce accidents. Further investigation needs to be done to judge the economic feasibility of these countermeasures. However, a bigger dataset is expected to increase the accuracy of the ANN models. Especially, for the case of predicting accident severity, we would encourage researchers to examine the effect of a bigger data set.

Application of HSM model was also explored for prediction of accidents and it was found that it requires some effort to calibrate the model for each set of conditions. The first and foremost problem with regards to calibration of the model is the nature of safety function which is developed for specific types of facilities. Moreover, it is dependent upon AADT which does not change on a short-term basis; hence, any recalibration or further development of the model would require a very long-term observation of traffic volume for the type of site under consideration. The process would also have to be repeated for other types of sites as well. Furthermore, it is also acknowledged by HSM that there are certain unexplained variances in the crash data which must be incorporated with a calibration factor for different jurisdictions. These issues put restrictions on the use of HSM models at multiple levels, even though after going through the calibration process. Hence, the model is not generic, as is the case with ANN. Secondly, the accuracy attained by HSM model in predicting accidents is less than that achieved by ANN. The accuracy was compared by using both, ANN and HSM, models to calculate the number of accidents for 2017 and 2018, which were not considered in the training and development of these models. HSM model was observed to overestimate and this could be because it is significantly affected by AADT which increases annually in most of the cases. Hence, there is a conflict between the pattern followed by the independent variable (AADT) and the dependent variable which is the number of crashes. Traffic patterns are growing in nature while the crashes are rare and random events, hence, any mathematical model which is based on AADT for prediction of crashes is bound to be predicted on the higher side most of the times.

4. Conclusions

This study aimed at developing and testing models for predicting number and severity of traffic accidents at intersections in Bahrain. ANN was able to predict the number of accidents with 97% accuracy while it was able to predict the severity of accidents with an accuracy of 80% for the test datasets. Both models can be considered robust since their accuracy does not degrade significantly for validation datasets.

The ANN models in this study also incorporated countermeasures for the accidents as inputs. Hence, the ANN models from this study can be conveniently used by the authorities for evaluating reasons for having high number of accidents at an intersection and suggesting countermeasures for them. The data provides preliminary evidence that the number of accidents can be brought down if appropriate solutions are implemented. The accident severity prediction model can be used to determine which factors are more likely to increase the severity of an accident based on field recorded data.

The adoption of HSM model for some of the blackspot intersections was also explored as an alternative to the ANN model for predicting number of accidents. The calibrated HSM model from this study can be used for other GCC countries as well. However, it was found that this adaptation would require extensive efforts in field data collection and computations for model calibration. Moreover, the resulting model had lower accuracy and was less robust, compared to ANN model. Hence, it is recommended to use ANN for predicting the number of accidents. Based on the results of this study, it is further recommended to enhance the ANN models with the inclusion of deep learning approach, provided that a larger dataset is used for this purpose.

Author Contributions

U.G. supervised the research work, contributed to the conceptualization of the study and carried out the review of initial draft and the write up of final draft; A.H. contributed to the data collection, analysis and write up of the initial draft; Y.Y. contributed to the data collection and the writing of initial draft.

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Institutional Review Board Statement

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Informed Consent Statement

Not applicable.

Data Availability Statement

The data related to the research is part of the research paper.

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Conflicts of Interest

The authors declare no conflict of interest.

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