



Automobile Accident Prediction and Avoidance System Using Multilayer Perceptron Neural Networks

النظام الذكي للتنبؤ بالحوادث وتجنبها باستخدام الشبكات العصبية

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Dedication

I would like to thank Dr. Oleg Viktorov for his help support and patience.

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List of Abbreviations

3D: Three Dimensional.

ACC: Adaptive Cruise Control.

AI: Artificial Intelligence.

ANN: Artificial Neural Network.

BAC: Blood Alcohol Concentration.

FFBP: Feed Forward Back Propagation.

GIS: Geographical Information System.

GPS: Geographical Positioning System.

MLP: Multi-layer perceptron.

NN: Neural Network.

RMSE: Root Mean Squared Error.

SIS: Signal In Space.

SPS: Standard Positioning Service.

TIS: Traffic Information Server.

VATS: Victorian Activity and Travel Survey.

Automobile Accident Prediction and Avoidance System Using Multilayer Perceptron Neural Networks

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Abstract

Road accidents are the most known cause of death. Many organizations and transportation manufacturers are considering transportation safety improvement as one of their top priorities. This study contributes to the area of transportation safety by identifying the roads and intersection dangerous sections that plays a role in different types of road accidents and use these information to warn the clients in the real time about the possible danger. The drivers mistakes that can lead to accidents are also identified based on the previous driver mistakes to help another clients and road users to avoid them in the future.

The first phase of this study was to classify the accidents types into collision, pedestrian and turn over accidents, and accidents loses into slight, serious injuries and fatalities. Then build a model for a system to predict these accidents, its types and loses using the clients smart devices capabilities and communicating with external servers that manages the operation and the relations between clients and road users.

The system utilizing a strong prediction method called “Artificial Neural Networks” with “Back-propagation” learning algorithm that is considered one of the supervised learning algorithms to analyze the previous accident conditions and reasons to predict them in the future.

A database for the previous accidents conditions and reasons was built for each type of accident that contains various information about different accidents and results to learn the neural network that can predict the relation between them and the accident result to help the road user avoiding the predicted danger at real time. The system also enables its administrator to define a danger places manually to warn system users about these dangers before they reach the danger places so they can avoid these dangers.

Keywords: Artificial Intelligence, Accidents, Neural Networks.

النظام الذكي للتنبؤ بالحوادث وتجنبها باستخدام الشبكات العصبية

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بإشراف الدكتور: اوليج فيكتروف

ملخص الدراسة

تعد حوادث الطرق من ابرز اسباب الوفيات حول العالم لذلك يدأب مصنعو المركبات وشركات النقل على تحسين وتطوير امان مركباتهم ويعتبرونها احد اهم اولوياتهم التي يعملون بشكل دائم على تطويرها وتحسينها.

هذه الدراسة تعد من احد الوسائل والتحسينات التي تساهم في جعل وسائل النقل اكثر امانا من خلال التعرف على التقاطعات و اماكن الخطر في الطرقات وجمع المعلومات والمتغيرات التي تساهم في زيادة احتمال حصول الحادث بالاضافة الى جمع المعلومات عن الحوادث السابقة واستخدام هذه المعلومات لتحذير السائق من اخطاء السائقين المحتملة لهذه المناطق و درجة خطورة الوضع الحالي.

المرحلة الاولى للدراسة هي جمع المعلومات وتصنيف الحوادث الى حوادث تصادم ومشاه وتدهور وتصنيف اضرار الحوادث الى حوادث طفيفة وبليغة وحوادث وفيات، والمرحلة الثانية هي بناء نموذج لنظام قادر على التنبؤ بالحوادث اعتماداً على هذه المعلومات و من خلال التواصل مع خوادم خارجية لادارة العملية و تنظيم العلاقات وتدفق والمعلومات بين مستخدمي النظام.

يعتمد النظام في التنبؤ بالاحطار والحوادث على طريقة تحاكي طريقة عمل دماغ الانسان تسمى بالشبكات العصبونية الذكية، حيث يمكن لها ان تتعلم تدريجيا بالاعتماد على المعلومات عن الحوادث السابقة و تزيد من مهارة النظام كلما تم تدريبها على معلومات اكبر واكثر دقة.

بالاضافة الى التنبؤ بالاحطار، يمكن لمدير النظام ان يعرف اماكن خطر جديدة للنظام لتنبيه مستخدمي الطريق اذا كانت هناك عوائق او احطار موجودة في الطريق مما يجعل النظام اكثر مرونة وتأقلم مع المتغيرات الطارئة التي تحدث للطريق والتي لم يتم تدريب النظام عليها.

الكلمات المفتاحية: الذكاء الاصطناعي، حوادث السير، الشبكات العصبية.

Chapter One

1. Introduction

1.1 Preface

Road accidents are one of the most dangerous and a complex situation that a driver can face, the huge number of vehicles and pedestrians enlarges this problem and increases its complexity. Statistics says that the number of people who were killed by car accidents in the year 2010 in Jordan are six hundreds and seventy person and the number of injuries in the same year was seventeen thousand three hundreds and fourteen person in a total of 139.4 thousand road accidents (Department of Statistics, 2010). Outside Jordan, in the European Union there are about 375 million road users. Every year, 1.4 million road accidents result in over 40,000 fatalities and 1.7 million injures (European Commission, 2006). In Australia three hundred and sixty six from each one hundred thousand persons were killed in twelve months period until October 2011 (Transporte Centre for Road Safety, 2011). Many scientists and specialists are trying to design more intelligent systems to limit these expensive human, society and economical loses, thus the need for studying and classifying this phenomenon and understand the factors and probabilities of them is very urgent and important.

1.2 Problem Definition

The rapidly increasing numbers of vehicles contributes to huge number of vehicles on roads. This will lead us to develop our roads facilities and technologies to enhance their safety. For this time road accidents are one of the most common contributors of death and handicapping of humans in many places in the world. It's been more critical currently since the roads is the major transportation environment that are been used by people. Therefore, road safety is an important component. We can use the power of software and increasingly developing hardware to support this component and enhance it.

1.3 Contributions

The contributions of the thesis are as follows:

1. Collecting, identifying and classifying the variables of road accidents crashes.
2. Build a model can use the power of smart phones and devices to reduce and minimize the loses of road accidents by predicting possible crashes and driver mistakes.

1.4 Significance

The importance of this research comes from its new idea of utilizing the smart devices technical capabilities its wide spread for predicting the possible accidents at real

real time. The system considers all the road users safety including the drivers, passengers and pedestrians.

The model depends on a real accident data and accidents statistics to predict the possible dangers and it considers the human factors of the accidents so it's more accurate and realistic.

1.5 Limitations

1. The system doesn't predict intersection turnover and pedestrian accidents.
2. The system just predicts the danger to alert the user but it doesn't take a real action to prevent the accident.
3. This research covers a subset of the human factors of accident because some of the human factors are very hard to extract.

1.6 Thesis Outline (Thesis Organization)

Thesis is organized as follows:

Chapter Two: this chapter will focus on the related works in the field of

Road accidents prediction and avoidance systems and techniques

The chapter will discuss also the main reasons of road accidents and classify them based on the driver, environment and vehicle factors.

Chapter Three: this chapter will explain briefly the Neural Networks and the Geographical Information System that are related to this work and used in system description.

Chapter Four: this thesis will discuss step by step the methodology that are used to model the Accident Prediction and Avoidance System. And it will show the results of training the system using example data.

Chapter Five: this chapter contains the conclusion of the thesis and the future work that can be done to enhance the Accident Prediction and Avoidance System.

Chapter Two

2. Literature Survey

2.1 Introduction

The rapidly increasing numbers of vehicles contributes to huge number of vehicles on roads. This will lead us to develop our roads facilities and technologies to enhance their safety. This chapter will present some knowledge about different accident factors and it will present some examples for existing road safety systems that are related to this work domain.

2.2 Factors of Accidents

The term ‘accident’ is defined generally as an occurrence involving one or more transportation vehicles in a collision that results in property damage, injury or death. The term accident also implies a random event that occurs for no apparent reason other than “it just happened” (Lester, Nicolas, & Waded, 2010).

A road accident is defined generally as an occurrence on the public or private road due to negligence of or omission by any party concerned (on aspect of road users conduct, maintenance of vehicle and road conditions) or due to environment factor (excluding natural disaster) resulting in a collision (including “out of control” cases and collision of victims in a vehicle against object inside or outside vehicle such as bus passenger) which

involved at least a moving vehicle whereby damage or injury is caused to any passenger, property, vehicle, structure or animal and is recorded by the police (Fajaruddin, 2005).

The causes of road accidents are usually complex and include many factors. Based on the studies we can abstract the main factors that can influence the road accidents.

Road accidents are caused due to interaction of vehicle, driver, roadway and environmental factors (Aworemi, Abdul-Azeez, & Olabode, 2010). Accidents influenced by many factors, there are four main factors that causing accidents which are driver related factors, road factors, environmental factors, and vehicle factors (Esnizah, 2008).

2.2.1 Driver Factors

The major contributing factor in most accident situations is the performance of the driver. The driver errors has many types including inattention to the road and surrounding traffic conditions to yield the right interaction, and disobedience of traffic laws. These mistakes can occur due to unfamiliarity of driver with road conditions, going at high speeds, drowsiness, drinking, using cell phones, or dealing with other distractions within the vehicle (Lester, Nicolas, & Waded, 2010).

Human factors are the most complex and difficult to extract were they are very temporary and dependable in nature. Considering knowledge, attitude, alertness, health, driving skill, age, customs, habits, weight, strength, and freedom of movement. The emotional factors are the most challenging attributes and it's hard to extract them.

2.2.1.1 Age

Old driver which is in ages of above 60, have a bad vision which were not clear and they tend to drive slowly. While younger driver which is in ages of 16 to 25 year is tend to drive fast and have lack of experience in driving and skills of handling vehicle (Esnizah, 2008).

2.2.1.2 Driver Fatigue

The average sleep hours needed for normal person are 8 hours every day (24-hour). Sleep prior to work is the most important factor that the effects the person state after waking and the level of alertness of the driver (Horne, 1992) . A chronic lack of sleep is the result of not having enough sleep during a long time period. An acute lack of sleep can occur after just one day of short sleep or bad sleep conditions. There is a complete and partial lack of sleep, if there was no sleep for 24 continuous hours and if there was less than the average sleep hours for the same period orderly. In addition to the sleep quantity, sleep quality also has a great importance. If the sleeping hours is interrupted regularly, this will lead to as having little sleep period.

- Internal body clock

Fatigue is linked to the circadian rhythm (internal biological clock). It coordinates the physiological priorities for the daily activities like sleep, digesting, temperature and other variables. Therefore, it has an effect on driver alertness, performance. The brain and

the body are accustomed to the normal body cycle and they resist any changes. The body has a greater need for sleep at certain times in the (24 hour) than at other times (between midnight and 4 a.m.) and to lesser need for sleep from about (2 p.m. until 4 p.m.). If this cannot be given way to then a sleepy feeling occurs. For instance, sleepiness is a typical characteristic amongst most shift workers (Akerstedt, 1995).

- Time-on-task

A very long activity leads to physical and mental fatigue. Researchers have related activity duration (time-on-task) to fatigue symptoms. For example, one of the causes of driver fatigue is the time-on-task (time spent while driving). The effects of very long driving fatigue can be decreased by taking frequent breaks (Philipa, et al., 2005). For professional drivers time-on-task is better other drivers. And they often perform many more tasks than the driving (SafetyNet, 2009).

- Monotonous tasks

When a task stimulants and don't change or the changes are predictable or the task contains a high level of repetition then it called a monotonous task. Suburban highways where road environment changes are limited and there is a small volume of traffic match are example of these tasks (SafetyNet, 2009). Driving on a monotonous road is equal to a vigilance task (O'Hanlon & Kelley, 1977). Also, driving on a long and boring driving environment has negative effects on driver valid peripheral visual field (Rogé, Pe'bayle, Hannachi, & Muzet, 2003).

2.2.1.3 Alcohol and Drugs

Accidents resulted from alcohol or drugs are more likely to be ended as a high severity crash. The probability of a fatal crash rises significantly after 0.05 percent Blood Alcohol Concentration (BAC) and even more rapidly after 0.08 percent. Drivers with BACs at or above 0.15 percent are at very high risk of dying in a crash or sustaining severe injury.

BACs at or above 0.08 percent. Since 1982 there has been a 35 percent decline in the percentage of passenger vehicle drivers killed in crashes who had BACs at or above 0.08 percent. And also There has been a substantial decline (34 percent) in the percentage of fatally injured passenger vehicle drivers with BACs at or above 0.15 percent (Insurance Institute for Highway Safety, 2012).

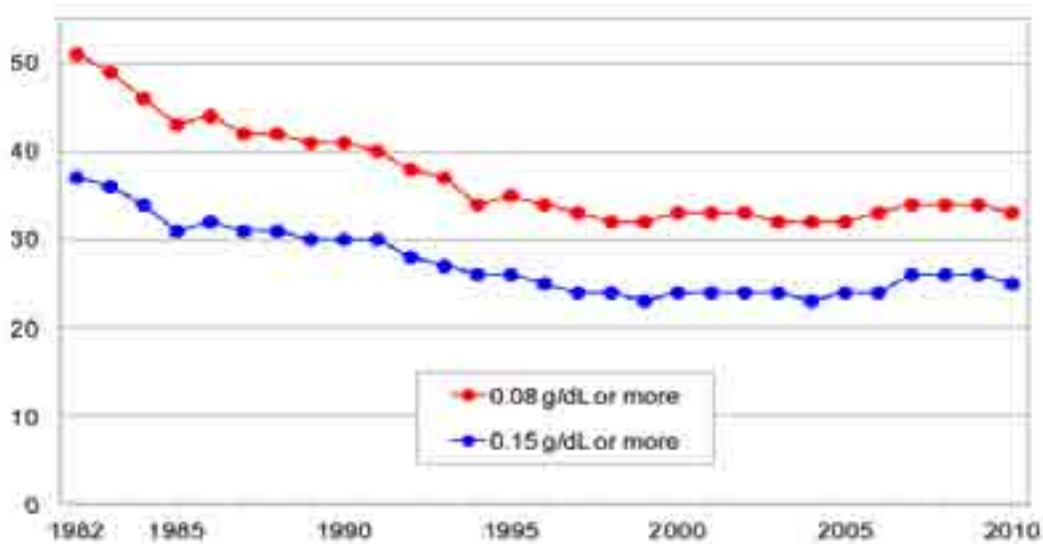


Figure 2-1: Percent of fatally injured passenger Vehicle Drivers with BACs At or Above Specified Thresholds, 1982-2010

2.2.1.4 Driver Behavior

The speed of vehicle is the main factor of the road accidents and traffic injuries. Speed increases the risk both crash occurrence and crash consequence. Also higher speeds shrink time for a driver to stop the vehicle and avoid an accident situation when the vehicle is going faster. Accident risk increases as speed increases, especially at road junctions and while overtaking as road users underestimate the speed or overestimate the distance of the vehicle.

2.2.2 Vehicle Factors

There are a small percentage of accidents that are caused by mechanical failure in the vehicle, such as tire failure, brake failure, or steering failure (Aworemi, Abdul-Azeez, & Olabode, 2010). Faulty brakes can cause accident between vehicles or vehicle with other things. Worn tires also can cause the vehicle involve in an accident, so that vehicle maintenance is very important to make sure that the vehicle is in safe condition.

2.2.3 Road Factors

The condition and quality of the road, which include the pavement, intersection and the traffic control system, plays a role in road accidents. The road must be designed to provide adequate sight distance at the design speed so the driver will be able to take the proper action and avoid the accident. The road side equipment such as, street

lightning, signs and all equipment for road must be provided to guarantee the safety of the road users. The super elevation of highway must be carefully laid out with the correct radius and the appropriate transition sections to assure that vehicles will not slide on curves and get out its side (Lester, Nicolas, & Waded, 2010).

When the roadway is not leveled and straight the chance of accidents with higher increases but when a crash occurs on an urban or rural places the probability of having a more severe injury decreases (Esnizah, 2008).

2.2.4 Environmental Factors

The environmental conditions and climate can also be a factor in road

Accident crashes. Transportation systems function at their best when the weather is sunny and the skies are clear. Weather conditions on roads can contribute in road accident occurrence; for example wet pavement reduces friction and flowing, standing water can cause the vehicle to hydroplane. Many severe crashes have occurred during conditions of smoke or fog which can greatly reduce visibility (Aworemi, Abdul-Azeez, & Olabode, 2010).

When the crash occurs on a wet road surface, it seems to be ended with a lesser severe crashes. This may be due to the fact that the drivers are more cautious under severe weather conditions and tend to drive at lower speeds. On the other hand, when the

crash occurs under dark conditions in urban areas, the severity of the crash is going to be higher.

2.3 Classification of Road Accident

Jordan traffic institute has classified vehicle crashes into three main types. The first type is the collision accidents, the second type is the pedestrian accidents and the third type is the turn over accidents, collision crashes severity and danger is higher than the other types of accidents because of its losses.

Traffic accidents losses are classified into three types too, property damage, injuries and fatalities (Jordan Traffic Institute, 2011).

