Neural Technique for Predicting Traffic Accidents in Jordan

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Abstract: Jordan has a highest rate of traffic accidents, which raise the number of deaths and injuries. The paper aims to design and implement a neural technique for predicting the behavior of car accident in Jordan. MPL neural network is used to utilize the predictor system for estimating the number of car accident over the time. Efforts are paid to analysis the recorded data about the traffic accidents like number of accident, types and reasons for the regression part. The experiment recorded an excellent accuracy in the classification of accident type. The accuracy and call precision are 100%. The paper presents analytical study and develops equations that help to control the behavior of growing of traffic accidents. Thus, the governments, planners and traffic engineers can easily overcome the problems associated with traffic accident type in order to determine the requirements for future.

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1. Introduction

Generally, the road traffic accident take a lot of local interest when it occurred, especially when it involving deaths or injuries. Moreover, the traffic accidents are obvious prompt on the damage for vehicles and people that any time can cause a tragedy. The latest statistics of the World Health Organization (WHO), the road traffic accidents claim many lives of people all over the world more than is caused by malaria. Road accidents are the primary cause of death among young people aged 5 to 29 years, especially in developing countries. Worldwide are infected each year up to 50 million people in traffic accidents (Andrew 2003, Report 2011, Andersson 2011, Rahim et al., 2011). The number of the world's population grows increasingly, as well as the number of cars also is increased due the increasing in population rate. Furthermore, the jamming and stop moving the traffic as a result of traffic accidents all over the world is increasing. On the other hand, the traditional procedures implemented to reduce traffic accidents such as improvements of streets engineering design or cars are not effective. As well as, the improving congestion management strategies and find alternative ways to solve the problems of traffic jams. One of the solutions is to civilize drivers by involve them into sessions for understanding the meaning and conditions of safe driving (Delen 2006). There is an adequate range of finding out new developments to foretell mishap models which help to reduce the numbers of lose (Christopher 2009, Florence 2006, Guy 2012, Helai 2010 and Kathleen 2011; Saba and Rehman, 2012). Generally, during the survey of traffic accidents and follow-up reports on the numbers of injuries and deaths, we clearly found that the implemented procedures are not effective and not often feasible or they cost-prohibitive. The current Statistics showed that traffic accidents are the main cause of fatality. Besides, the reports indicate a steady increase in the number of cars on the roads (Ercan 2008; Saba and Altameem, 2013). This requires an analytical study to determine the proportion of the increase in the number of cars and drivers.

As a result, the size of the infrastructure requirements for handling the increasing in traffic accidents can be estimated effectively. The most important reasons and factors affect the traffic accidents are traffic density, road network system and the average speed of vehicles on the highways, and the surrounding environmental and weather conditions. The more traffic density increased incidence of accidents. The artificial neural network is a computational model that simulates the structure and functional aspects of biological neurons. The Artificial Neural Networks (ANN) is one of the most learning and computational techniques which is learned from historical and rare data. This characteristic of neural networks is helping to map a complex relationship between the variables that are unknown or difficult to handle computationally. A neural network is trained for achieving a fastidious function by adjusting the values of weights of connections between elements (Yousif 2011-B, Yousif 2008; Haron et al., 2011; Saba et al., 2011).

This paper presents a modelling technique for achieving high accuracy in classification and recall precision of traffic accidents. Besides, it is aims to design and implement a neural predictor based

Multilayer Perceptron (MLP) for identifying and control the behavior of traffic accident in Jordan. Basically, the ANN is able of implementing highly nonlinear relationships between analyst variables, the input (Accident factors) and the output variable (prediction factors). The neural networks have unique features that effectively make it applied in number of applications such as image processing, information extraction and retrieval, machine learning and translation, speech recognition, grammar spelling checkers, etc. The MLP is one of the most techniques which are used in neural computations because it can easily apply in many applications. The MLP neural network is a feed-forward supervised approach because it requires input and output data in order to achieve the desired figures. MLP are used to many models of input and output using previous knowledge to estimate the behavior and performance of data (Yousif 2012, Yousif 2013, Selamat et al., 2010).

2. Car Accident in Jordan

Jordan has the highest rate of traffic accidents in comparison with the countries in the world. As a result, the increases in traffic accidents are lead to increase the number of deaths and injuries. The Jordan population is estimated more than six million people, while the number of vehicles is estimated more than one million vehicles (Al-Khateeb 2010). The statistics and reports showed that traffic accidents in Jordan are the main cause of death (Obaidat 2012). The number of accidents in 2011 is 142588 and the number of death is 694. While the number of injures are 18122. However, according to Jordan Traffic Institute reports about 90% of the causes of accidents in Jordan are due the failing to follow safety rules to and the drivers mistakes (Al-Masaeid 2009, Rehman et al., 2009). Figure 1 shows the number of road deaths for Arabic countries per 100,000 which is reported by WHO. Libya is home the highest centralization of road deaths (34.7 per 100,000 persons), then it is followed by Oman. Subsequently in the second level countries like Saudi Arabia, Qatar, UAE and Egypt are recorded. While Jordan takes place in the third level with Kuwait.

The statistics also showed that more than 85% of the errors were caused by the speed of drivers. However, the 10% recorded as a result of deficiencies in the road engineering and weather factors such as rain and snow according to Jordan Traffic Institute reports (Obaidat 2012). Figure 2 shows the number of registered car in Jordan from 2002 until 2011 which indicate a steady increase in the number of cars on the roads. Moreover, the number of traffic accidents is increased among the year's corresponding to the increasing in registered cars. The reports of Jordan Traffic Institute as depicted in Table 3 shows that the number of traffic accidents in 2002 are 52913, while it is increased to 142588 in 2011(more than three times). Figure 3 illustrates the number of traffic accidents in Jordan from 2002 to 2013.

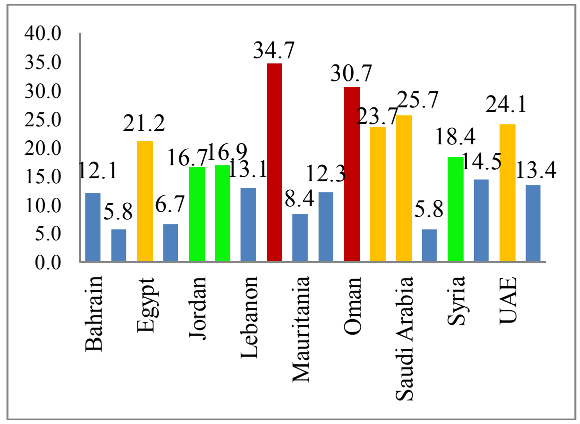

Figure 1. Percent of road deaths rate per 100,000 in Arab countries.

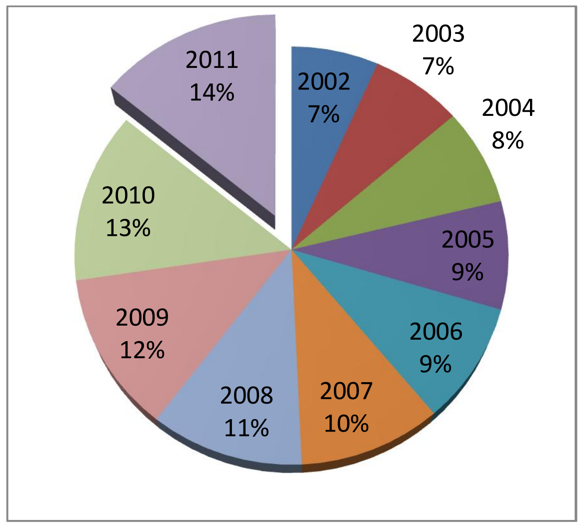

Figure 2. Registered Vehicles in Jordan 2002-2011

As a result the number of deaths due to traffic accidents is increased corresponding the significant increasing in the number of cars and incidents. Figure 4 depicts the number of deaths due to traffic accidents in Jordan in the period from 2002 to 2011. It is explains clearly that 2011 has maximum number of traffic accidents (142588), while 2002 has the minimum number of traffic accidents (52913). In 2008 the numbers of traffic accidents go down about (9000).

This increasing in number of cars requires an analytical study to estimate the size of the infrastructure requirements to handle it. The most important reasons and factors affect the traffic accidents are traffic density, road network system and the average speed of vehicles on the highways, and the surrounding environmental and weather conditions. The more traffic density will affect to increase incidence of accidents. Therefore, it is clearly that we are facing a crucial problem outcome for the increase of the number of deaths due traffic accidents and the failure of many human suffering of the affected families as a result of human losses. As well as, the economic losses caused by damaged cars, roads, buildings and disrupted of work in some cases.

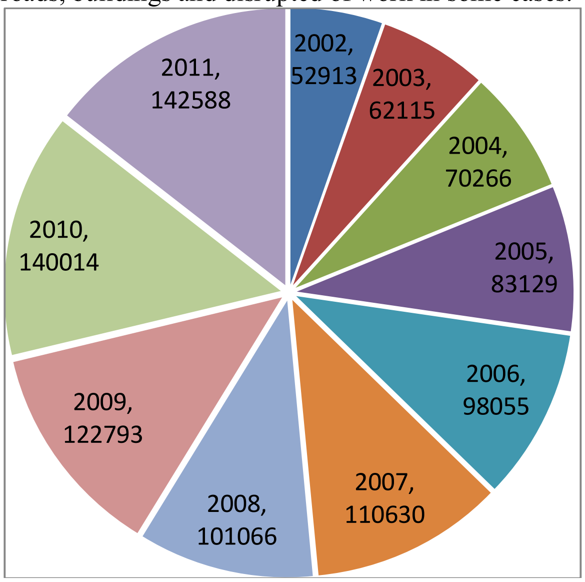

Figure 3. Number of traffic accidents in Jordan 2002-2011

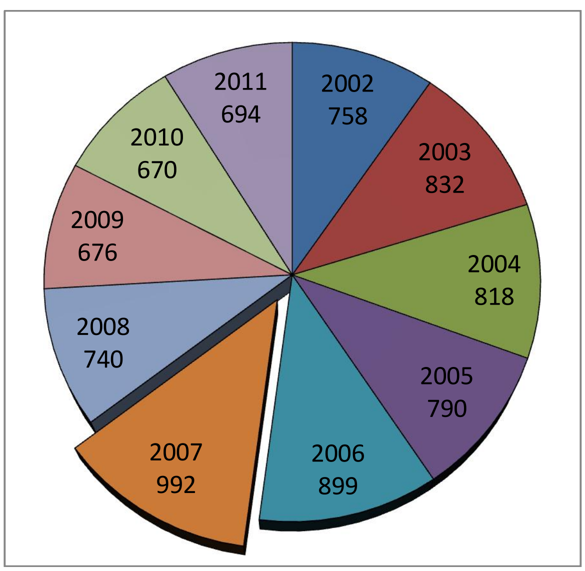

Figure 4. Number of deaths due traffic accidents in Jordan 2002-2011

3. Related Work

The researchers implemented a variety approaches for studying the aspects of traffic accidents (Andrew 2003, Dai 2011, Ercan 2008, Eleni 2000, Al-Khateeb 2010, Al-Masaeid 2009, Kenneth 2008, Hamdar 2009, Sharon 2005, and Taimur 2010). **Saini D. Kumar and Yousif Jabar H. (2012):** They presented a soft computing technique in the prediction of the mishaps behaviours in Oman. They utilized a Multilayer Perceptron (MLP) neural network technique to analysis and predict the mishap factors. They focused on the summarization of past research on the road mishaps causes and the analytical techniques in the area of analysis the factors of mishap. The most important factors like collisions, run over, overturn and collision with the fix objects are taken from Royal Oman Police. Besides, the performance of Multi-Layer Perceptron Networks for classifying and predicting classification accuracy is investigated. **Ali, Galal et al. (2011):** They implemented a comparative analysis and prediction of traffic accidents in Sudan using artificial neural networks and statistical methods. The Input variables of ANN are selected through investigating the strength of the correlation between the annually number of traffic accidents and related variables such as annual population growth, gross domestic product, number of driving licenses issued, etc. The study showed that MLP are appropriate for interpolation rather than extrapolation because it is supervised technique which needs predicting the data inside a specific range. Nevertheless, the study demonstrates that ANNs provide a potentially powerful tool in analyzing and forecasting traffic accidents and casualties. **Abdelwahab and Abdel-Aty (2001):** They utilized an artificial neural networks approach for mapping the relationship between driver injury severity and accident factors such as driver, vehicle, roadway, and environmental conditions. **Mehmet M. Kunt, et.al. (2011):** They highlighted the predicting the severity of freeway traffic accidents by employing twelve accident related parameters in a genetic algorithm (GA), pattern search and artificial neural network (ANN) modelling methods. The multi-layer perceptron (MLP) neural network architecture is consisted of a multi-layer feed-forward network with one hidden layer based sigmoid and linear output neurons that could also fit multi-dimensional mapping problems arbitrarily well. **Mussone et al. (1999):** They implemented an artificial neural networks approach to analyze vehicular accidents that happened at a connection in Milan, Italy. They choose a feed-forward MLP based back propagation learning algorithm. **Rezaie Moghaddam F., et al. (2011):** They illustrated the simultaneous affect of human factors, road, vehicle, weather conditions and traffic features including traffic size and flow speed on the crash severity in urban highways. They implemented a series of artificial neural networks to model and estimate crash severity and to identify significant crash-related factors in urban highways. The research is evidenced that the most significant factors increasing crash severity in urban highways are highway width, head-on collision, type of vehicle at fault, ignoring lateral clearance, following distance, inability to control the vehicle, violating the permissible velocity and deviation to left by drivers. **Miaou et al. (1993) :** They presented the statistical properties of four regression models to reproduction vehicle accidents and highway geometric design relationships. The Highway Safety Information System is used for providing the data in this research which is performed to discover the limitations of these models. The research gives evidence that the Poisson regression models are have the attractive statistical properties in developing the relationships.