Table 2-1: Traffic Accidents count by type from the Jordan Traffic Center

Accident Type	Property	Injuries	fatalities	total
Collision	130541	7031	317	137889
pedestrian	0	3031	192	3223
Turn over	531	857	88	1476
total	131072	10919	597	142588

2.4 Accident Data

Collection and investigation of accident data is very important element of any strategy that aims to reduce, predict or prevent accidents. Because the system model must be based on these data since realistic targets can only be established by using accident real information which is recorded by the police.

2.5 Neural Network Models

Many papers have been published in the nineties that utilize the application of neural networks in different areas of transportation. Neural networks have been used to predict driver behavior, vehicle detection/classification, traffic pattern analysis, traffic forecasting, traffic operations, etc. (Dougherty, 1995). The following are examples for the accident prediction and prevention systems.

1- Accident prevention by improving driving skill with sensors: driver's behavior when driving normally is quantified. The driver's behavior includes the angle of driver's neck and time required when checking both sides, the speed of making a turn and timing of pressing the accelerator/brake pedal. By quantifying the behavior, it is possible to find the driver's habits and clarify the difference between the ideal ways of driving. The aim is to reduce the chance of accidents by making the drivers realize the results of objective assessment (Intelligent Robotics and Communication Laboratories, 2011).

2- Adaptive head lights: system moving headlights when turning into bends and adjusting the luminous intensity in order to avoid dazzling (European Commission, 2006).

3- Adaptive Cruise Control (ACC), which helps keep distance from the car ahead thus avoiding rear-end collisions (European Commission, 2006).

4- Accident avoidance with wireless communication technology: safety system that adjusts and maintains a safe distance between vehicles. This system derives the relative distance and velocity between the vehicles. If the distance between the vehicles becomes too short or the speed of the occupant's vehicle becomes too high, a warning is generated or the speed of the driver's vehicle is automatically reduced to maintain a safe distance (Murata Company Ltd., 2011).

5- Automated system of traffic accident prevention: system can evaluate space required for vehicle, watch rear view, warn driver about hazards, and block hazardous driver's actions. It is also able to measure speed, find road lines, right border, and estimate vehicle reaction on driver's actions. During movement, it can warn about approaching obstacles, approaching vehicles, decipher road signs and traffic lights, and recommend motion modes (Kovbasa, Pidgurskiy, & Shayda, 2006).

6- White line recognition using a video camera (Murata Company Ltd., 2011).

7- Crash severity prediction in urban highways and identifying significant crash-related factors. A study that used ANN approach to predict crash severity, after omitting less important variables, 25 independent variables found that have highest effect on network

output (crash severity by fatality-injury crash percent) were selected. Studies showed that Feed Forward Back Propagation (FFBP) networks like MLP models yield the best results.

The research was concluded MLP neural network had a better classification accuracy and smaller network size compared to the fuzzy ARTMAP, it was concluded to be the better model for predicting the injury severity level. To compare the MLP neural network and Ordered Probit models, a test for the difference of two proportions was performed. MLP neural network showed better performance in this test and was hence declared to be the better of the two models. Hence the MLP neural network was found to be promising in modeling injury severity. (Moghaddam, Afandizadeh, & Ziyadi, 2010).

8- Geographical Information Systems (GIS) in traffic safety. Transportation professionals around the world have discovered and embraced GIS as an important tool in transportation management, planning, and developing transportation systems. GIS has been used for many purposes from modeling travel demand 20 years in the future to tracking a systems and from analyzing the annual capital improvement plans to identifying noise regulation violations around airports and many other applications.

The analytical capabilities of GIS support a wide range of services and tasks such as crash location and reporting, accident analysis and "hot spot" analysis and identification, safety engineering and traffic improvement, etc. The research is being carried out to analyze and study transportation safety from a geographic viewpoint, so as to find the relations between the safety issues with locational details (Nawathe, 2005).

For example, Kam (2003) presented a disaggregate approach to crash rate analysis. The approach involved a combination of two disparate datasets on a geographic information systems (GIS) platform by matching accident records to a defined travelling way. As an illustration of the methodology, travel information from the Victorian Activity and Travel Survey (VATS) and accident records contained in Crash Statistics were used to estimate the crash rates of Melbourne residents in different age–sex groups according to time of the day and day of the week. The results shown a polynomial function of a cubic order when crash rates are plotted against age group, which contrasts distinctly with the U-shape curve generated by using the conventional aggregate quotient approach.

A new Geographic Information System (GIS) application for the display and analysis of crash data. Multi-year crash data from Tuscaloosa County are mapped on a map, and the crash locations are compared with existing roadway features. After geocoding the base map with nodes, links, and route-milepost data, spatial analysis and “hot spot” identification is done using thematic mapping, buffering, and route impedance (Data, 2003).

2.6 Accident Repetition Areas (Dangerous Areas or Hot Spots)

Hot Spots are defined as the area where many accidents has accrued in, or an area where the chance of road accident occurrence is high, or the area where the loses of accident occurrence is high and the is either a section of the road or an intersection (General Directorate of Jordan Civil Defense, 2002).

2.7 What Distinguishes This Thesis?

The systems, methodologies and systems used in the studies described above have proved that they aren't efficient tool for predicting and avoiding the accidents before its happening because all of them are either focused on assisting and monitoring the driver behaviors or the road dangers, but none of these systems are directed toward the car and all the road users at the real time.

Although a lot of research has been performed in improving the safety of the traffic, not many studies have concentrated on the smart device sensors and its increasing processing power to improve the safety of the roads although it's wide spread powerful processing and acceptable coasts. Hence the present study will try to utilize these devices to predict the collision possibility and the treatment source and it will alert the road users about the possible dangers that treat them through their smart device.

Chapter Three

3 Artificial Neural Network & Geographical Information System

3.1 Introduction to Artificial Neural Networks (ANN)

The research of Jones (1997) about the potential systems of artificial intelligence looks to the brain for models rather than looking to technology for ideas from which to model the brain. A number of scientists are looking at the development of artificial intelligence from the basis of a developing understanding of the architecture of the human brain. This work is now represented in two interlocking disciplines: Computational neurobiology which involves understanding human/animal brains using computational models and Neural Computing or simulating and building a machine to emulate the real brain. The analysis is made on two levels: coarse grained, examining and elucidating networks of interacting subsystems which is largely a neurophysiological activity; and fine grained, building theories and models of actual Artificial Neural Networks as subsystems.

Lippmann (1987) defined that Artificial Neural Networks or simply “Neural Nets” go by many names such as connectionist models, parallel distributed processing models, and neuromorphic systems. Whatever the name, all these models attempt to achieve good performance via dense interconnection of simple computational elements.

In this detail, artificial neural net structure is based on our understanding of biological nervous system. Neural net models have greatest potential in areas such as speech and image recognition. Instead of programming with sequential instructions, neural net models explore many competing hypotheses simultaneously using massively parallel nets composed of many computational elements connected by links with variable weights.

Lynn (n.d.) confirmed that Artificial Neural Networks (ANN) offer a different approach for analyzing data, and for recognizing patterns within that data, than traditional computing methods, therefore Artificial Neural Networks have been used in many applications such as: classification (Medical diagnosis, target recognition, character recognition, fraud detection, intruder detection and speech recognition), Function Approximation (machine diagnostics), and Data Mining (Clustering, data visualization and data extraction).

3.2 Biological Neural Network Model

The fundamental processing element of a biological neural network is a neuron. In the human brain, a typical neuron collects signals from others through a host of fine structures called dendrites. The neuron sends out spikes of electrical activity through a long, thin strand known as an axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that

inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes (Singh & Verma, 2011).

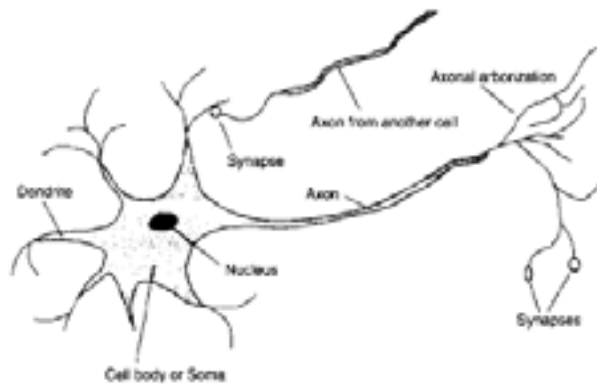


Figure 3-1: Biological Neural Cell

The Artificial Neural Networks try to replicate only the most basic elements of this complicated, versatile, and powerful organism. They do it in a primitive way. But for the software engineer who is trying to solve problems, neural computing was never about replicating human brains. It is about machines and a new way to solve problems (Reingold & Nightingale, 1999).

3.3 Artificial Neural Network Model

According to Haykin (1998) Artificial Neural Network (ANN) is a massively parallel distributed processor that has a natural propensity for storing knowledge and

making it available for use. So it resembles the brain in two aspects: knowledge is acquired by the network through a learning process, and the interconnection strengths known as synaptic weights are used to store this knowledge.

The basic unit of neural networks, the artificial neurons, simulates the basic functions of natural neurons. Figure 3.2 (PrismNet, n.d.) below shows a fundamental representation of an artificial neuron.

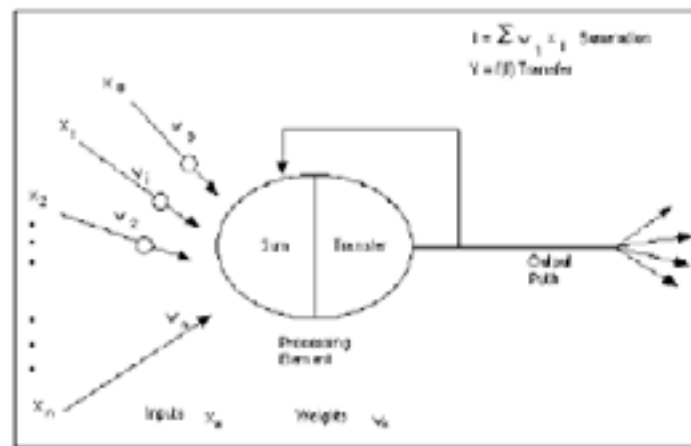


Figure 3-2: Basic Artificial neural network

In Figure 3.2, various inputs to the network are represented by the mathematical symbol, x_n . Each of these inputs is multiplied by a connection weight. These weights are represented by w_n . In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then neural output is provided (Naoum, 2011).

3.4 Artificial Neural Network Advantages

Stergiou (1996) stated 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. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

Other advantages include:

1. **Adaptive learning:** An ability to learn how to do tasks based on the data given for training or initial experience.
2. **Self-Organization:** An ANN can create its own organization or representation of the information it receives during learning time.
3. **Real Time Operation:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. **Fault Tolerance:** Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

3.5 Artificial Neural Network Architecture

A neural network has an input layer, output layer, and zero or more number of hidden layers. All these layers contain a number of neurons, the basic element of neural networks (Li, Zhang & Gu, 2004).

Bernacki & Włodarczyk (2004) presented the diagram of a neuron's operation Figure 3.3. The figure consists of some inputs emulating dendrites of the biological neuron, a summation module, an activation function and one output emulating an axon of the biological neuron. The architecture of this ANN consists of one input layer, one output layer and two hidden layers. Input layer consists of two neurons, first and second hidden layers have three and two neurons respectively, and finally the output layer contains a single neuron. The importance of a particular input can be intensified by the weights that simulate biological neuron's synapses. Then, the input signals are multiplied by the values of weights and next the results are added in the summation block. The sum is sent to the activation block where it is processed by the activation function (Transfer Function). Thus, we obtained neuron's answer y for the input signals " x_1 " and " x_2 ".

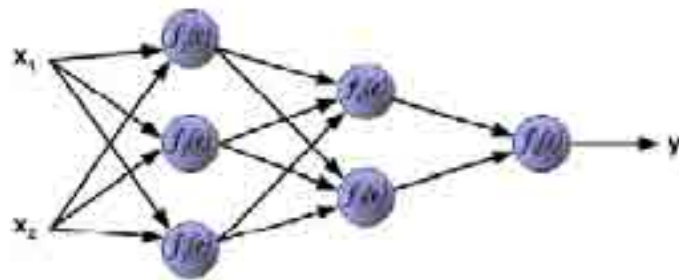


Figure 3-3: Artificial Neural Network

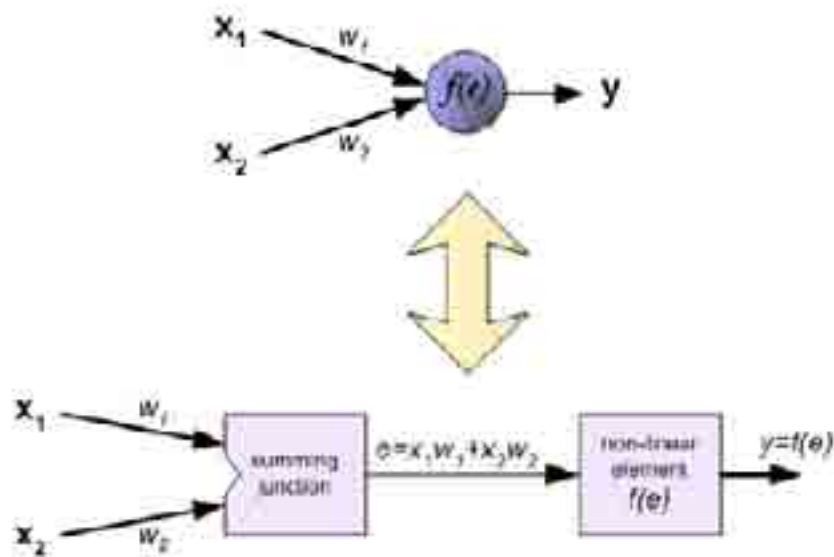


Figure 3-4: Summation and Transfer function

3.5.1 Layers

Reingold & Nightingale (1999) clarified that the most significant difference between artificial and biological neural nets is their organization. While many types of artificial neural nets exist, most are organized according to the same basic structure.

There are three components to this organization: a set of input nodes, one or more Layers of 'hidden' nodes, and a set of output nodes. The input nodes take in information, whether the information is in the form of a digitized picture, or a series of stock values, or just about any other form that can be numerically expressed, this is where the net gets its

initial data (from the environment). The information is supplied as activation values, that is, each node is given a number, higher numbers representing greater activation.

The MIT Press declared that in order for the artificial neural net to carry out a useful task, one must connect the neurons in a particular configuration, set the weights, and choose the input-output functions (transfer function). The simplest artificial neural net would consist of a layer of input units connected to a single middle or “hidden” layer, which is linked to a layer of output units. To initialize the artificial neural net, whatever raw data is needed to perform the task is first fed into the input units. The resulting signal received by a neuron in the hidden layer depends on how the incoming raw data is weighted, and how it is modified by the transfer function. This procedure is repeated for the signal flowing out of the hidden layer before going on to the subsequent level.

For instance, gender recognition net might be presented with a picture of a man or woman at its input nodes and must set an output node to 0 if the picture depicts a man or 1 for a woman. In this way, the network communicates its knowledge to the outside world.

3.5.2 Transfer (Activation) Functions

Naoum (2011) clarified that the transfer function describes how a neuron's firing rate varies with the input it receives. Every neuron has an activation level. The summation function will compute this level, and according to this level we will have an exit value from the neuron or not. The relation between the activation level and the output

maybe linear or non-linear and this relation can be represented by so called transfer function.

A neuron may sum its inputs, or average them, or something entirely more complicated. Each of these behaviors can be represented mathematically, and that representation is called the transfer (activation) function. Transformation is essential in order to improve the levels of outputs to a reasonable value between 0 and 1, due to in some cases outputs may be very large when we have more than one hidden layer (Naoum, 2011).

Remember information in ANN depends on the mathematical activation function.

This function typically falls into different numbers of categories, such as (Naoum, 2011):

1. Sigmoid Transfer Function:

$$f(x) = \frac{1}{1 + e^{-ax}}$$

2. Hyperbolic Tangent Sigmoid Transfer Function (MathWorks, 2012):

$$f(x) = \frac{2}{1 + e^{-2x}} - 1$$

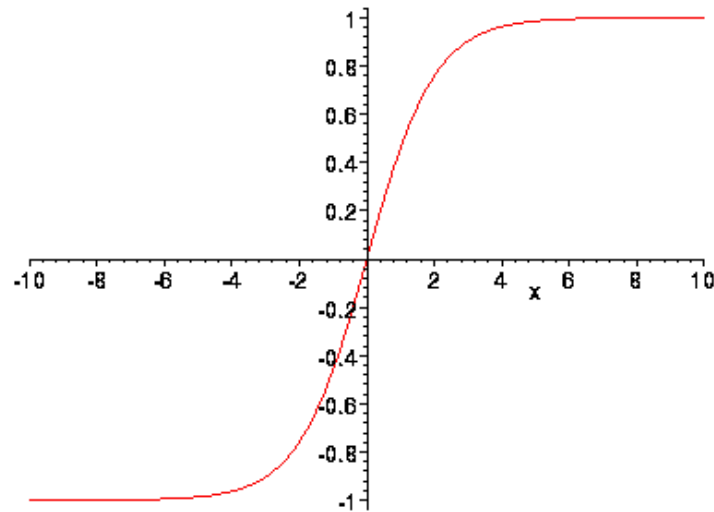


Figure 3-5: Hyperbolic Tangent Sigmoid (Willamette University, n.d.)