4. Materials and Methods

4.1 Data Analysis and Neural Network

The latest analytical techniques in data mining and artificial intelligence are used significantly to determine the factors of the traffic accidents (Becky 2007, Hand 2001). Besides, the increased number of deaths and injuries resulting from traffic accidents has a major impact on society. The Accident information analysis is recorded in order to conclude the causes of an accident which can be helped to prevent further incidents of a related kind. The analysis comprises the coding of the levels of selected variables of the accident data. As well, specifying the membership significance of the data based cluster analysis and data mining techniques. This pushed the researchers to put immense efforts in order to decrease the affect of accidents loses. A number of studies have been addressing the using artificial neural techniques to utilize and identify the main factors in traffic accidents (Andrew 2003, Delen 2006 and Saini 2012). These include neural network, nesting logic formulation, log-linear model, etc. ANN can used to formulate traffic accident data which can smooth the progress of understanding the accident factors connected with different injury severity. The most factors are the driver's behaviour, road condition and weather condition (Florence 2006, Yousif 2011A, Yousif 2012 and Kenneth 2008).

This paper presents the using of MLP neural networks to construct a model that can effectively predicate and simulate the number of traffic accidents in Jordan. A MLP is a feed forward neural network with one or more hidden layers. The neural networks are consisted of an input layer of source neurons and in between it have hidden layers (one or more) as adjustment computational neurons. Lastly it is comprised of output layers (one or more) of computational neurons to present the results. The input layer acknowledges the input signals and the resend these signals to all neurons in the hidden layer. The output layer assents a stimulus pattern from the hidden layer and establishes the output pattern of the entire network. The ANN is employed in the areas that usually had been utilized as statistical methods. A neural network is a powerful data modelling method which is help to utilize and characterize complex input and output relationships for both linear and non-linear variables (Yousif 2011-A). The artificial neural network is considered as one of the most computational model and learning techniques that can learn from the rare data. Particular characteristics can motivate researcher to implement neural network techniques in solving problems (Yousif 2011-B, Mika 2010 and Patrick 2008). The main characteristics of ANN include the following: parallelism, uniformity, generalization ability, distribution representation and computation, ability to learn, train and adapt. Neural approaches have been implemented effectively in a number of applications such as classification and prediction domain, image processing and noise filtering, speech recognition, NLP, and pattern recognition (Paul 2011 and Poul 2003).

4.2 Contributory Factors to Road Accidents

The system of contributing factors is developed to provide some facts about the accidents which help to answer how and why accidents are occurred. These contributing factors are designed to illustrate the basic procedures and failures that lead directly to the actual reasons of the incidents. It used to assist the investigation of how they can prevent accidents in the future. Obviously, it is non-objective factors to a large extent, but it reflects the opinion of a police officer who is responsible for issuing the report. Nevertheless, it is not necessarily it will be the result of extensive investigation, but it is a process of recording accident evidence. This information is a valuable because it helps in improving the road and traffic safety. However, at the same time these factors must be interpreted with caution**.** The report contributory factors comprise a list of 77 contributory factors. These 77 factors divided into nine main categories as flows: Road environment contributed, Vehicle defects, Injudicious action, Driver errors or reaction, Impairment or distraction, Behavior or inexperience, Vision affected by external factors, Pedestrian factors (casualty or uninjured) and Special codes. The human factors including drivers and pedestrians are considered as one factor in most of the accidents. Besides, the curves, sidewalks, traffic marking and lighting considered as road factors that can affecting the accident happened.

For example the most commonly reported contributory factor in Great Britain (GB) is failed to look properly which is reported in 42% of all accidents reported to the police in 2011. The driver errors or reaction contributory factor is reported in more than 60% of fatalities in the road accidents. The loss of control is reported in the 34% of fatal accidents. The Pedestrian failed to look properly is the main contributory factor which is reported in the 59% of accidents of pedestrian how injured or killed (Reported 2011). Figure 7 shows he number of Traffic Accidents in Jordan by Type form 2002 to 2011. For example the most commonly reported causes factor is collision which is reported in 96.2% of all accidents recorded in the police station in 2011. While the pedestrian reported as contributory factor of accidents in 2.4%. Lastly the turnover is repeatedly reported in 1.4% of all accidents. The severity rate is decreased is Jordan to 0.13 in 2011in comparison with 0.34 in 2002. The severity rate is reported from 2011 t0 2001 accordingly as follows: 0.34, 0.31, 0.25, 0.22, 0.19, 0.17, 0.14, 0.13, 0.13, and 0.13 as depicted in Table 3.