Naoum (2011) explained that for sigmoid (logical) activation function, the output varies continuously non-linearly as the input changes. The sigmoid function is bounded and differentiable real function and has positive derivative, and it has lower limit bound (0 or -1) and upper limit bound (+1).

3.6 Training an Artificial Neural Networks

Once a network has been structured for a particular application, then the network is ready to be trained. To start this process the initial weights are chosen randomly. Then, the training, or learning, begins. There are many approaches to training: supervised, unsupervised, and reinforcement training.

3.6.1 Supervised Training

Reingold & Nightingale (1999) described that in supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked. The set of data which enables the training is called the "training set." During the training of a network the same set of data is processed many times as the connection weights are ever refined.

Figure below (Aboshosha, n.d.) represents the supervised learning schema.

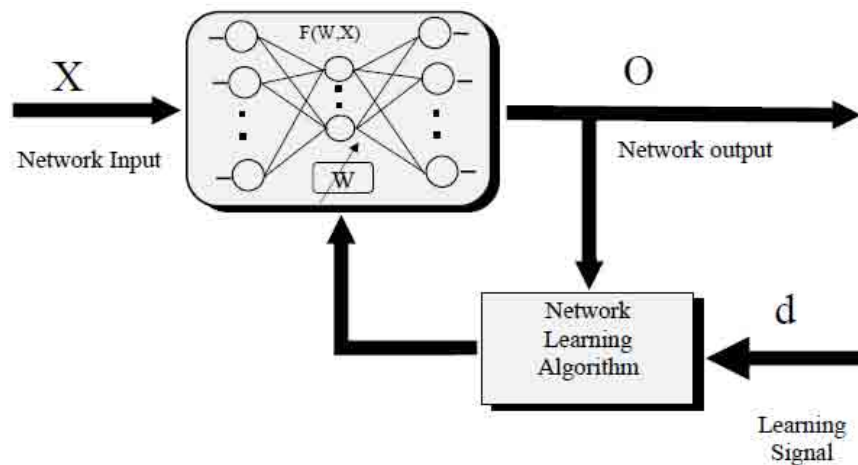


Figure 3-6: Supervised Learning Diagram

Haykin (2001) identified that this form of learning assumes the availability of a labeled (i.e., ground-trusted) set of training data made up of N input—desired examples:

$$T = \{(x_i, d_i)\}^N$$

Where x_i = input vector of i th example

d_i = desired (target) response of i th example

N = Training set size

$$E(n) = \frac{1}{N} \sum_{i=1}^N (d_i - y_i)^2$$

Stergiou & Siganos (1996) stated that a three-layer neural network can be trained to perform a particular task using the following procedure:

1. Present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units.
2. Determine how closely the actual output of the network matches the desired output.
3. Change the weight of each connection so that the network produces a better approximation of the desired output.

3.6.2 Unsupervised Training

Naoum (2011) described that in unsupervised or self-organized Learning, the network is not given any external indications as to what the correct responses should be

nor whether the generated responses are right or wrong; it is based upon only local information.

It is simply exposed to the various input-output pairs and it learns by the environment, that is, by detecting regularizations in the structure of input patterns. This is often referred to as self-organization or adaption, figure 4.7 (Aboshosha, n.d.).

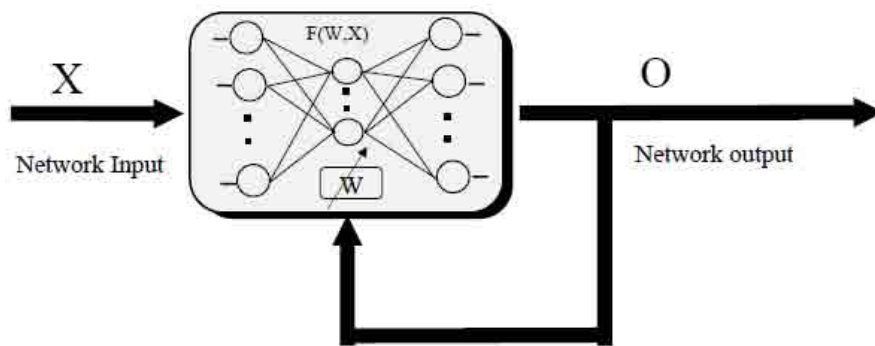


Figure 3-7: Unsupervised Learning Diagram

3.7 Backpropagation learning algorithm

One neuron cannot solve a complex problem that's why neural network composed of many neurons (Kukielka & Kotulski, 2008). For the purpose of this research Multilayer Perceptron (MLP) will be used.

One of the architectures that are used most frequently is the MLP (Multilayer Perceptron). In such a network each neuron's output of the previous layer is connected with some neuron's input of the next layer. The MLP architecture consists of one or more

hidden layers of neurons followed by an output layer. The signal is transmitted through the network in one direction from the input to the output, that's why this architecture is called feed forward. The MLP network is usually learned using the Backpropagation algorithm (BP).

Figure 3.8 (Aboshosha, n.d.) represents the backpropagation neural network algorithm which is one of the most powerful supervised neural networks. It has the same structure as multilayer perceptron and mainly used in complex logical operations, pattern classification and speech analysis. Like in multilayer perceptron, Backpropagation neural network has three layers: input, output and hidden layers (Li, Zhang & Gu, 2004) .

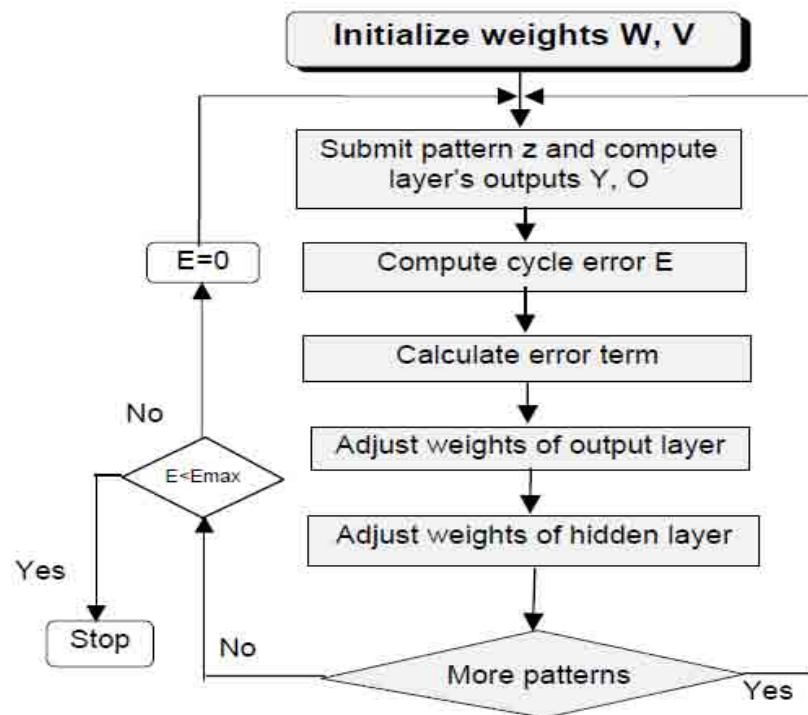


Figure 3-8: Backpropagation Algorithm Diagram

The Backpropagation training algorithm (Lippmann, 1987):

The backpropagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a multilayer feed-forward perceptron and the desired output. The following assumes a sigmoid logistic non-linearity function which is used as the activation function, $f(x) = 1/(1+e^{-ax})$

Step 1: Initialize Weights and Offsets. Sets all weights and node offsets to small random values.

Step 2: Present Input and Desired Outputs Present a continuous valued input vector $x_0, x_1, \dots, x_{n-1}$ and specify the desired outputs $d_0, d_1, \dots, d_{m-1}$. If the net is used as a classifier then all desired outputs are typically set to zero except for that corresponding to the class the input is from. The input could be new on each trial or samples from a training set could be presented cyclically until weights stabilize.

Step 3: Calculate Actual Outputs. Use the sigmoid nonlinearity from above formula to calculate the outputs $y_0, y_1, \dots, y_{m-1}$.

Step 4: Adapt weights. Use a recursive algorithm starting at the output nodes and working back to the first hidden layer. Adjust weights by:

$$W_{ij}(t+1) = W_{ij}(t) + \mu \delta x_t$$

In the previous equation $w_{ij}(t)$ is the weight from hidden node i or from an input to node j at time t , x_i is either the output of node i or is an input, μ is the gain term, and δ is an error term for node j . If node j is an output node, then

$$\delta_j = y_j (1 - y_j)(d_j - y_j)$$

Where d_j is the desired output of node j and y_j is the actual output. If node j is an internal hidden node, then

$$\delta_j = x_j (1 + x_j) \sum_k \delta_k w_{jk}$$

Where k is over all nodes in the layers above node j .

Step 5: If the Mean Square Error is above some predefined value then repeat by going to step 2. Otherwise the Neural Network has been trained correctly.

The main advantages of Backpropagation neural nets are that they are great at prediction and classification. On the other hand, there is always a lack of explanation of what the net has been learned, suffers from local minima, slow training and temporary unstable (Naoum, 2011).

In order to solve the Backpropagation problem, many algorithms have been proposed so far to deal with the problem of appropriate weight-update by doing some sort of parameter adaptation during learning. These updated algorithms have a high performance, which they can converge from ten to one hundred times faster than the

simple backpropagation algorithms. One of the fastest algorithms is the Resilient Backpropagation learning algorithm (Riedmiller & Braun, 1993).

3.8 Resilient Backpropagation learning algorithm

Riedmiller & Braun (1993) explained that the basic idea of the backpropagation learning algorithm is the repeated application of the chain rule to compute the influence of each weight in the network with respect to an arbitrary error-function E

$$\frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial S_i} \frac{\partial S_i}{\partial_{neti}} \frac{\partial_{neti}}{W_{ij}}$$

Where w_{ij} is the weight from neuron i to neuron j , s , is the output, and $netj$ is the weighted sum of the inputs of neuron j . Once the partial derivative for each weight is known, the aim of minimizing the error-function is achieved by performing a simple gradient descent (Riedmiller & Braun, 1993):

$$W_{ij}(t + 1) = W_{ij}(t) - \epsilon \frac{\partial E}{(\partial W_{ij})(t)}$$

Obviously, the choice of the learning rate ϵ , which scales the derivative, has an important effect on the time needed until convergence is reached. If it is set too small, too many steps are needed to reach an acceptable solution; on the contrary a large learning rate will possibly lead to oscillation, preventing the error to fall below a certain value. Riedmiller

& Braun (1993) defined RPROP which stands for 'resilient propagation' as an efficient new learning scheme, which performs a direct adaptation of the weight step based on local gradient information. In crucial difference to previously mentioned adaptation technique, the effort of adaptation is not blurred by gradient behavior whatsoever. To achieve this, they introduce for each weight its individual update-value Δ_{ij} , which solely determines the size of the weight-update. This adaptive update-value evolves during the learning process based on its local sight on the errorfunction E , according to the following learning-rule:

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^+ * \Delta_{ij}^{(t-1)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t-1)} * \frac{\partial E}{\partial w_{ij}}^{(t)} > 0 \\ \eta^- * \Delta_{ij}^{(t-1)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t-1)} * \frac{\partial E}{\partial w_{ij}}^{(t)} < 0 \\ \Delta_{ij}^{(t-1)} & , \text{ else} \end{cases}$$

where $0 < \eta^- < 1 < \eta^+$

The adaptation-rule works as follows: Every time the partial derivative of the corresponding weight w_{ij} changes its sign, which indicates that the last update was too big and the algorithm has jumped over a local minimum, the update-value Δ_{ij} is decreased by the factor η^- . If the derivative retains its sign, the update-value is slightly increased in order to accelerate convergence in shallow regions. In all of their experiments, the choice of $\eta^+ = 1.2$ gave very good results, independent of the examined problem. Slight variations of this value did neither improve nor deteriorate convergence time. So in order to get parameter choice more simple, they decided to constantly fix the

increase/ decrease parameters to $\eta^+ = 1.2$ and $\eta^- = 0.5$ Once the update-value for each weight is adapted, the weight-update itself follows a very simple rule: if the derivative is positive (increasing error), the weight is decreased by its update-value, if the derivative is negative, the update-value is added:

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t)} > 0 \\ +\Delta_{ij}^{(t)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t)} < 0 \\ 0 & , \text{ else} \end{cases}$$

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)}$$

3.9 Geographical Information System

The Geographical Information System (GIS) is an information system designed to work with data referenced by spatial geographical coordinates. In other words GIS is both a database system with specific capabilities for spatially referenced data as well as a set of operations for working with the data. It may also be considered as a higher-order map or an intelligent map on which computer analysis can be performed (Bhattacharya, 2008).

3.9.1 Digital Image

Digital Image is a Multi-spectral image data set recognized as a three dimensional (3D) pixel array where the third axis (z) access is the band number, or more correctly the wavelength of the band (channel) (Bhattacharya, 2008).

3.9.2 Geographical Positioning System

Geographical Positioning System (GPS) is a special radio receiver measures the distance from your location to satellites that orbit the earth broadcasting radio signals. GPS can pinpoint your position anywhere in the world (McNamara, 2004).

According to the United State Government report of the Global Positioning System (GPS) Standard Positioning Service (SPS) “with current (2007) Signal-in-Space (SIS) accuracy, well designed GPS receivers have been achieving horizontal accuracy of 3 meters or better and vertical accuracy of 5 meters or better 95% of the time”. The following picture abbreviates the positioning process.

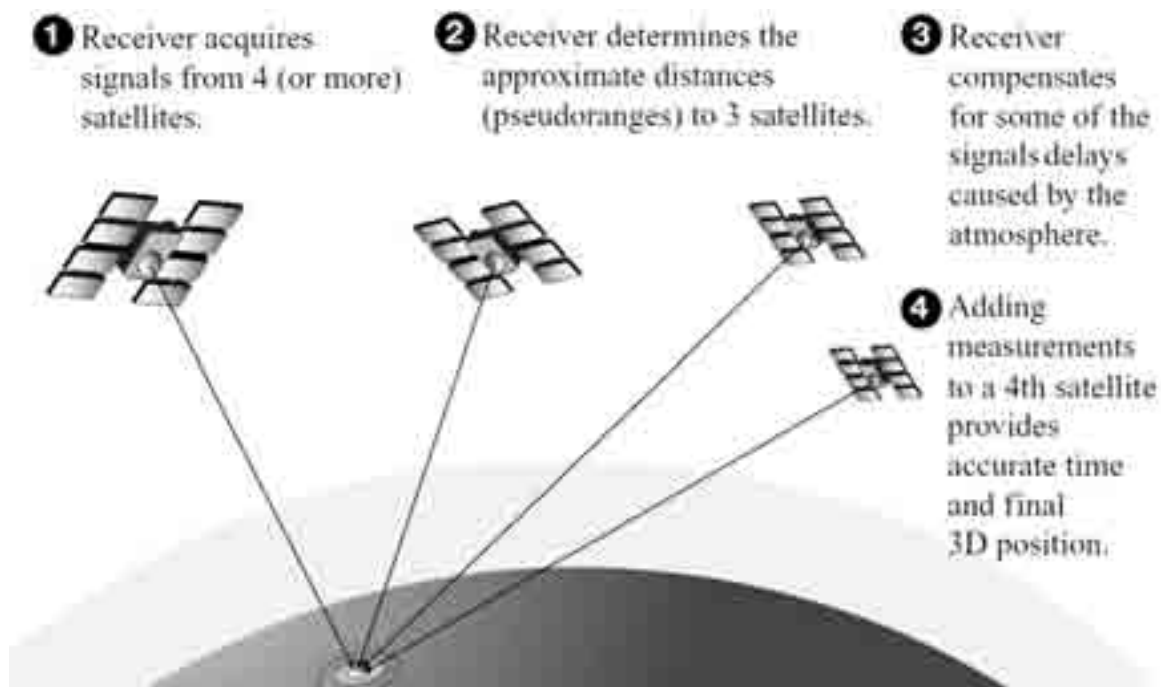


Figure 3-9: The Geographical Positioning System action steps

Chapter Four

4 Proposed Model & Methodology

4.1 Proposed Model

The system consists of two main subsystems one of them installed and managed on a server device (Traffic Data Manager) system and the other installed on the client smart device (Real-time monitoring system).

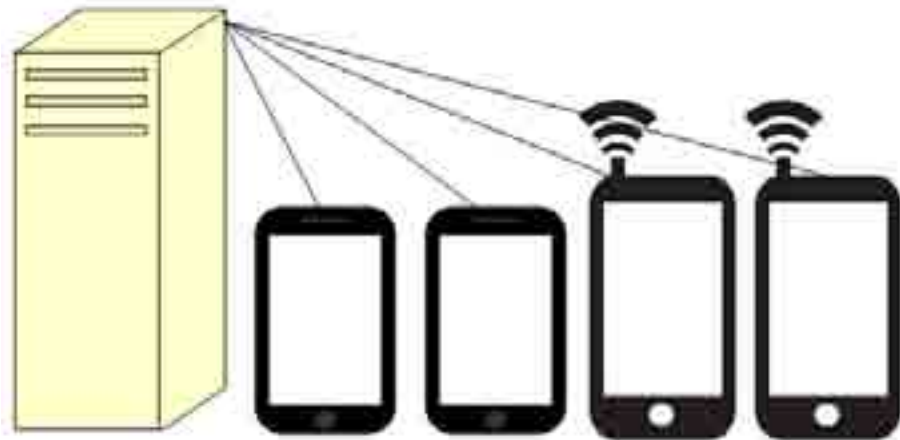


Figure 4-1: System Overview

4.2 Traffic Data Manager System

Traffic Data Manager System is the software piece that is responsible for receiving clients data process these data archiving them in its database and index these data to access them instantly later and serve clients as fast as possible. And it responsible on the communication with a Geographical information system (GPS) application program interface (API) to determine the client's roots and distances from the hot spots and from other clients. The (GPS) system contains a digital map that has the roots and hot spots predefined in it so it can determine the client's root and hot spot areas from the client's position (Longitude and latitude).

4.3 Real-Time Monitoring System

Real Time Monitoring System is the part of the software that is installed on the client device and that is responsible for monitoring the client safety state and communicating with the server to keep the client with the latest traffic information around and utilize these information to predict the possible road dangers and warn the driver about them.

4.4 Traffic Data Manager System Database

Traffic Data Manager System Database is the data container that the Traffic Data Manager System Use to store and manage the data needed about the clients, paths, vehicles and hot spots to return the appropriate info and responses to serve the clients.

The following is the ER Diagram of Traffic Data Manager System Database.

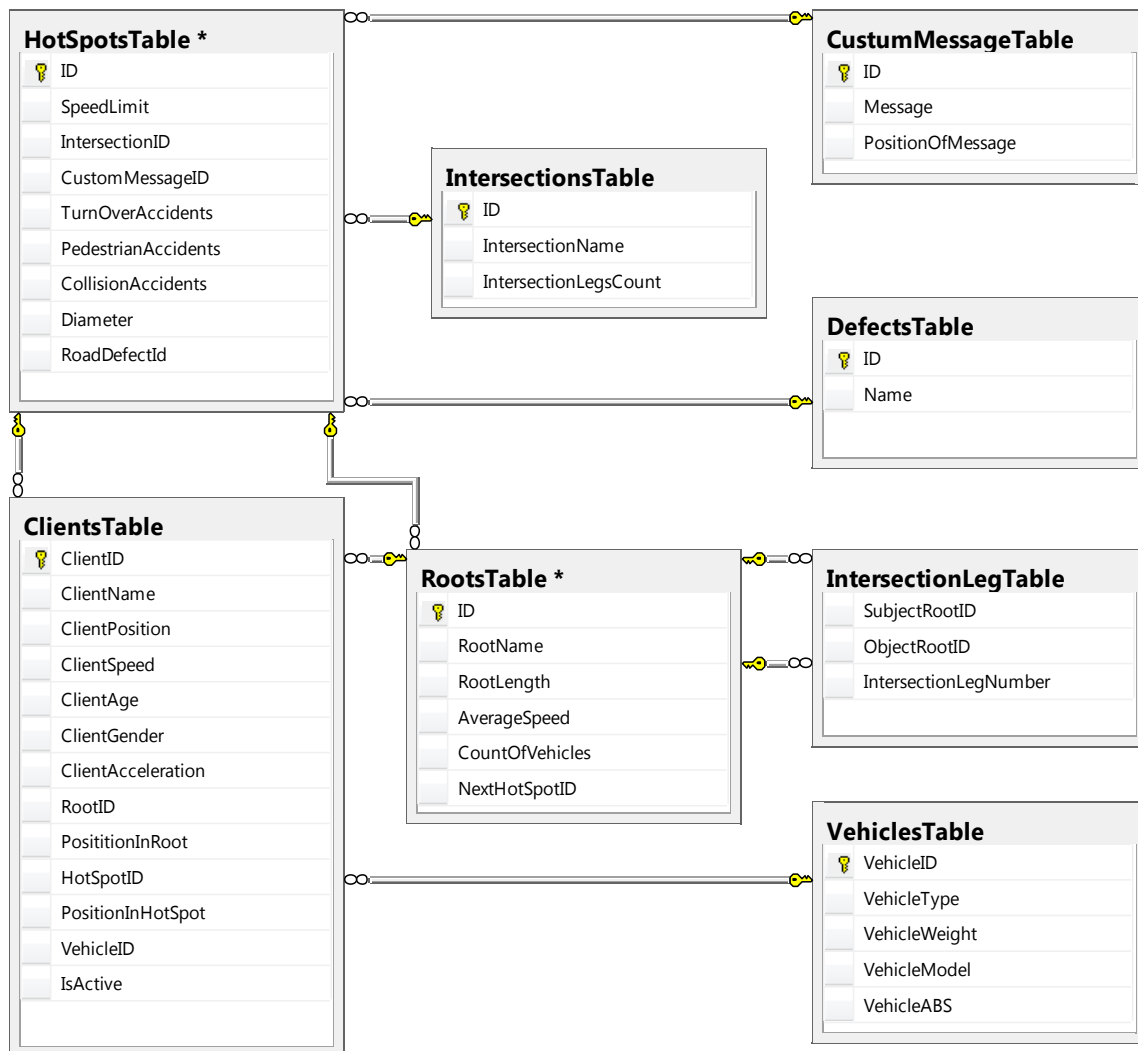


Figure 4-2: Entity Relationship Diagram of the (Traffic Data Manager System Database)

The database consists of the following eight tables:

1- Roots Table:

RootsTable *	
	ID
	RootName
	RootLength
	AverageSpeed
	CountOfVehicles
	NextHotSpotID

Figure 4-3: Roots table Diagram

From its name the roots table stores all the roots that connects between every “hotspot” (sections of road or intersections) and other.

The “AverageSpeed” field is the average speed of the vehicles that are travelling in the specified root and the count of vehicles is the count of the vehicles that are travelling in the root at this moment. The last two columns are filled automatically by the TIS when it receives a navigation messages that will explained later, and The root name column is the name of the root and the “rootLength” column is length of the root.

2- Vehicles Table:

The vehicles table is a table that contains all the cars models and its options and details that have an effect on the safety and accident occurrence probability like the vehicle type, weight, model and antilock breaking safety system etc....

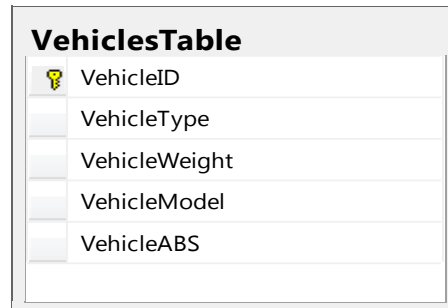


Figure 4-4: Vehicles Table Diagram

3- Hot spots Table:

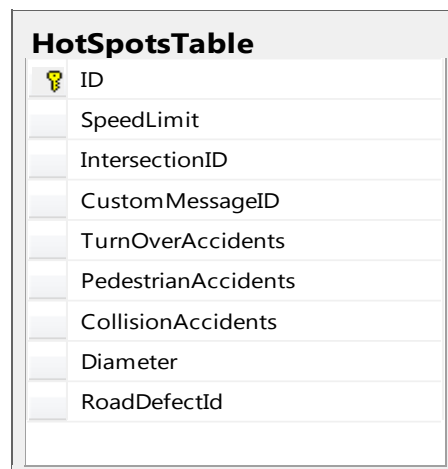


Figure 4-5: Hot spots table Diagram

This table contains a record for each hot spot in a defined area and the speed limit, intersection id, custom message, number of turn over accidents, number of pedestrian accidents and the number of collision accidents for the hot spot.

“Speedlimit” is the speed limit of the hot spot, intersection id (filled if the hot spot was an intersection), Custom message ID this is a foreign key where the administrator of the system can define a custom hot spot with custom message.

Turnover, pedestrian and collision accidents columns contain the number of the accidents that already occurred in the hot spot area, the diameter is the diameter of the complement circle of the hot spot curve shape and “RoadDefects” is the hot spot road defect number in the road defects table if exist (as explained in appendix).

4- Clients Table:

ClientsTable	
	ClientID
	ClientName
	ClientPosition
	ClientSpeed
	ClientAge
	ClientGender
	ClientAcceleration
	RootID
	PositionInRoot
	HotSpotID
	PositionInHotSpot
	VehicleID
	IsActive

Figure 4-6: Clients Table Diagram

This table contains a record for each client that using the system on his smart device and the information of that client such as his name, position, speed, age, gender, acceleration, the root id where the client currently travelling, position in root (distance that has passed by the client from the start of his current root over the total length of the root), hot spot id, position in hot spot (the distance that has passed by the client from the start of his current hot spot over the total length of the hot spot) , vehicle id and if the user active (moving) or not. Automatically set to active when the TIS receives a navigation message (will be explained later in this chapter) from the client and not active when the TIS receives deactivation message from the client.

5- Custom message table:

CustumMessageTable	
	ID
	Message
	PositionOfMessage

Figure 4-7: custom message table Diagram

This table contain custom messages that the administrator of the system can insert them as they are needed Ex.(when there is works on the road) to warn the drivers.

6- Intersections Table:

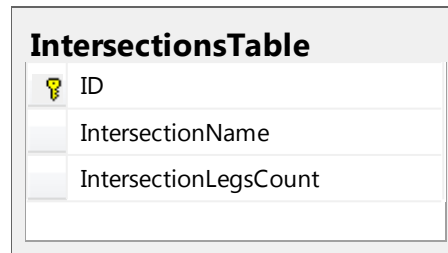


Figure 4-8: Intersections Table Diagram

The table contains a record for each intersection for the defined area of the system with the intersection name and number of legs of the intersection.

7- Defects table: The table contains the information about hot spots road defects.

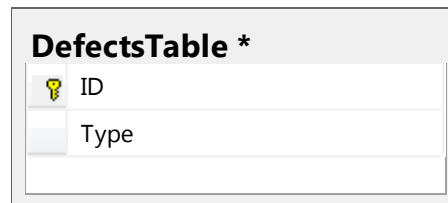


Figure 4-9: hot spots defects table

8- Intersection leg table:

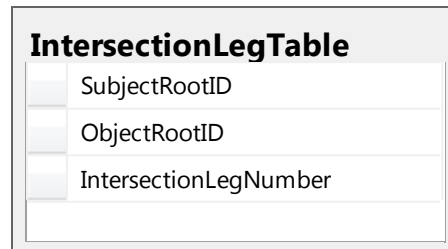


Figure 4-10: Intersection leg table

This table contains $(n^2 - n)$ records for each intersection where “n” equals the legs count of the intersection. “SubjectRootID” column is the root id of the sender client, “ObjectRootID” is the root id of the nearest client from the sender client and the “IntersectionLegNumber” is the leg number of the intersection that the nearest client will come from.

4.5 How the System Works

When a client installs the client part of the system on his smart device the system initializes the client system data by asking the user to insert the needed data to initialize the new client such as the client age, gender and his vehicle information (if the client owns one), after that the system sends an initialization message to the server to insert a new record for the new client and his information in the clients table in the (Traffic Data Manager) system database.

The following is an example for the client initialization message.

```
<?xml version="1.0" encoding="utf-8" ?>
<message type="initialization">
  <client>
    <name>client name</name>
    <age>30</age>
    <gender>male</gender>
  </client>
  <vehicle>
    <type>mercedes</type>
    <model>1997 E200...</model>
  </vehicle>
</message>
```

Figure 4-11: Initialization message format

The following is as example for the real time monitoring system initialization interface.



The image shows a mobile application interface for system initialization. It features a white background with a black border. The form includes the following elements:

- Name:** A text input field.
- Age:** A text input field.
- Gender:** Two radio button options: ☒ Male and ☐ Female.
- Vehicle type & model:** A text input field containing "Mercedes E200 1999" and a heart icon on the right.
- Initialize:** A large button at the bottom.

Figure 4-12: Real-Time Monitoring System initialization interface

When the sever receives an initialization message it inserts a new record for the new client in the clients table and bind the needed data for the new client based on the data that the client has provide in the initialization message; it finds the car id in the vehicles table and binds its (id) for the client in the clients table and after the new client

has initialized the server responds to the initialization message with initialization state, the following is an example for the initialization message.

```
<?xml version="1.0" encoding="utf-8" ?>
<message type="initializationresponse">
  <state>success</state>
  <client>
    <id>17</id>
  </client>
  <timer>597311</timer>
</message>
```

Figure 4-13: Initialization Success Response message format

The message contains the state of initialization and the new client id (in the server database) and the timer value.

The client system saves the id because it is the identifier that the server will use it later to distinguish the client.

The timer is a number that is used to synchronize a time between the server and the client application to make the timing more precise between the client and the server and the other clients, this number starts with zero at the start of day and increases by one every millisecond until the end of the day it will reach number (86399999).

If the initialization process has failed then the server will respond to the user that the initialization process has failed then the client have to reinitialize itself and send the initialization message to the server again.

The following as an example for the initialization failed message.

```
<?xml version="1.0" encoding="utf-8" ?>
<message type="initializationresponse">
  <state>failed</state>
  <error>22</error>
</message>
```

Figure 4-14: Initialization Failed Response message format

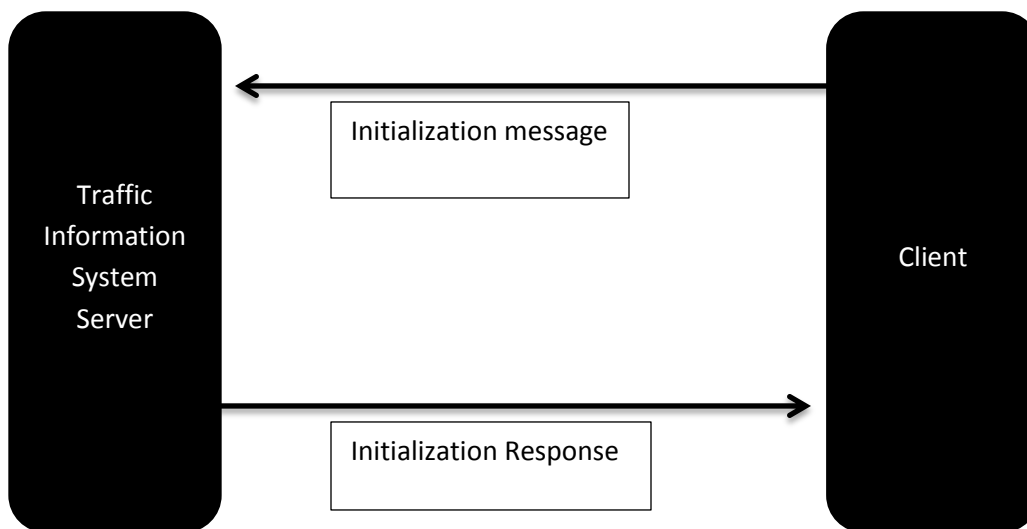


Figure 4-15: System initialization Process

The message contains state failed and the error number.

When the client has activated successfully then he can benefit from the system services to enhance the safety of his driving experience were if the client was registered

and activated then his application will send a “navigation messages” continuously to the server when the client speed is more than 20 km/h.

The following is an example for the navigation message.

```
<?xml version="1.0" encoding="utf-8" ?>
<message type="navigation">
  <client>
    <id>17</id>
    <position>40.575331,19.975993</position>
    <acceleration>-11</acceleration>
    <speed>47</speed>
    <time>11993</time>
  </client>
</message>
```

Figure 4-16: Navigation message format

The id is the user identifier in the server, the position is the longitude and latitude values of the client GPS, the acceleration it the client acceleration value that has measured by the device accelerometer, the speed is the client speed measured by the GPS and the time is the client application timer value.

When the Traffic Information Server (TIS) receives the navigation message it update the state of the client in the clients table; first the client position sent to the GIS interface which returns the client root, progress of the client in the root (passed distance from the start of root over the overall root length), hot spot id and the progress of the client in the hot spot (passed distance from the start of the hot spot over the overall hot

spot length), if the client wasn't passing a hotspot then the (TIS) will return -1 to the system so the system will know that the client is not in hotspot area.

After the client data is updated the "TIS" updates the roots table average speed (average speed of the cars in the root) and the count of the cars in the root and it does one of the following:

If the client hot spot is an intersection then the TIS will look for the nearest vehicle client with different root id and the same hot spot id sends its position and the sender client position to the GIS to determine the leg number of an intersection that the nearest vehicle will appear from, and the nearest pedestrian client and return their information to the client in addition to each accident type counts.

If the hot spot wasn't an intersection then the system will return the same information but about the client with the same root id and the same hot spot id and without the leg number.