4.3 Data Collection

In order to achieve the objectives of this paper, a set of data were collected and integrated from Jordan Traffic Institute and Traffic Department which include the following information: number of vehicles involved in accidents, numbers of death and injuries in accidents, fatalities for hazardous locations, type of accidents if it is collision, crash or pedestrian. Table 3 presents the statistics of accident data for the last 10 years, which is obtained from Jordan Traffic Institute and Traffic Department. Along with this, a lot of data needs to be collected and analysed by using data mining techniques (Hand 2001). The collected data are encoded to suitable form that can be used later in neural network. Obviously, the road safety works form a complex concern and occupy a number of functions, which require a multidisciplinary method to capture the problems with the aim of achieving more practical results. This study used datasets that issued by the Jordan Traffic Institute and Traffic Department. This datasets sampled from the annual accident reported in Jordan which contains traffic accident records of 10 years from 2002 to 20111. The variables are already categorized and represented based on accident categories (collision, turnover and Pedestrian). The research aims to predict the accident factors and causes for year 2002 to 2011.

4.4 MLP Configuration & Design

The supervised learning techniques are used in the classification task that has data sets for training and learning phases. Multilayer Perceptron (MLP) neural network topology is used in the analysis of behaviour of accidents. The discriminate functions take shapes which are not definite but it gives the shapes according to the input data set cluster. In order to achieve a superior performance, the Normalization of input data set is needed. The output is a binary form Two-Class 0 or 1 clusters, which is optimum from a classification phase (Yousif 2011-A). For the sake of learning and generalization of the network, the Back Propagation learning algorithm is implemented. The adaptation of weights in the layers of PEs is performed by initializing all the weights and threshold levels to small random numbers. Then the actual output of the neurons in the hidden layer is calculated. In addition, the main factors causing the accident is processed and categorized. The ANN is implemented for predicting future values. The Neuro solution software is used to implement and design the MLP neural network which has one hidden layer, 11 PEs as input, 3 PEs as output, data set of 100 pairs (year, type of accidents). The maximum number of epochs is 1000. The TanhAxon as transfer function is implemented in hidden and output layer. The **TanhAxon** function applies a bias and **Tanh** formula to each neuron in the layer which flattens the range of each neuron between [-1 and 1]. Such nonlinear elements provide a network with the ability to make soft decisions. The back propagation learning algorithm (BP) is used to propagate the errors through the network and permits to accomplish the adaptation of weights in the hidden PEs. Bp learning method with the error function is performed as follows:

$$E(w) = \sum_{p=1}^{pt} \sum_{i=1}^{Epoch} (di(p) - yi(p))^2$$

Where E (w) = error function to be minimized,
w = weight vector, Pt = number of training patterns,
Epoch = number of output neurons,
$d_i(p)$ = desired output of neuron i.
$y_i(p)$ is actual output of the neuron i.

In the training phase, the procedure is continued computing new weight vector w until the error function is minimized. Once the error function is equal to small value (threshold), then actual output is coming closer to the desired output and stopped. With the aim of adaptation of each weight in the network, the theory of gradient learning techniques is used. It corrects the present value of the weight as follows:

$$Wij(n+1) = Wij(n) + \eta\delta i(n) + x\mathrm{j}(n)$$

Where the local error $\delta i(n)$s computed from $Wij(n)$ at the output PE or can be computed as a weighted sum of errors at the internal PEs. The constant step size is η. For the sake of improving the straight gradient descent, the Momentum learning is used which is speed up and stabilize convergence of network. The update of the weights in momentum learning is computed as follows:

$$Wij(n+1) = Wij(n) + \eta\delta i(n) + xj(n) + \alpha(Wij(n) - Wij(n-1))$$

The best value of α (momentum step) is between 0.1 and 0.9. In the current study, the experiments give evidence that the best value for α is 0.7.

5. Results.

The study analyzed the causes of the traffic accidents in Jordan. This study focuses on three factors of traffic accident (collision, pedestrian and overturn). The data of main factors are taken from Jordan Traffic Institute reports as depicted in Table 3. These data are used for investigating the performance of Multi-Layer Perceptron Networks in classifying and predicting accidents factors. The NeuroSolutions software package and Microsoft excel 2010 are used to perform the required analysis of this study. Numerous step of analysis is applied to find the best relationship between several independent variables or predictor variables and a dependent or criterion variable. Regression analysis approximates the relationship between the variables so that a given variable can be predicted from one or more of other variables (Uriabi 2009). By using regression analysis, you can extend a trend-line in a chart beyond the actual data to predict future values.The numbers of accidents caused by collisions are estimated as polynomial trend-line function that because the MSE is very small. It is as follows:

$$y = 141.41x^2 - 3282.4x + 102839.$$

The trend accuracy is 89.2% as presented in Figure 5.

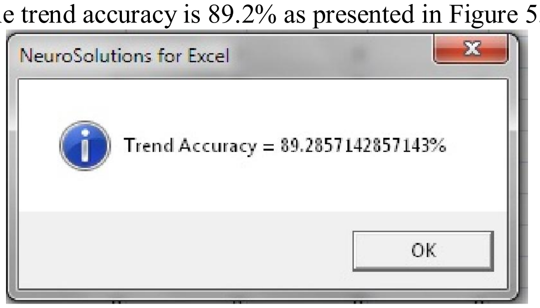

Figure 5. The Trend Line Accuracy for Output Variable "Collision"

The numbers of accidents caused by turnover are estimated as polynomial trend-line function as follows:

$$y = -0.3597x^2 + 0.0357x + 1608.6$$

The numbers of accidents caused by pedestrian are estimated as polynomial trend-line function as follows:

$$y = 0.4852x2 - 16.566x + 2787.7$$

The correlation coefficient is denoted by **"r"** which determines the strength of the straight-line or linear relationship between two variables (accident type, year). The correlation coefficient has values in range between **+1 and -1**.

In this experiments, the study got correlation values as follows (**Collision**: 0.999984957, **Pedestrian**: 0.999835455, **TurnOver**: 0.999952141). The Values between 0.7 and 1.0 explains a strong positive linear relationship in the firm linear rule. And the values between -0.7 and -1.0 shows a strong negative linear relationship in the firm linear rule. That mean we have a strong relation between the two variables (accident type and year). Based on results of experiment, the study achieved excellent accuracy in classification phase to identify the accidents type. The accuracy is 100%. As well the precision is 100%. The experiments give evidence that 2002 has the lowest value of sensitivity about the mean. This denotes it has the minimum number of accidents. While in 2011 has the highest value of sensitivity about the mean which denote it has the maximum number of accidents. Moreover, in the years 2003, 2004, 2005 the sensitivity values about the mean are going down. On other hand, in year 2009,2010, 2011 the average is going down and in year 2002, 2006, 2005 values of sensitivity about the mean are going up. The Figures 12, 13,14,15,16 and 17 depict sensitivity about the mean for three factors of accidents (collision, pedestrian and turnover).