The following is an example for the navigation response message from the server.

```

<?xml version="1.0" encoding="utf-8" ?>
<message type="navigationresponse">
  <client>
    <root>36</root>
    <hotspot>34</hotspot>
    <hotspotprogress>.91</hotspotprogress>
    <diameter>409</diameter>
    <defects>2</defects>
    <custommessage>excavations ahead of you be carefull</custommessage>
    <messagepoint>.60</messagepoint>
  </client>
  <nearestclient>
    <legnumber>3</legnumber>
    <defects>3</defects>
    <acceleration>-11</acceleration>
    <speed>47</speed>
    <time>11993</time>
    <root>36</root>
    <hotspot>34</hotspot>
    <hotspotprogress>.91</hotspotprogress>
    <age>39</age>
    <gender>female</gender>
    <vehicle>
      <type>mercedes</type>
      <weight>1500</weight>
      <model>1997</model>
      <abs>true</abs>
    </vehicle>
  </nearestclient>
  <pedestrian>
    <acceleration>-11</acceleration>
    <speed>47</speed>
    <time>11993</time>
    <root>36</root>
    <hotspot>34</hotspot>
    <hotspotprogress>.91</hotspotprogress>
    <age>39</age>
    <gender>female</gender>
  </pedestrian>
</message>

```

Figure 4-17: Navigation Response message format

The message contains the root id, hot spot id and the hot spot progress of the sender client, and contains the age, gender, acceleration, speed, time, root id, hot spot id,

hot spot progress, custom message, message point, vehicle type, model, weight, ABS information of the nearest vehicle client (from the root id the client can infer if the hot spot is an intersection or not), the pedestrian is the client who is not in a vehicle (walking) and his information. If the hot spot wasn't an intersection then the (TIS) will respond with the same message but in this case it will return the information of the nearest client with the same root id.

The client program will receive the message information returned from the (TIS) and send them the neural network system based on the accidents records count as follows:

- If the hot spot is a section of road then the system will send the inputs to the (ANN) based on the count of each type of accidents Ex. If the hot spot has a 250 collision, 490 pedestrian and 780 turn over accidents then the system will send the inputs to the turn over NN to get the possible driver mistake and loses of the predicted accident.
- If the hot spot was an intersection then the inputs will be sent to the intersections NN to get the possible driver mistake and loses of the predicted accident (intersections NN just predict the collision accidents).
- If there was a custom message for the hot spot the system will read it to the client (vehicle or pedestrian) before sending the inputs to the NN system.
- When the output of the NN system is received then the system will warn the user about possible mistake and if the possible loses output was slight injuries then the system

fires one warning for the client and if the expected losses were serious the system fires a louder augmented warning, if the expected losses were fatality then the system will fire a continuous louder warning for the client.

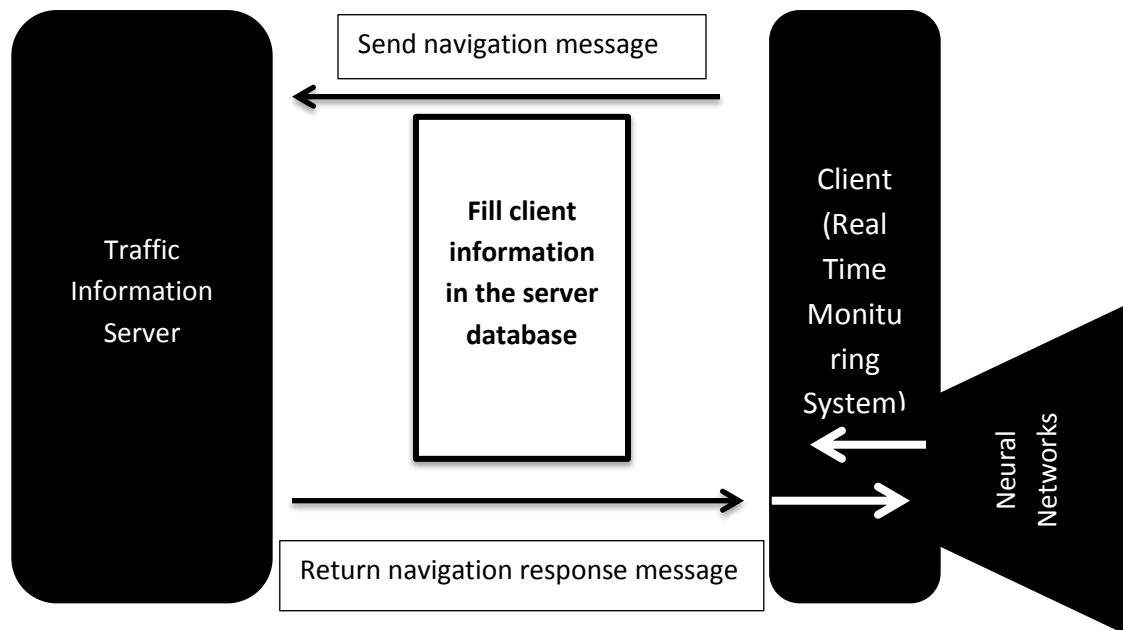


Figure 4-18: Navigation Messages flow.

4.6 Using Neural Networks to Predict Possible Danger

The main objective of this study is to predict the possibility of turnover, collision and pedestrian accidents and to predict the factors that can lead to these accidents and the degree of danger for the current situation and condition around the client. To predict the previous information a database of hotspots for some sample areas has developed (intersection and sections of roads) to learn the neural networks that will predict the possible accidents.

4.6.1 Sections of road accident prediction Neural Networks.

Three Neural networks have been developed to predict sections accidents; one for Turnover accidents the second NN. To predict the collision accidents and the third for pedestrian accidents Turnover accidents neural network has the following inputs:

- Hot spot progress
- Hot spot diameter.
- Vehicle speed.
- Vehicle acceleration.
- Vehicle weight.
- Vehicle ABS.
- Driver age.
- Hot spot speed limit.

- Hot spot defect number (look classification of accidents based on road defects in appendix).
- Weather status number (look classification of accidents based on weather status in appendix).
- Temperature.
- Time of day.
- Day of week number (look classification of accidents based on day of week in appendix).

And the outputs are two values:

- The driver possible mistake number (look classification of accidents based on weather status in appendix).
- Accident possible loses number (look classification of accidents based on type of accident in appendix).

The second neural network is responsible on predicting the sections collision accidents with the following inputs:

- Vehicle1hot spot progress
- Vehicle2 hot spot progress
- Vehicle1 speed.
- Vehicle2 speed.
- Vehicle1 acceleration.

- Vehicle2 acceleration.
- Vehicle1 weight.
- Vehicle2 weight.
- Vehicle1 ABS.
- Vehicle 2 ABS.
- Driver1 age.
- Driver 2 age.
- Hot spot diameter.
- Hot spot speed limit.
- Hot spot defects number (look classification of accidents based on road defects in appendix).
- Weather status number (look classification of accidents based on weather status in appendix).
- Temperature.
- Time of day.
- Day of week number (look classification of accidents based on day of week in appendix).

And the following outputs:

- The driver possible mistake number (look classification of accidents based on weather status in appendix).

- Accident possible losses number (look classification of accidents based on type of accident in appendix).

The third neural network is responsible for predicting the sections pedestrian accidents with the following inputs:

- Vehicle hot spot progress
- Pedestrian hot spot progress
- Vehicle speed.
- Pedestrian speed.
- Vehicle acceleration.
- Pedestrian acceleration.
- Vehicle weight.
- Vehicle ABS.
- Driver age.
- Pedestrian age.
- Hot spot diameter.
- Hot spot speed limit.
- Hot spot defects number (look classification of accidents based on road defects in appendix).
- Weather status number (look classification of accidents based on weather status in appendix).
- Temperature.

- Time of day.
- Day of week number (look classification of accidents based on day of week in appendix).

And the following are the NN. outputs:

- The driver possible mistake number (look classification of accidents based on weather status in appendix).
- Accident possible loses number (look classification of accidents based on type of accident in appendix).

4.6.2 Intersections accident prediction Neural Networks.

The final neural network is responsible on predicting the intersections collision accidents with the following inputs:

- Vehicle1 hot spot progress
- Vehicle2 hot spot progress
- Vehicle1 speed.
- Vehicle2 speed.
- Vehicle1 acceleration.
- Vehicle2 acceleration.
- Vehicle1 weight.

- Vehicle2 weight.
- Vehicle1 ABS.
- Vehicle 2 ABS.
- Vehicle 1 intersection leg.
- Vehicle 2 intersection leg.
- Driver1 age.
- Driver 2 age.
- Hot spot speed limit.
- Root1 defects number (look classification of accidents based on road defects in appendix).
- Root2 defects number (look classification of accidents based on road defects in appendix).
- Weather status number (look classification of accidents based on weather status in appendix).
- Temperature.
- Time of day.
- Day of week number (look classification of accidents based on day of week in appendix).

And the following outputs:

- The driver possible mistake number (look classification of accidents based on weather status in appendix).

- Accident possible losses number (look classification of accidents based on type of accident in appendix).

The neural network models were used to predict the accidents on the hotspots. The Multi-Layer Perceptron (MLP) Neural Network model have been used in this study. The MLP models have been used frequently in many traffic safety studies, and have often been found to be very effective in analyzing the crash frequencies (Nawathe, 2005).

4.7 Crash Prediction using MLP Neural Network

A program was written in MATLAB to build the MLP neural networks. The program performed the following functions:

- The input variables are normalized. This operation was carried out because the contribution of an input will depend on its variability relative to other inputs of the Neural Network. So it is essential to rescale the inputs so that their variability reflects their importance.
- Take an input of the crash collected data from the central directorate of traffic for the sample areas.
- Take the first 70% of the sample data for learning the networks and the 15% for testing purpose and the rest 15% for validation.

- Use one hidden layer of Neural Network nodes for training the data. The Back Propagation neural network was used in the training. The activation function is the sigmoid and linear fitting functions respectively.
- Calculate the root mean squared error (RMSE) by adding the squares of the difference of the actual value and result values of the network, averaging them over the hot spots used in the testing, and taking the square root of this value.
- Change the number of hidden nodes as follows (10, 15, 20).
- Find the result with the lowest error and consider it.

The following Table contains 150 examples of section turn over accidents records information that are used in the process of learning the neural network (the sections turn over NN):

Table 4-1: section turn over NN inputs

Hot spot progress	Hot spot diameter	Vehicle speed	Vehicle acceleration	Vehicle weight	Vehicle ABS	Driver age	Hot spot speed limit	Hot spot defects	Weather status	Temperature	Time of day	Day of week
60	773	117	2	80	1	61	850	1	4	12	18	7
16	469	71	-8	80	1	65	100	0	4	37	18	2
79	117	76	8	60	1	38	150	2	1	29	16	2
67	112	99	-5	50	0	50	750	1	3	6	11	1

41	317	81	-6	70	0	59	150	4	4	4	9	3
61	620	75	1	80	0	43	150	-1	0	32	21	5
82	327	65	-2	50	0	37	100	0	1	14	5	5
67	109	92	8	80	1	62	120	2	1	37	16	6
60	123	76	-5	40	1	36	750	0	3	24	6	5
82	222	114	-4	40	1	35	850	4	3	13	3	2
16	231	99	-6	80	0	55	100	3	2	9	19	3
70	110	93	-2	40	1	48	850	4	4	5	2	2
94	572	89	5	50	0	29	120	1	1	19	20	7
42	728	69	-8	70	1	45	150	0	2	28	7	4
30	730	115	-5	40	1	29	150	0	2	4	18	1
12	833	87	-7	60	0	46	850	2	0	6	13	3
27	752	83	3	80	1	39	150	4	3	36	1	2
83	890	71	-9	40	0	39	100	3	4	15	22	7
56	997	77	5	50	1	56	120	1	3	14	12	4
22	570	81	-4	80	1	27	850	1	4	5	7	1
93	339	108	1	60	0	51	120	0	3	20	22	3
6	518	81	-2	80	1	50	100	5	0	8	6	1
77	103	101	-7	80	0	38	850	5	3	5	16	1
22	109	101	10	70	1	37	100	2	4	37	18	7
14	905	91	-13	40	1	35	100	1	4	10	22	6
21	798	60	-10	70	0	55	120	3	4	34	22	3
24	111	93	-7	80	1	40	120	-1	3	33	20	5
38	589	100	9	80	0	66	120	3	4	22	8	2
62	244	69	-3	80	1	20	150	1	2	36	0	7
43	738	119	-11	80	0	29	750	5	1	9	17	6
34	121	96	0	40	0	62	150	-1	2	29	15	7
14	110	118	9	80	1	62	750	-1	2	33	13	7
32	341	70	3	70	0	51	750	1	0	4	19	4
85	325	78	-7	40	0	39	120	-1	1	7	22	4
38	110	109	-7	60	1	65	750	4	3	21	10	6
70	123	110	5	70	1	22	100	5	3	29	17	3
55	362	62	-7	70	0	52	750	3	4	11	1	5
24	113	83	-11	50	1	58	850	3	2	7	6	5
15	112	63	-2	40	0	42	750	0	4	39	10	1
42	993	97	-12	40	1	53	750	3	1	5	18	4
89	119	64	10	70	1	66	750	5	4	7	3	6
6	808	89	10	40	0	50	850	1	0	28	11	2
45	775	83	-3	70	1	51	150	0	2	5	6	1
6	693	109	-2	80	1	62	100	3	0	29	16	1
65	340	65	-1	80	0	41	100	2	2	32	11	1

10	702	64	6	40	0	53	120	1	0	22	20	1
16	810	109	7	60	1	53	100	1	2	24	16	5
65	103	99	0	40	0	18	120	2	2	17	17	1
24	124	69	-6	80	1	48	150	0	4	26	14	1
9	100	94	4	80	1	22	850	4	4	14	18	2
48	111	80	4	40	0	21	850	2	3	18	1	5
99	300	117	-3	80	0	63	120	5	1	12	16	4
85	922	105	-3	40	1	42	150	-1	3	18	11	6
17	790	104	1	40	0	51	850	2	4	17	8	1
26	111	71	-1	70	0	18	150	3	1	23	0	5
54	771	108	8	50	1	62	750	5	1	12	7	2
6	210	70	-6	70	0	20	750	3	3	25	12	1
29	731	66	0	40	0	46	850	3	0	22	13	5
82	683	112	-4	60	1	28	100	-1	4	20	6	5
16	123	97	9	80	0	35	850	0	2	5	7	2
4	973	108	-4	80	1	53	750	2	2	9	4	1
66	560	100	-8	60	1	32	100	-1	3	31	16	2
31	458	86	0	40	1	21	850	5	2	27	14	1
82	778	99	1	50	0	53	150	2	0	23	0	7
40	230	102	10	40	0	52	150	1	2	25	0	4
34	347	107	5	80	0	47	850	4	3	33	10	2
32	121	87	5	50	1	43	750	2	0	26	20	3
61	118	90	-2	40	0	47	120	-1	2	39	18	2
51	663	91	0	50	1	45	120	4	3	10	13	2
69	709	83	8	40	0	59	100	1	3	34	7	5
76	107	81	-9	50	0	65	750	1	0	26	19	6
75	563	85	8	40	0	62	120	1	0	20	4	4
83	119	96	-11	70	1	29	150	-1	3	23	12	3
70	854	70	-6	60	1	20	850	1	2	7	12	4
51	659	110	-4	70	1	65	120	3	0	20	7	3
93	837	67	2	70	1	36	120	3	1	27	1	5
67	369	68	-4	60	1	45	850	0	4	32	16	1
64	777	88	-12	70	1	66	750	4	2	12	17	7
24	366	97	7	40	0	34	120	0	4	30	4	4
96	988	118	5	80	0	63	100	0	4	16	13	5
96	284	95	7	70	1	49	100	0	2	28	6	5
61	594	61	-4	70	1	59	750	4	1	9	1	5
90	109	77	-13	50	0	32	100	0	1	18	9	1
83	805	61	3	50	0	40	750	4	2	24	18	1
63	948	97	-8	80	0	55	750	-1	3	13	6	1
42	208	68	-4	40	1	18	150	5	1	4	0	7

86	832	89	-9	50	1	27	850	3	2	35	22	3
96	867	61	7	70	1	39	850	5	2	4	7	4
94	104	87	4	60	1	27	120	3	0	25	18	4
52	282	108	5	60	0	37	150	3	1	25	1	4
25	838	95	10	40	0	59	120	4	1	32	20	2
26	104	86	-4	60	0	18	850	0	1	21	2	1
72	118	103	-6	60	1	51	120	1	2	17	13	1
11	120	97	4	70	1	61	850	-1	2	13	6	7
15	241	72	-13	50	0	62	750	4	4	9	11	7
95	421	72	8	50	0	57	100	1	0	27	12	5
49	419	105	3	50	0	19	100	3	3	30	8	3
26	915	114	-5	40	0	29	150	-1	3	6	2	3
18	691	86	6	80	1	41	150	3	3	16	1	4
69	688	85	-7	60	0	44	120	4	0	23	22	1
18	501	114	-3	60	1	46	120	0	2	6	20	5
20	111	103	2	80	1	33	100	4	3	15	18	1
60	800	88	-5	50	1	58	120	1	0	29	4	2
67	687	95	-4	80	0	35	120	0	3	10	4	1
99	896	92	-4	60	1	49	100	-1	0	22	21	2
18	263	101	7	70	0	40	120	5	4	35	8	7
96	651	72	-6	80	0	25	850	5	0	19	22	5
11	757	103	1	60	0	41	150	0	1	11	10	7
16	984	78	-11	80	1	18	150	3	1	12	17	1
22	102	119	-7	80	0	60	750	5	4	7	6	3
81	116	70	6	40	1	61	120	-1	2	36	18	3
78	121	61	-2	50	1	58	850	5	3	29	20	3
95	802	119	-8	80	0	57	100	4	0	21	18	1
23	112	72	-12	50	0	41	100	2	4	39	10	5
60	695	63	9	50	0	62	150	-1	1	37	20	5
71	122	116	9	80	1	50	850	0	4	8	17	3
63	631	112	-2	70	0	57	850	3	1	17	20	6
3	116	82	-9	60	0	26	120	1	2	25	11	1
44	101	83	-6	60	1	26	120	4	2	34	12	5
91	300	81	-11	70	1	21	750	2	3	34	2	3
84	824	89	-7	80	0	65	150	2	0	33	6	6
44	949	115	-9	60	1	48	120	1	0	20	5	7
2	680	118	9	40	1	29	750	-1	2	20	12	5
58	820	117	-5	40	1	58	120	-1	1	7	7	3
34	684	86	-2	60	0	19	750	0	2	28	14	7
30	241	100	-5	40	0	49	120	5	0	39	0	1
93	632	63	8	40	1	47	150	0	3	29	13	1