Table 1 shows the best network results for the training and cross validations of data. It is clearly presents the final MSE of training phase is (**0.000026**), while the final MSE of cross validation phase is **(0.000049)**. Figure 6 clearly shows that the MSE is very reasonable and it is coming very close to the real values which validate our claims. Figure8 shows the number of real collision is coming out closely to the output of MLP network, which gives us the correct values and indicates that we can predicate the number of collision in the future. Figures 9, 10 present the output of our MLP network which is closely to the real data of the turnover and pedestrian number of accidents. It give clear indicates that we can predicts the number of accidents happening at any time for these factors.

6. Discussions

The variables used in this test are collisions, turnover, and pedestrian. The Table 1 illustrates the best network results for the training and cross validation phases of the MLP network. And Table 2 presents the Sensitivity values of factors over mean which it is depicted in Figure 11.

Table 1. The best network results

Best Networks	Training	Cross Validation
Epoch #	1000	1000
Minimum MSE	0.000026	0.000049
Final MSE	0.000026	0.000049

The following conclusions were founded based on the analysis of undertaken data and experiments results which conducted in this research are:

1. The study achieved excellent accuracy (100%) in classification phase to identify and classify the

accidents type. As well the recall precision is 100%.

2. The study addresses way for predicting the accident factors and finds analytical equation that can control the behavior of growing of car accident. This can help the governments, planners and traffic engineers easily to overcome the problems associated with car accidents in order to determine the requirements of new challenges.
3. The experiments approved that the year 2002 has a lowest value of sensitivity about the mean. This gives indicate it has the minimum number of accidents.
4. The 2011 had a highest value of sensitivity about the mean which give indicate it has the maximum number of accidents.
5. The values of sensitivity about the mean in 2003, 2004, 2005 are going down which means that the accidents number are decreased.
6. The values of sensitivity about the mean were gone up in 2009, 2010 which means that the accidents number are increased.
7. The final Mean Square Error (MSE) of training phase is (0.000026), and the final MSE of cross validation phase is (0.000049), which is very small amount of error in comparison with the original data sets.
8. The preponderance of traffic accidents in Jordan was the Collision accidents. The collision is most commonly causes factor which is reported in 96.2% of all recorded accidents at the police stations in 2011. While the pedestrian is reported in 2.4% of all accidents. Lastly the turnover is repeatedly reported in 1.4% of all
9. Jordan has high injury rates in comparison with other countries in the world.
10. The group of age between 18 to 42 years had the highest proportion (43.9 %) of fatalities. As well it had the highest proportion (57.4 %) of injuries.

Table 2. Sensitivity of factors over the mean

Sensitivity	Collision	Pedestrian	Turn Over
2011	50857.9578	263.3080	56.36290
2010	57909.9199	1411.9868	127.9291
2009	18615.0374	787.6855	135.6014
2008	2937.80154	638.5933	269.46870
2007	4146.79944	771.4968	320.9982
2006	6408.37146	2402.8399	932.5031
2005	19178.1867	2514.3640	713.0042
2004	17243.3221	3557.7721	1065.8030
2003	25280.7661	3306.1562	827.76711
2002	79859.9868	2416.9447	681.6969

6.1 Future Work

This study includes only three factors, So in future the number of factors can be extended and found new relationship among them which help to discover new reslts. Beside, the extending the number of data stes to use for training and learning the network in future will give more evidence and accurate results. The optimization techniques can be used for optimizing the features selection like the values of transfer function and threshold.

More analysis can help to reduce the dimensionality of the dataset which decrease the training and learning time of the network. The research can be extended to implement new type of softcomputing techniques like genetic algorithm (GA), fuzzy logic, reccurent neural network (RNN) and self organezation feature map(SOSM).

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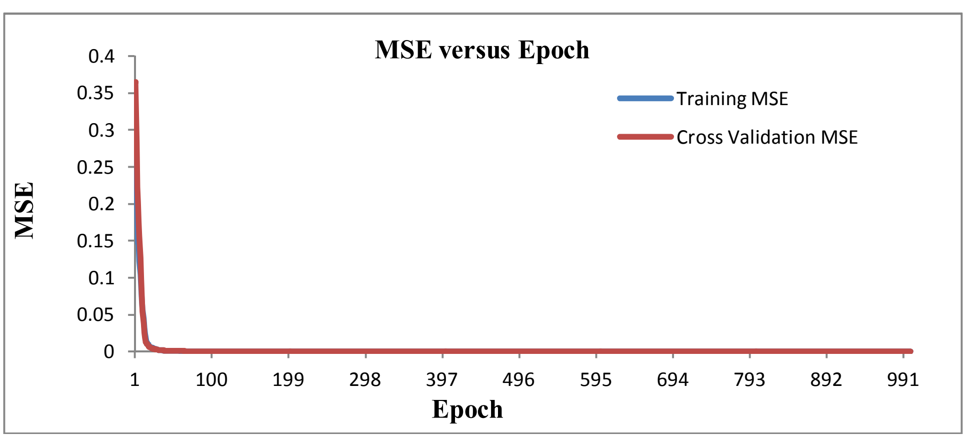

Figure 6. MSE value versus Epoch numbers for training and cross validation phases.

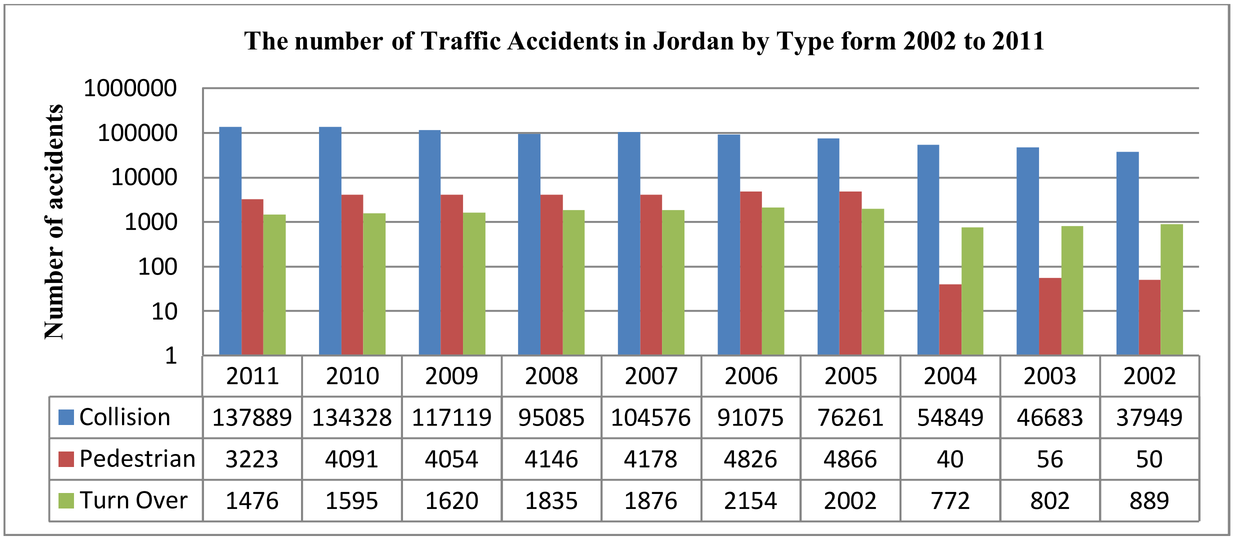

Figure 7. The number of Traffic Accidents in Jordan by Type form 2002 to 2011

Table 3. The traffic accidents data for the last 10 years according to Jordan Traffic Institute reports.

Year /events	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Accidents	52913	62115	70266	83129	98055	110630	101066	122793	140014	142588
Fatalities	758	832	818	790	899	992	740	676	670	694
Injuries	17381	18368	16727	17579	18019	17969	13913	15662	17403	18122
Registered Vehicle	542812	571498	612330	679731	755477	841933	905592	994753	1075453	1147258
103 ×Inhabitants	5329	5480	5350	5473	5600	5723	5850	5980	6113	6249
Accident per day	145	170	192.5	227.8	268.6	303.1	276.89	336.4	383.6	390.7
Fatality per day	2.1	2.3	2.2	2.2	2.5	2.7	2.03	1.9	1.8	1.9
Injury per day	47.2	50.3	45.8	48.2	49.4	49.2	38.12	42.9	47.7	49.6
Acc. per 10.000 Vehicle	974.8	1086.9	1147.5	1223	1297.9	1314	1116.2	1234.4	1301.9	1242.9
Fatality per 10.000	14	14.6	13.4	11.6	11.9	11.8	8.17	6.8	6.2	6
Injury per 100.000	320.2	321.4	273.2	258.6	238.5	213.4	153.63	157.4	161.8	158
Fatality per 100.000 Per.	14.2	15.2	15.3	14.4	16.1	17.3	12.65	11.3	11.0	11
Injury per 100.000 Per.	326.2	335.2	312.6	321.2	321.8	314.0	237.83	261.9	284.7	289.9
Severity Rate	0.34	0.31	0.25	0.22	0.19	0.17	0.14	0.13	0.13	0.13
Costs (Million JD)	170	190	202	220	258	281	245	258	311	314.5