42	746	93	-6	40	0	53	750	0	3	8	17	2
62	911	89	-4	60	0	40	100	-1	3	39	8	3
81	245	76	-11	50	1	55	750	-1	0	14	14	7
71	516	115	3	70	1	23	120	0	4	11	18	3
24	346	94	-6	80	1	65	150	2	3	32	3	4
17	124	68	0	60	0	56	100	4	0	24	9	7
7	466	90	0	40	0	31	120	4	3	21	17	2
71	883	76	-7	70	0	45	750	4	0	31	15	3
99	222	112	-2	80	0	63	120	2	3	10	20	4
73	109	97	-3	50	1	58	850	2	0	11	10	4
43	106	114	-6	40	1	61	150	-1	1	5	5	5
47	104	79	-8	80	0	37	750	1	3	20	7	6
10	110	62	-2	80	1	18	100	3	0	39	4	4
43	124	107	2	60	1	27	150	0	0	4	6	2
11	285	86	-13	40	0	66	850	3	0	29	13	3
35	433	71	8	70	0	19	850	3	1	14	16	1
88	347	61	8	80	0	27	150	3	4	4	12	7
54	415	70	5	80	0	21	850	0	4	22	7	3
68	488	108	-3	70	0	32	120	2	4	16	17	2
69	610	100	5	50	0	34	150	4	4	11	20	3
22	890	114	2	40	1	47	100	1	4	35	3	2
85	461	60	10	50	1	19	120	1	3	23	10	5
34	122	96	8	60	1	44	850	5	3	6	21	5

The following Table contains the results of the previous 150 turn over accidents records information that are used in the process of learning the neural network (Target array of the neural network):

Table 4-2: section turn over NN Targets

driver possible mistake	Accident possible loses (degree of danger)
12	2
9	1
3	2
9	2
1	2
10	2
1	1
12	1
11	2
7	2
6	2
7	2
10	1
13	1
9	3
10	1
13	1
13	3
13	3
12	1
13	2
2	2
8	2
13	3
11	2
12	1
9	2
1	1
2	1
4	1
6	2
1	1
9	2
9	3
4	3
4	1
9	2
8	3

8	1
13	2
2	1
4	1
13	2
9	2
4	3
12	1
6	1
10	1
8	3
10	1
11	1
8	3
2	3
8	1
11	1
9	3
2	3
1	1
4	3
3	1
10	1
6	2
1	2
9	3
9	1
3	2
7	3
8	3
8	2
3	1
12	2
11	1
2	1
10	2
10	1
3	3
10	2
5	3
11	1

11	3
1	1
9	3
1	3
6	1
5	1
10	3
7	3
4	2
4	1
6	1
10	1
2	1
13	1
12	3
7	3
1	2
8	2
2	1
10	1
1	1
7	2
3	2
10	1
5	3
4	1
7	2
9	1
13	3
8	2
10	3
2	2
10	2
2	1
4	1
12	1
10	1
4	1
8	1
13	2
7	3

12	1
9	2
5	2
12	3
8	1
8	1
5	1
1	1
9	3
6	2
1	2
12	1
3	1
4	2
2	1
13	3
12	1
11	3
12	1
2	2
4	1
6	2
7	2
11	3
4	2
8	1
2	3
9	2
4	2
5	1

The column on the left is the driver mistake number and the column to the right is the loses of the accident (1 means slight injuries, 2 means serious injuries and 3 means fatalities).

The following are the results of training the network with 10 hidden layers:

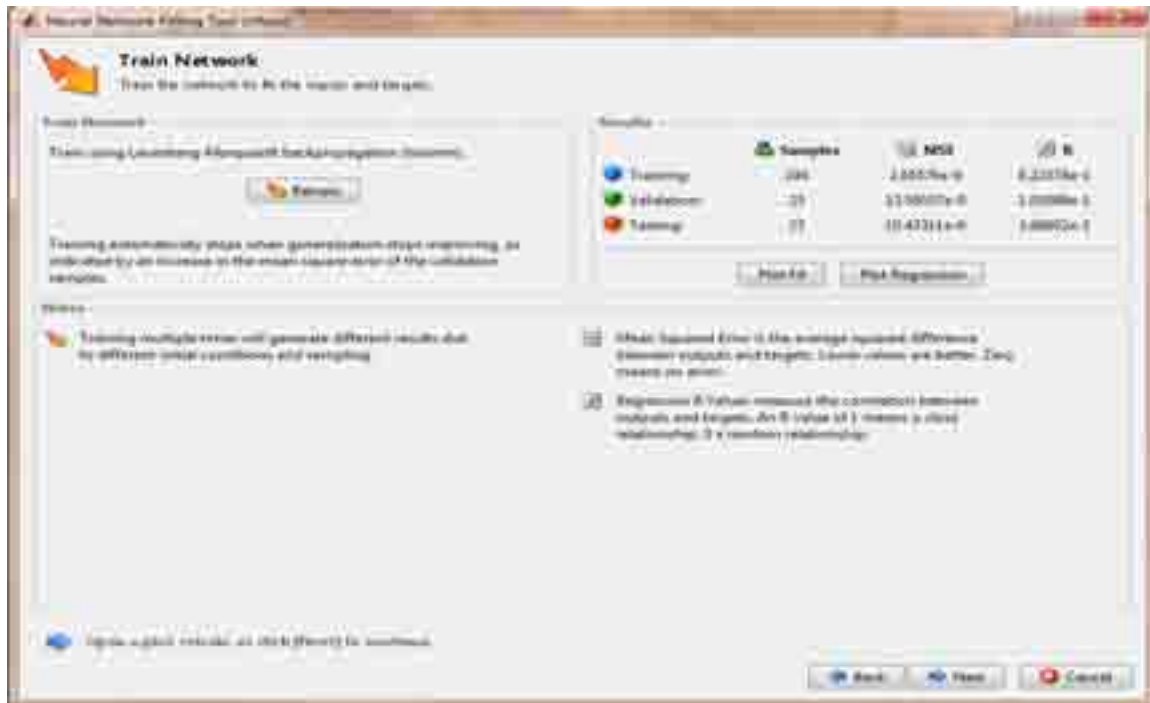


Figure 4-19: section turn over NN result (10 nodes hidden layer)

The following are the results of training the network with 15 hidden layers



Figure 4-20: section turn over NN Regression plot (10 nodes hidden layer)

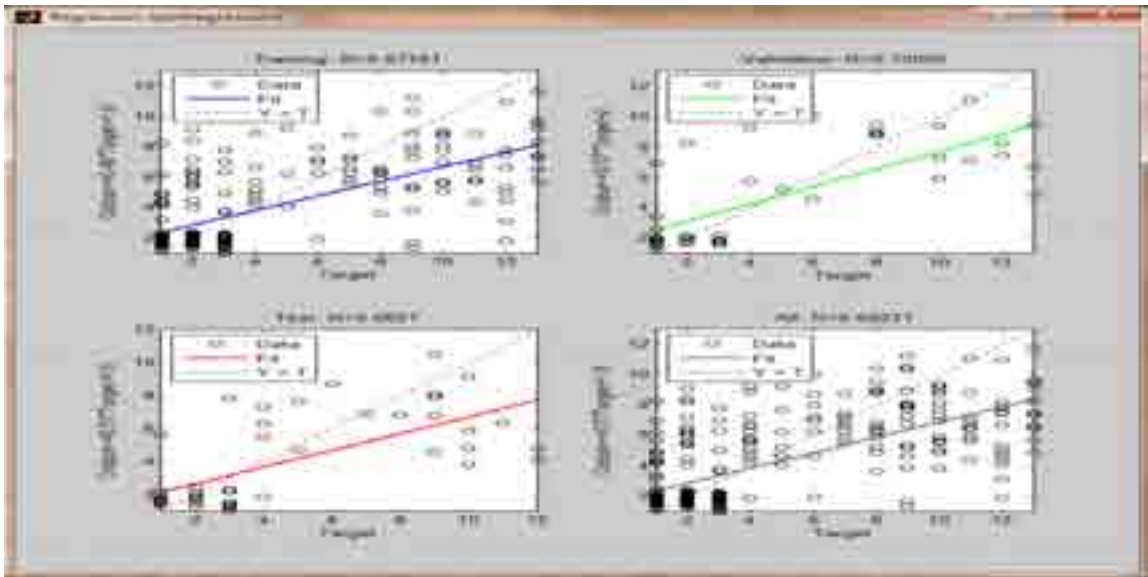


Figure 4-21: section turn over NN result (15 nodes hidden layer)

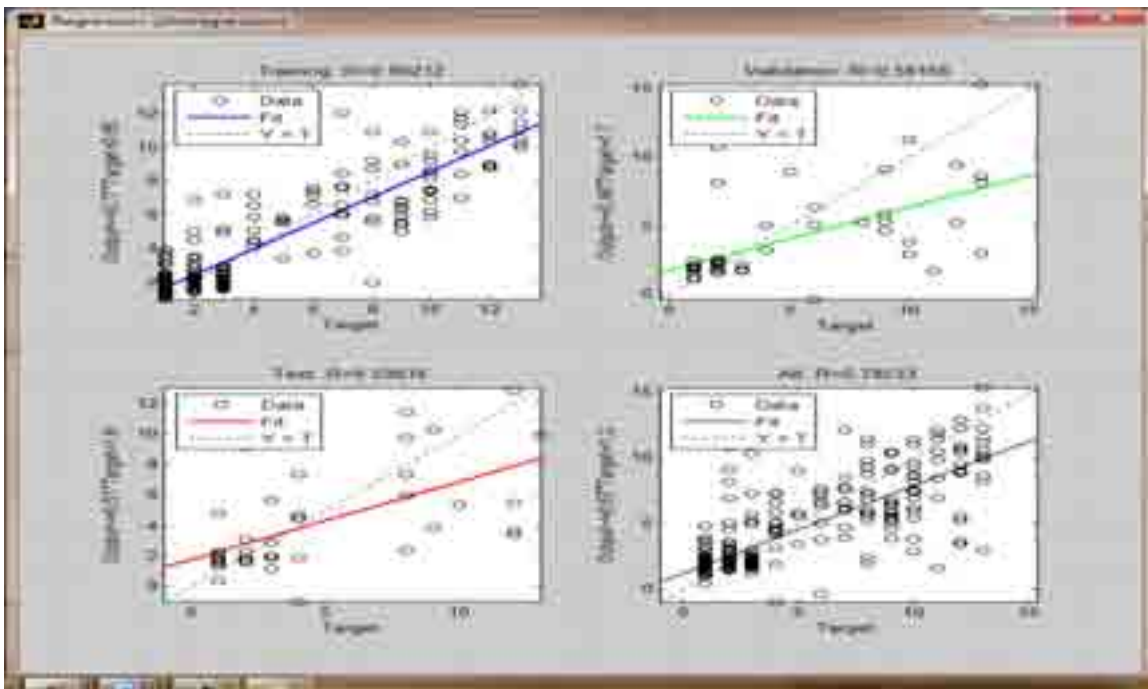


Figure 4-22: section turn over NN Regression plot (15 nodes hidden layer)



Figure 4-23: section turn over NN result (20 nodes hidden layer)

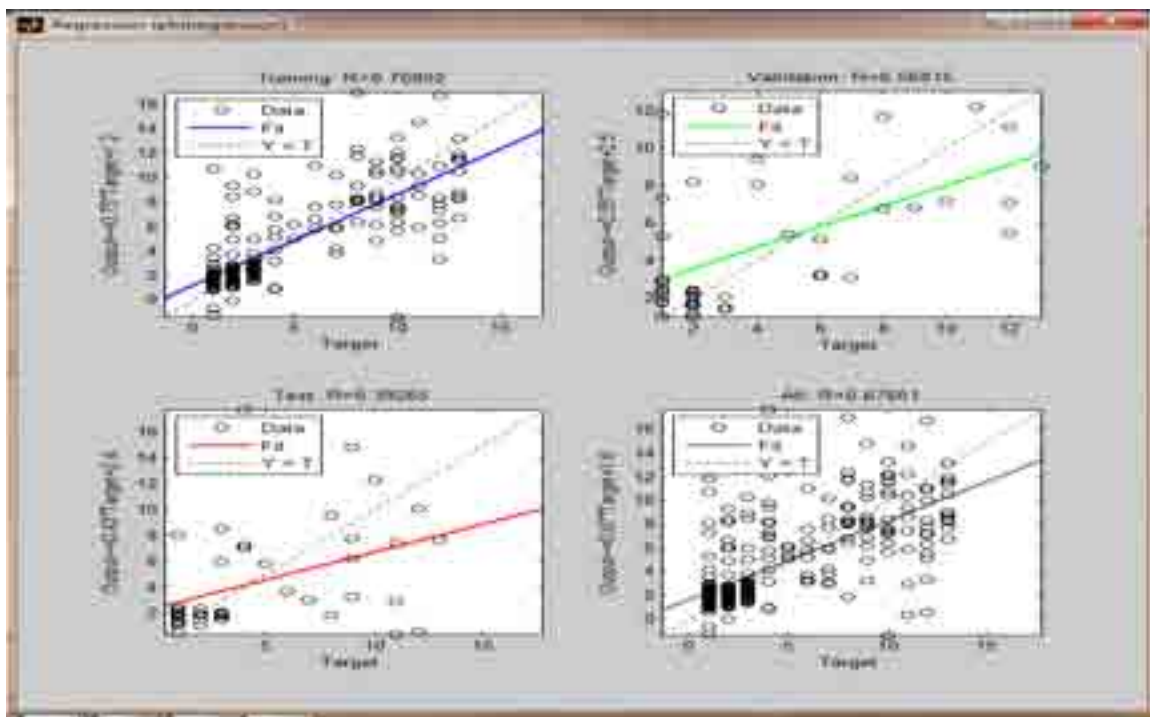


Figure 4-24: section turn over NN Regression plot (20 nodes hidden layer)

We note that the NN with 15 nodes in the hidden layer has the lowest (MSE) so it will be used in the system.