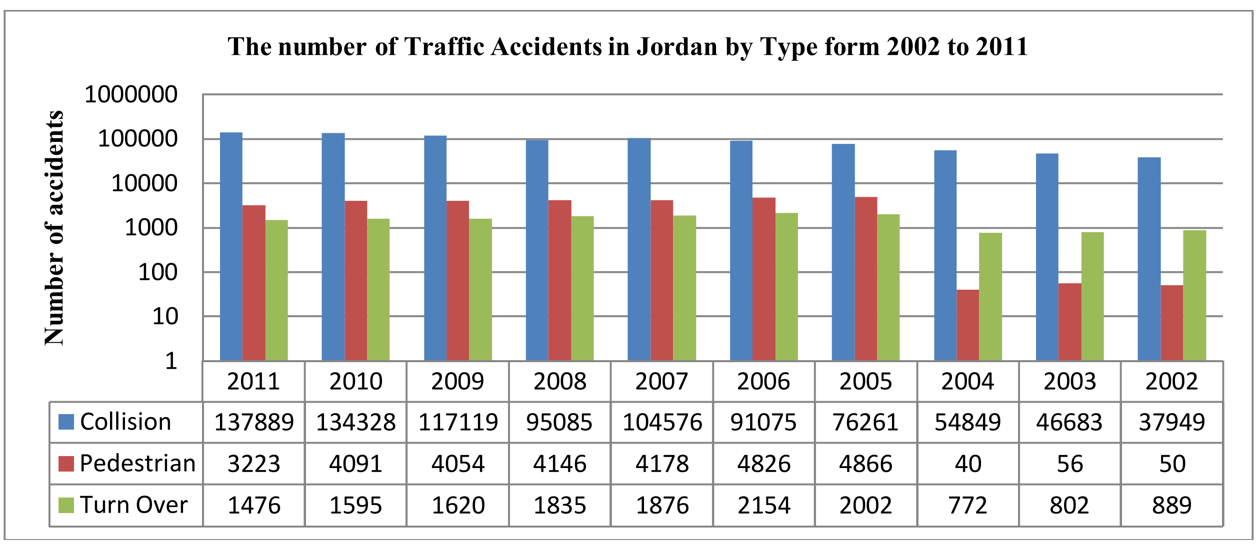

Figure 7. The number of Traffic Accidents in Jordan by Type form2002 to 2011

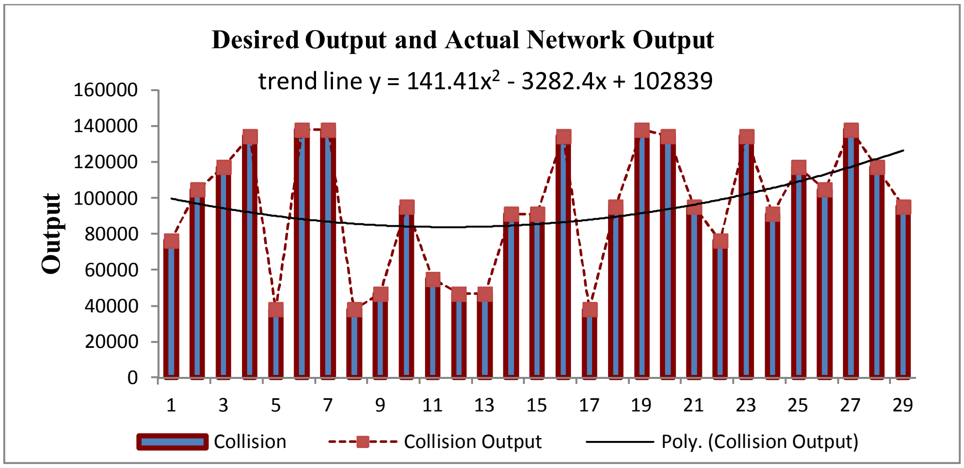

Figure 8. the resuls of real numbers of collision accidents and network output

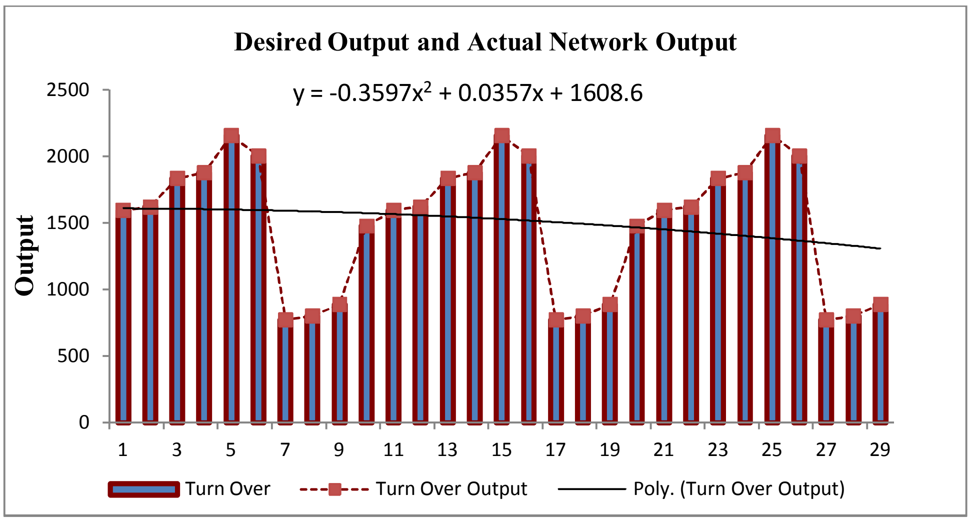

Figure 9. the resuls of real numbers of turnover accidents and network output

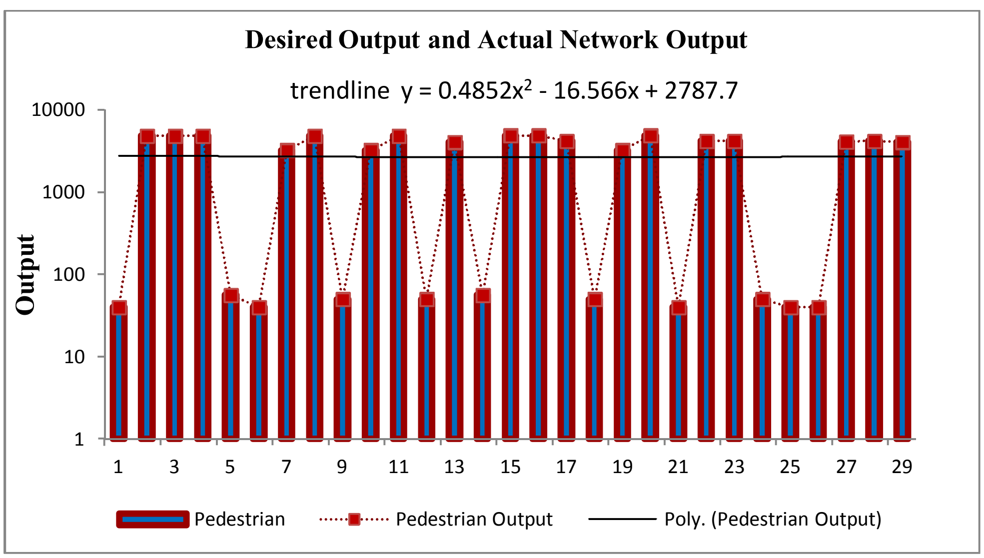

Figure 10. the resuls of real numbers of pedestrain accidents and network output

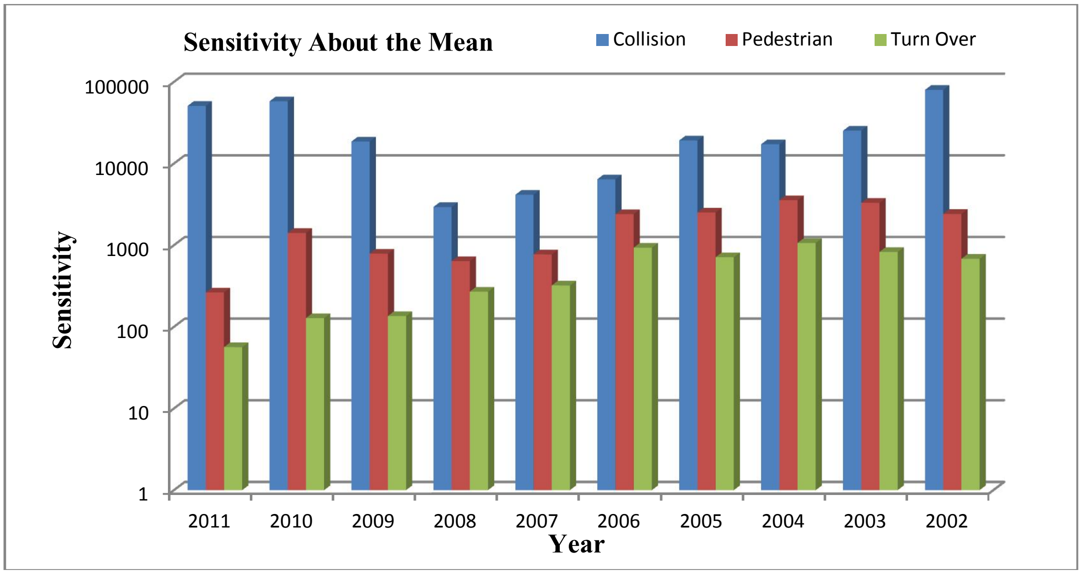

Figure 11. the resuls of sensitivity about the mean for all four factors.