The following Table contains 150 examples of section collision accidents record information that are used in the process of learning the neural network (the sections collision NN):

Table 4-3: section collision NN inputs

Vehicle1 hot spot progress	Vehicle2 hot spot progress	Vehicle1 speed	Vehicle2 speed	Vehicle1 acceleration	Vehicle2 acceleration	Vehicle1 weight	Vehicle2 weight	Vehicle1 ABS	Vehicle 2 ABS	Driver1 age	Driver 2 age	Hot spot diameter	Hot spot speed limit	Hot spot defects	Weather status	Temperature	Time of day	Day of week
44	39	105	113	-2	-12	750	150	0	0	25	43	645	60	3	2	13	1	5
79	16	132	129	-2	0	120	150	1	1	33	20	879	40	0	0	31	2	3
61	36	81	94	-2	3	100	750	0	1	45	37	216	80	5	1	19	1	4
16	16	109	75	0	-12	120	850	1	0	29	41	1166	60	5	2	11	9	5
45	21	128	84	-1	9	120	850	0	0	52	60	1009	60	0	4	10	2	1
77	44	106	79	-12	4	750	850	1	1	21	38	952	70	4	0	14	6	6
12	34	104	116	-1	-10	120	100	0	1	50	50	1006	60	0	3	12	1	7
80	68	92	103	-6	-4	850	150	1	0	18	38	1207	60	1	4	30	3	5
9	17	74	61	1	-5	120	850	0	1	45	23	756	50	1	2	7	1	6
28	34	78	84	6	-1	100	100	1	0	36	50	630	60	2	3	29	1	4

85	24	80	63	8	7	100	120	0	0	44	20	522	40	5	4	16	1	6
46	62	65	121	-7	-11	120	850	0	1	66	43	936	80	2	3	22	2	2
40	51	84	98	10	-4	750	750	0	0	38	47	387	80	5	0	37	1	4
6	5	137	106	-7	-5	100	150	1	0	55	36	706	80	0	1	13	1	1
21	40	61	139	8	4	150	750	1	1	55	61	834	40	-1	4	9	9	7
12	20	93	117	-6	-13	850	750	1	1	18	47	910	80	4	2	5	2	1
10	88	96	77	3	-11	750	850	0	0	38	22	218	80	1	4	35	1	5
80	98	102	107	6	-4	120	120	0	1	55	49	229	80	-1	1	39	1	7
81	63	71	123	-11	7	100	100	1	1	32	19	1206	70	1	0	6	1	2
71	91	128	66	10	-6	100	150	0	0	63	47	606	50	5	4	4	1	2
46	80	75	125	6	-7	150	120	1	1	48	57	234	80	4	4	39	2	4
25	52	114	68	-10	-4	750	750	1	1	65	58	601	60	5	0	19	9	1
7	91	68	87	1	4	150	850	1	1	48	40	217	80	2	1	27	1	5
14	42	115	68	8	-8	120	750	0	0	24	56	535	60	5	4	23	1	1
11	48	85	57	-9	-6	850	750	1	1	58	30	453	50	4	1	27	7	5
32	20	119	109	-2	-11	150	120	0	0	23	23	219	50	2	3	8	1	3
54	90	105	51	8	-8	100	120	1	0	41	26	468	60	4	3	36	7	6
89	99	89	78	10	-9	120	150	1	1	52	49	958	60	1	3	33	1	2
88	44	56	60	7	-2	120	120	1	1	27	44	867	50	1	4	16	2	5
65	82	55	93	2	10	850	120	1	1	64	54	222	40	4	2	17	1	7
58	83	61	83	10	-9	150	100	0	0	38	52	1215	70	0	0	16	1	7
45	14	108	107	-12	-9	120	120	0	1	62	60	1154	40	2	2	30	1	4
8	30	50	95	-10	-1	850	120	1	0	56	65	608	70	2	1	30	2	2
6	19	56	81	-3	10	750	100	1	1	42	26	707	60	5	3	27	1	5
51	14	116	72	9	5	850	100	1	0	41	49	959	60	2	2	13	0	7
56	55	138	52	6	-7	100	120	0	0	42	60	1012	80	-1	2	5	7	7
14	57	57	88	2	-8	750	750	1	1	63	21	858	70	3	4	6	1	1
93	97	91	132	-12	-11	750	850	1	1	47	25	722	40	1	4	17	1	1
33	80	119	72	3	-7	850	850	1	0	21	21	233	80	5	1	38	1	5
2	34	107	126	-5	-6	750	100	0	1	32	60	548	50	5	0	15	3	6
76	65	111	114	-10	-7	150	150	1	0	45	55	595	40	4	2	32	1	7
43	92	97	125	9	-3	100	850	1	1	21	52	867	50	0	4	39	7	5
49	60	112	111	1	-10	120	750	1	1	47	63	388	60	1	3	32	5	6
74	27	101	139	8	10	100	100	1	1	25	31	973	40	0	1	16	1	2
94	67	55	76	2	0	750	150	1	0	31	42	644	70	0	2	16	2	5
79	72	57	104	10	1	150	100	1	1	18	32	204	80	2	1	9	1	7
92	43	119	69	1	-5	150	750	1	1	45	44	1047	50	4	4	22	1	1
11	68	129	63	-7	9	120	120	0	1	60	37	223	80	1	4	10	0	4
46	24	79	101	-12	7	850	850	0	1	30	20	248	60	-1	2	14	0	2
51	28	116	90	-5	-1	120	750	1	1	38	33	805	80	-1	1	33	1	1
84	31	136	111	2	9	750	100	1	1	64	35	316	80	5	2	12	1	6

96	4	65	109	5	2	150	150	1	0	19	19	465	70	0	0	38	1	5
8	52	80	56	-12	-9	150	850	0	0	51	38	1022	70	-1	4	6	1	5
20	5	128	73	-5	-5	150	120	1	1	64	55	1167	80	3	3	13	1	7
13	47	64	83	-2	-6	120	150	0	0	28	65	294	60	1	1	23	4	2
99	72	74	72	8	3	850	100	1	0	24	20	1019	40	-1	2	10	0	5
38	94	81	109	-1	1	100	100	1	0	47	47	306	60	5	3	12	1	2
25	66	61	115	-8	-8	750	850	0	1	65	65	355	50	5	4	15	1	1
74	66	89	60	-1	-6	750	120	0	1	56	46	1112	70	5	3	4	5	2
12	45	88	75	-12	6	120	850	0	0	29	47	904	80	0	0	23	1	4
62	40	55	81	-12	3	150	750	0	0	26	43	1100	60	-1	2	26	7	3
39	29	106	53	4	0	120	750	0	1	51	46	636	80	2	3	33	1	1
36	59	86	106	5	-13	850	150	0	0	45	39	798	70	0	2	13	2	3
35	77	73	111	-1	0	100	150	1	1	37	63	520	60	2	4	32	2	5
86	2	90	123	-3	10	100	750	0	1	29	44	401	70	2	3	15	2	7
87	6	80	80	-1	-8	120	750	0	1	20	58	611	60	3	0	16	2	7
84	69	138	86	-6	8	100	120	0	0	60	56	411	80	5	0	25	1	5
94	59	90	130	-6	-8	750	120	1	0	46	44	287	80	1	1	11	2	5
4	45	138	69	5	6	850	750	1	1	43	34	1249	60	3	4	17	9	6
67	16	72	134	3	8	150	150	1	1	59	48	897	50	5	2	12	2	3
68	8	132	58	-8	10	850	150	1	1	37	60	1236	80	1	1	21	1	4
30	32	62	56	1	-9	750	850	1	0	20	23	687	80	5	3	30	1	1
4	93	81	62	-13	6	850	750	1	1	30	66	689	70	4	3	5	1	7
31	92	69	110	-2	1	100	120	1	1	66	24	907	60	1	3	24	2	2
11	27	70	53	-10	0	100	750	1	0	54	32	1186	40	4	2	9	1	2
86	53	94	138	-3	-8	120	150	1	1	20	64	351	70	5	2	30	1	7
7	12	129	91	10	-3	750	100	0	1	64	18	490	80	1	0	27	1	2
77	80	75	132	-13	1	100	100	1	1	21	54	1247	50	0	3	9	2	1
53	56	74	109	6	3	150	100	1	0	59	48	433	80	2	1	6	1	2
87	84	89	137	0	10	120	850	1	1	18	26	354	40	3	0	29	1	1
47	23	83	58	5	-3	150	120	1	1	44	21	402	80	5	0	11	2	5
69	67	123	92	3	8	150	120	1	1	48	54	984	80	5	1	39	1	6
67	54	123	52	-10	-7	100	100	1	0	27	66	595	80	-1	4	20	1	6
66	19	50	102	-12	-3	850	750	1	0	30	49	1221	70	2	2	5	2	5
67	20	76	81	9	2	100	100	0	1	48	18	683	70	0	4	24	1	7
75	59	134	58	1	-6	100	100	0	0	62	45	264	80	4	4	24	8	6
7	95	100	131	10	-3	750	850	1	1	54	55	1149	70	-1	0	5	1	1
69	5	84	56	-7	-10	850	850	1	0	48	52	899	60	4	3	4	4	5
97	68	90	54	5	1	100	150	0	1	65	57	1023	50	2	3	32	1	7
30	77	105	68	1	-9	750	850	0	0	26	26	305	80	1	3	18	5	7
63	48	121	95	-5	-3	150	850	1	0	27	56	1173	80	-1	4	36	8	4
86	86	102	78	-4	-5	120	150	1	1	38	41	248	60	4	0	18	1	2

29	78	138	134	-6	6	120	100	0	0	66	19	671	60	5	1	8	1	2
40	16	95	121	5	-5	100	120	0	0	24	61	949	50	3	0	28	2	7
26	50	96	126	0	-4	120	120	1	0	23	21	892	80	0	0	8	1	7
23	57	131	124	4	-10	750	850	0	1	57	34	469	60	0	3	28	2	3
94	41	128	96	-3	8	750	850	0	1	41	32	741	50	3	3	16	8	5
79	70	90	52	1	-8	750	150	1	1	39	28	794	50	4	4	24	8	1
45	91	109	127	2	-2	150	850	0	0	45	59	1096	60	5	0	25	1	3
27	31	75	64	-8	3	750	150	1	0	52	41	332	50	1	4	31	2	6
79	54	123	128	7	4	850	150	1	1	45	23	419	50	0	0	30	3	6
46	16	106	123	8	-8	100	100	0	1	44	43	448	80	4	3	34	1	4
42	44	132	138	-3	8	850	120	0	0	64	28	792	70	-1	3	28	3	6
93	63	74	64	7	-9	750	850	0	0	40	48	554	70	1	3	14	1	2
21	93	98	73	-11	-3	100	850	1	1	29	32	276	60	-1	2	32	3	2
6	81	84	104	-13	6	750	100	1	1	30	66	941	40	2	4	32	9	3
17	74	83	123	-12	-2	750	120	0	0	28	23	732	60	-1	2	17	1	3
52	43	54	132	8	5	150	150	1	0	45	47	540	40	2	4	23	1	7
31	11	131	137	2	-4	850	100	1	0	51	50	349	40	2	4	37	2	6
49	5	80	113	1	3	120	100	1	1	21	47	716	70	1	2	11	1	4
39	51	94	77	10	-4	120	100	0	0	60	29	723	80	3	0	38	2	3
32	28	126	133	-2	-2	150	150	0	1	55	48	453	50	2	3	15	2	6
36	32	117	67	-4	-13	750	150	1	1	56	47	646	60	4	1	10	1	5
2	83	77	104	2	2	150	120	1	1	19	25	615	50	0	3	7	1	1
46	89	90	115	-11	-12	100	850	0	0	38	64	512	40	4	4	36	1	5
10	55	116	65	-4	5	100	100	0	0	28	63	965	70	-1	0	28	1	1
20	55	71	84	-6	5	750	750	1	1	50	28	528	60	1	2	23	1	6
5	95	99	91	-13	7	750	750	1	0	27	23	246	60	4	4	9	1	2
43	40	69	116	6	1	150	750	1	0	35	30	789	50	5	2	9	1	1
22	51	66	107	-1	6	100	120	1	1	43	51	420	70	1	1	15	1	2
72	84	77	112	-8	5	850	120	1	1	21	62	871	50	-1	3	27	5	6
71	93	77	119	-11	-4	850	150	0	1	27	21	876	70	5	4	12	2	6
94	88	64	125	8	-11	100	120	1	0	24	66	932	40	2	0	13	9	1
21	31	127	56	-9	-5	100	150	0	0	51	31	1081	70	4	1	35	1	1
43	66	99	94	-2	-9	750	150	1	0	21	46	907	60	0	3	22	2	6
96	50	89	88	-11	3	750	850	0	0	60	54	929	60	0	4	18	1	6
36	86	65	113	9	3	850	150	0	1	50	18	547	50	-1	2	25	2	2
44	82	78	138	4	-5	150	850	0	0	42	44	991	40	3	3	37	1	6
51	75	118	52	-10	-2	150	850	1	1	49	66	810	80	0	1	39	1	7
45	35	75	86	10	1	100	750	1	1	49	41	322	70	4	2	21	1	6
15	50	59	57	-11	4	150	750	1	1	46	59	922	70	-1	1	20	5	3
78	41	108	75	3	-5	120	750	1	0	56	42	936	60	0	4	17	7	2
17	68	70	102	1	2	850	750	1	1	20	39	547	50	-1	4	17	1	2

41	74	71	110	-8	7	750	750	1	0	41	56	901	40	0	0	28	1	6
5	65	82	72	9	-7	100	150	0	0	45	48	1060	60	0	4	22	2	1
1	74	93	102	-2	4	100	750	0	0	24	27	687	50	2	2	24	1	4
31	42	119	58	2	6	850	150	1	0	42	21	898	40	3	2	7	1	1
88	50	90	70	-12	-6	850	750	0	0	30	64	844	80	-1	3	25	5	5
81	78	65	52	6	2	120	850	0	0	57	57	703	80	2	0	39	1	2
71	79	80	117	-9	-3	100	100	1	0	49	43	268	50	2	3	14	1	4
64	59	64	134	7	10	850	100	1	0	24	53	241	70	1	2	34	1	1
97	58	86	68	-13	-9	120	100	1	0	19	25	406	60	2	1	25	1	6
50	76	130	138	2	-4	150	100	1	1	50	57	819	50	0	3	35	5	3
15	76	50	91	0	10	150	120	1	0	43	44	1045	80	5	4	13	1	5
77	81	73	113	-8	5	750	150	0	1	63	52	868	80	0	2	7	1	3
35	98	130	94	6	-9	750	850	1	1	46	32	207	70	0	2	24	2	1
76	71	92	80	-7	-13	750	100	1	1	46	45	1149	60	5	3	26	2	3
44	50	65	95	-8	6	120	100	1	0	35	43	874	60	-1	3	25	2	5
60	47	124	106	-9	3	850	850	1	1	20	64	893	60	0	2	23	1	2
25	51	88	90	-12	0	100	750	1	0	60	54	587	80	5	1	34	1	7

The following table shows the results of the accidents (Target array of the neural network):

Table 4-4: section collision NN Targets

The driver possible mistake	Accident possible loses (degree of danger)
11	2
7	1
6	1
1	1
8	1
12	1
9	2
11	2
4	1
8	1
3	1
3	2
12	2
10	1

6	1
9	1
6	1
9	2
11	3
3	1
1	1
13	1
4	1
11	1
10	1
2	1
10	1
6	1
6	1
3	1
7	1
8	1
2	1
5	1
2	1
3	1
13	1
10	2
10	3
6	3
12	1
4	1
5	1
8	1
10	2
13	1
8	1
2	1
6	1
8	2
1	1
10	1
2	1
6	1
10	1

5	1
4	1
11	1
9	2
11	1
13	3
3	3
7	1
11	1
11	1
10	1
13	2
5	1
2	1
12	1
11	1
3	2
3	1
11	1
9	1
6	1
13	1
10	2
8	1
11	1
11	1
13	1
7	1
13	1
5	1
7	1
9	2
1	1
4	1
5	2
6	3
11	2
3	3
13	1
1	3
13	3

3	3
11	3
13	1
1	3
1	1
7	2
13	3
3	3
9	2
5	2
12	1
8	3
2	2
12	2
6	3
7	2
4	2
7	3
4	1
3	1
3	1
6	1
7	2
5	1
9	1
8	1
5	1
1	2
5	1
10	1
2	1
5	1
11	2
4	1
4	1
8	1
6	1
4	1
12	1
6	3
4	2

1	2
2	1
4	3
8	2
6	1
7	3
2	3
2	1
5	2
1	3
4	1
7	1
13	1

The column on the left is the driver mistake number and the column to the right is the loses of the accident (1 means slight injuries, 2 means serious injuries and 3 means fatalities).

The following are the results of training the network with 10 hidden layers:



Figure 4-25: section collision NN result (10 nodes hidden layer)

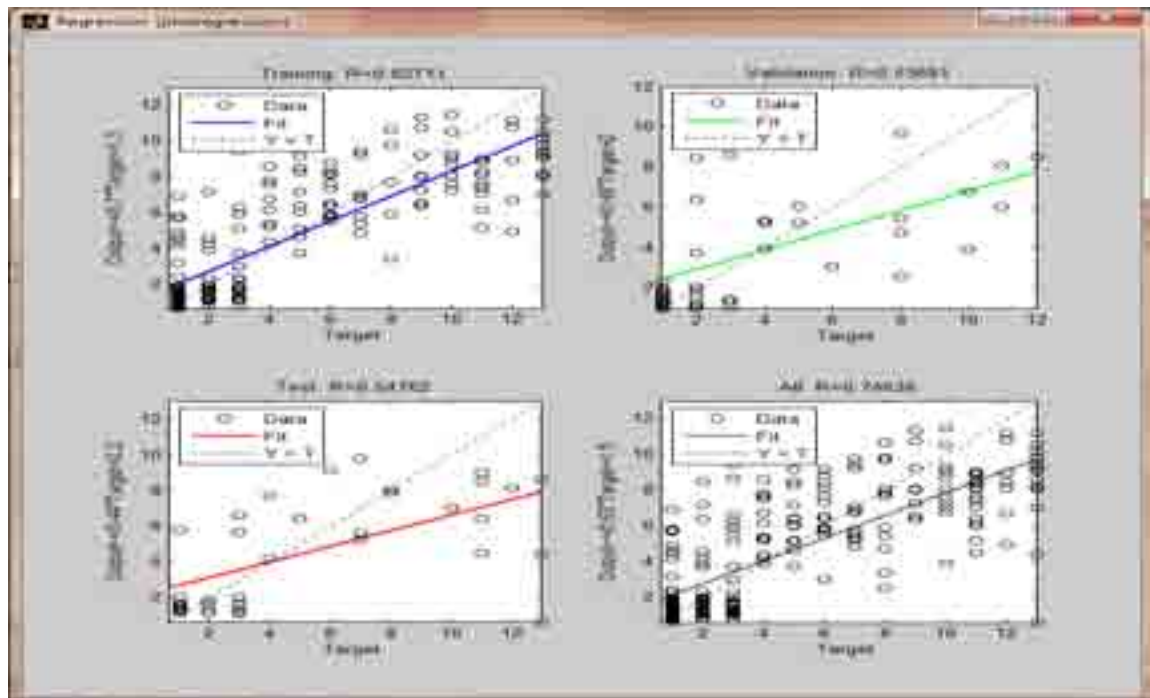


Figure 4-26: section collision NN Regression plot (10 nodes hidden layer)