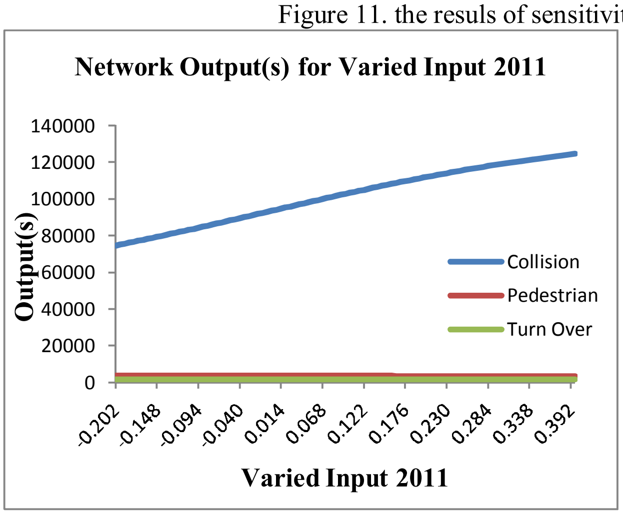

Figure 12. Varied input 2011

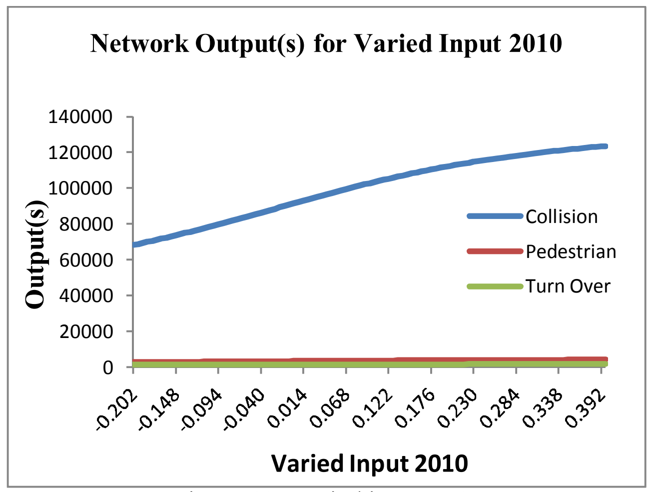

Figure 13. Varied input 2010

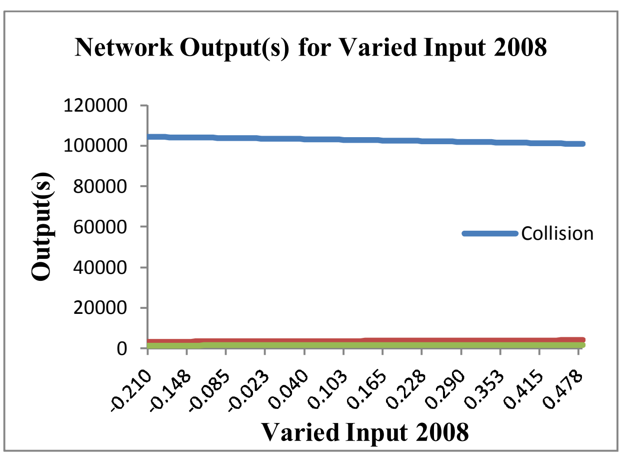

Figure 14. Varied input 2008

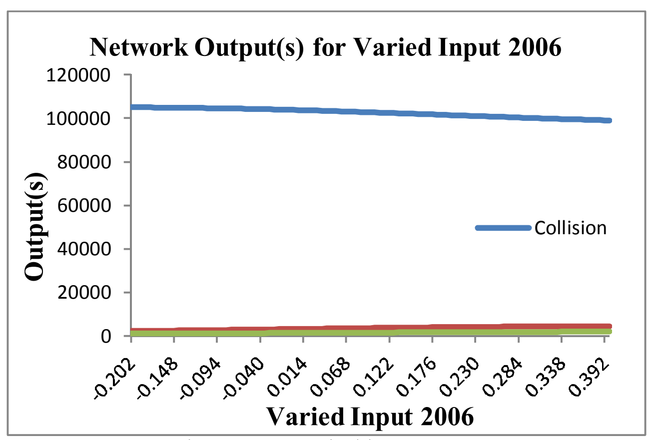

Figure 15. Varied input 2006

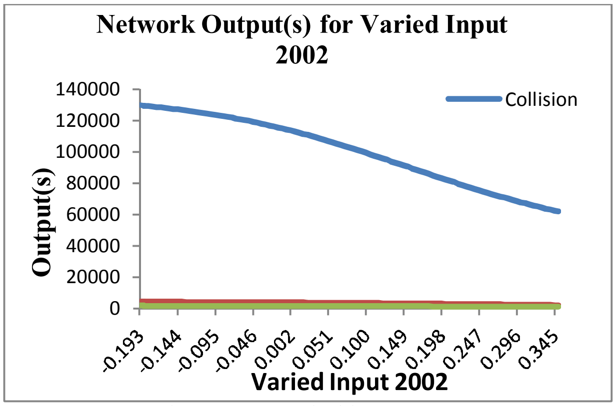

Figure 16. Varied input 2002

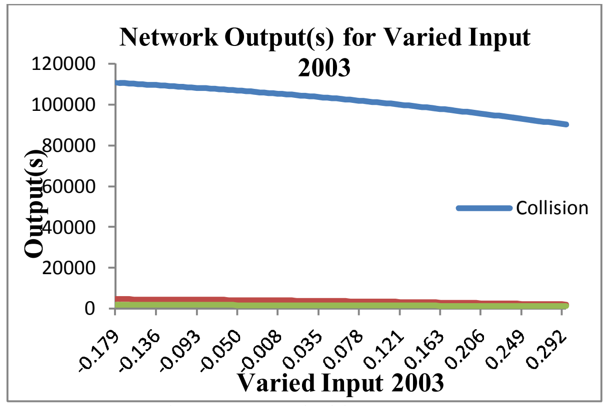

Figure 17.Varied input 2003

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