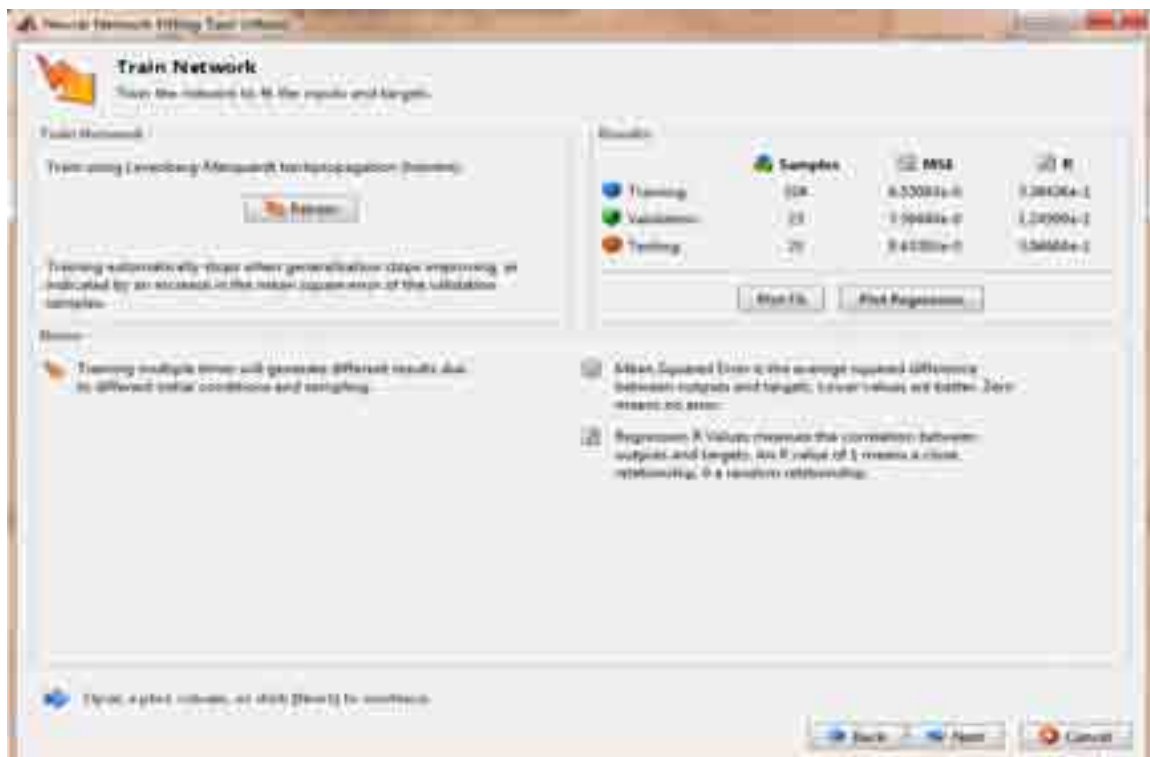


Figure 4-27: section collision NN result (15 nodes hidden layer)

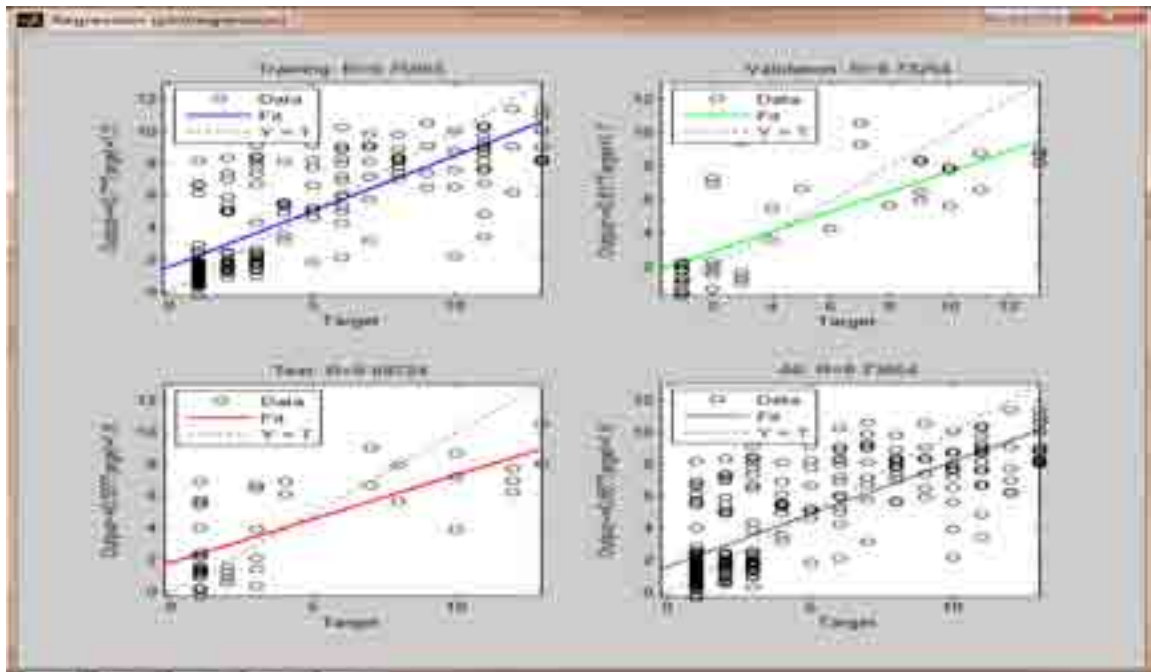


Figure 4-28: section collision NN Regression plot (15 nodes hidden layer)



Figure 4-29: section collision NN result (20 nodes hidden layer)

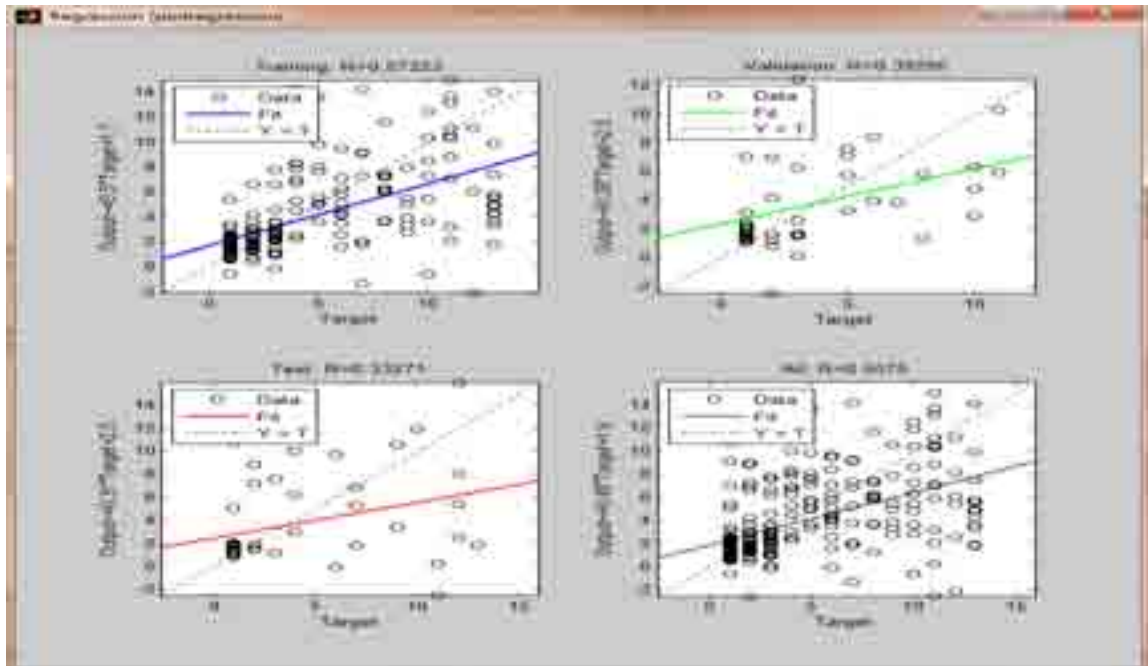


Figure 4-30: section collision NN Regression plot (20 nodes hidden layer)

We note that the NN with 10 nodes in the hidden layer has the lowest (MSE) so it will be used in the system.

The following Table contains 150 examples of section pedestrian accidents record information that are used in the process of learning the neural network (the sections pedestrian NN):

Table 4-5: section pedestrian accidents NN inputs

Vehicle hot spot progress	Pedestrian hot spot progress	Vehicle speed	Pedestrian speed	Vehicle acceleration	Pedestrian acceleration	Vehicle weight	Vehicle ABS	Driver age	Pedestrian age	Hot spot diameter	Hot spot speed limit	Hot spot defects	Weather status	Temperature	Time of day	Day of week
94	42	66	4	-8	3	10	0	32	50	12	70	1	3	16	11	5
65	16	71	2	0	1	75	0	31	27	10	40	4	0	24	7	4
70	64	85	9	8	2	15	0	20	57	56	70	2	4	26	10	1
57	29	56	3	-5	2	75	0	65	55	96	50	2	3	18	10	7
8	70	61	7	5	0	10	0	43	57	95	60	4	1	11	13	5
49	27	73	3	-5	2	85	1	63	65	11	70	2	0	38	6	4
85	92	80	4	6	3	10	0	59	18	62	70	-1	2	22	18	7
13	14	67	6	4	3	12	0	58	39	85	60	-1	3	31	4	2
41	29	72	3	3	0	15	0	42	58	11	80	4	2	19	20	5
6	81	56	9	-	-2	10	0	65	39	11	70	4	1	27	13	7
10	23	98	6	-3	2	10	1	30	20	12	50	-1	4	11	12	3
56	95	60	3	-6	-1	15	1	52	64	11	50	3	2	12	5	7
37	19	81	9	1	-2	15	0	60	66	72	40	5	2	28	5	4
84	68	94	6	6	3	15	1	54	56	79	40	3	3	31	21	1
62	2	65	4	9	3	10	1	39	30	48	80	4	2	11	2	2
58	54	11	4	0	-1	10	0	60	31	26	50	0	1	30	3	6
81	65	55	1	8	2	75	1	35	53	72	80	5	1	16	1	3
7	23	66	7	-	2	10	0	22	48	64	60	0	4	23	15	7
70	55	53	2	3	2	15	1	28	40	28	60	5	4	29	4	7
30	51	13	1	5	3	10	1	56	27	82	40	0	4	38	5	1
57	80	53	3	-5	0	10	0	59	35	73	70	0	3	29	8	2
60	3	11	8	9	2	10	0	61	45	36	60	-1	3	8	4	6
42	89	64	7	9	-2	10	1	63	41	12	50	2	2	35	18	7
24	93	98	3	2	-2	10	0	41	63	49	70	4	3	18	11	4
19	82	66	6	3	-2	75	1	18	29	82	80	1	4	14	14	1
40	18	10	5	5	2	15	1	39	22	47	50	-1	3	24	17	1
38	5	10	4	0	3	85	0	48	59	11	40	0	4	39	1	6
32	22	12	9	-4	-2	10	1	29	62	11	60	5	2	4	3	2
60	24	13	7	7	-1	85	0	25	64	10	60	1	0	13	5	3

45	36	12	2	10	-2	75	0	33	19	74	80	4	1	35	22	7
35	75	54	1	-2	3	15	1	30	20	93	60	5	3	26	6	4
1	66	74	1	2	-1	12	0	44	28	96	40	2	2	37	11	3
80	51	68	3	10	0	85	0	53	65	65	40	1	1	36	13	2
39	20	11	9	4	1	75	1	64	54	11	70	4	2	31	21	5
96	10	58	3	-	-1	75	1	62	29	65	50	0	4	33	13	3
17	74	12	4	-	3	75	0	20	48	54	70	5	2	28	2	6
29	80	96	8	-5	3	15	0	58	33	99	70	4	3	7	2	4
34	2	63	3	8	-2	75	1	66	49	94	40	5	3	30	2	3
67	2	54	4	6	2	75	0	31	49	47	70	0	4	12	12	3
14	66	13	5	-4	2	10	0	36	31	12	50	4	2	4	12	3
11	8	55	1	-1	-1	75	0	48	42	10	40	3	4	21	10	4
62	9	63	9	-7	0	15	0	38	45	30	80	1	0	13	5	7
73	16	92	3	1	0	12	0	57	26	86	80	3	2	22	18	2
94	92	85	4	7	2	10	1	24	49	12	50	0	2	23	19	6
8	31	50	3	-	1	85	1	41	26	12	60	4	0	24	0	2
14	34	12	5	8	0	75	1	40	59	11	80	3	3	7	2	7
38	21	12	1	8	-1	75	1	36	44	70	40	1	2	17	8	1
28	21	13	3	-9	3	12	1	45	55	55	60	5	2	35	8	6
72	38	68	2	-8	-2	15	1	43	62	75	60	-1	1	23	14	5
48	88	59	6	-9	0	12	0	34	44	10	50	2	0	25	18	4
80	2	63	9	-	-1	85	1	51	65	69	40	2	2	33	21	3
93	1	75	2	-1	-2	10	1	61	41	11	60	-1	3	37	14	4
51	52	94	6	-3	2	12	0	43	35	54	50	4	0	39	6	2
19	60	97	4	-7	3	15	0	25	51	56	40	3	0	23	12	1
94	30	91	6	-2	-1	10	0	19	51	27	60	-1	2	38	4	6
58	33	58	2	-8	1	15	0	31	19	70	80	4	0	32	15	6
14	68	12	6	3	-1	75	0	29	32	90	70	-1	1	18	21	7
61	22	90	8	3	2	15	0	28	30	12	40	0	2	14	18	2
27	27	81	2	8	-2	75	1	18	29	29	70	0	3	6	0	7
56	57	69	9	-3	3	75	0	40	20	31	40	-1	3	17	20	7
2	14	10	7	4	-1	10	1	52	42	84	60	-1	2	35	3	2
95	72	10	3	6	-1	85	1	38	66	11	80	5	2	29	20	2
73	94	88	3	7	0	15	1	53	38	73	40	1	2	12	20	6
84	66	75	7	-9	2	85	1	32	28	74	40	4	0	36	12	6
78	93	11	9	-	0	12	0	23	62	95	70	-1	2	28	21	1
61	5	10	5	0	-2	75	0	44	26	48	80	5	1	25	11	4
74	29	64	8	4	-1	10	0	21	61	87	50	0	3	33	4	5
44	86	13	3	-8	2	15	1	45	26	77	50	-1	2	8	4	4
71	40	11	3	8	2	75	0	40	30	65	40	1	2	19	14	3
93	74	10	3	-2	0	10	0	26	24	11	40	5	1	22	0	6

5	43	88	4	0	-2	12	0	56	44	44	60	0	3	7	17	6
60	38	10	2	-8	3	85	1	52	46	40	40	2	4	36	2	4
36	1	69	9	-5	1	15	0	53	64	48	70	5	1	33	7	2
77	14	82	6	6	1	75	0	59	44	85	40	0	3	15	9	6
41	11	97	9	-8	2	12	0	42	64	20	40	4	1	17	16	3
11	77	11	9	-1	0	75	0	43	21	32	80	2	1	38	8	1
95	70	11	3	0	0	10	0	33	45	35	50	-1	1	12	10	7
56	55	10	8	7	1	10	0	52	52	10	50	-1	3	6	18	5
27	67	13	2	0	0	85	1	28	62	11	40	2	3	35	9	5
72	40	11	3	-	-2	85	1	59	50	91	40	1	4	7	10	3
6	57	95	7	10	-2	85	0	50	53	76	50	0	4	36	20	4
95	65	57	4	-9	1	15	0	53	54	84	60	5	0	34	16	1
69	31	13	8	4	-1	85	1	38	35	10	60	3	3	32	5	6
94	43	82	9	7	3	12	0	31	37	97	80	4	3	29	11	1
27	59	13	6	-8	0	15	1	55	30	11	70	-1	0	33	4	1
7	41	83	2	6	0	75	0	40	59	88	80	3	3	6	1	4
43	19	73	2	4	-2	15	0	22	53	21	70	0	1	36	17	5
65	30	62	9	-3	-1	12	0	55	44	25	60	-1	3	32	15	5
61	64	13	8	-5	0	15	1	54	48	22	70	1	2	30	5	1
98	77	13	6	10	3	85	1	64	41	83	80	-1	0	11	1	5
74	27	12	7	-6	3	10	0	52	49	11	70	2	0	15	6	1
63	2	11	9	2	2	10	1	37	61	31	80	4	2	33	12	5
75	48	85	3	3	3	10	1	31	32	65	50	2	2	14	14	7
48	20	77	6	-	1	85	1	63	19	52	50	5	0	7	3	6
30	83	12	8	9	-2	85	0	34	38	35	70	5	2	33	5	6
4	61	71	1	2	3	75	0	55	58	39	50	1	0	16	2	5
15	47	11	2	-1	-2	75	0	56	24	31	40	-1	2	22	0	2
10	48	13	6	3	3	15	0	27	33	27	50	-1	1	32	14	2
30	34	92	6	-1	1	75	1	59	56	22	60	4	1	28	5	1
6	86	68	1	-2	1	75	1	34	53	12	80	4	4	15	9	6
28	16	98	5	1	3	15	1	57	24	96	80	2	0	18	21	7
22	94	88	2	6	2	10	1	26	59	41	40	-1	4	29	0	7
98	52	11	6	-2	3	10	0	50	38	49	80	5	3	25	22	7
64	37	13	6	-3	0	75	1	38	21	73	70	3	1	4	20	4
8	87	71	3	5	3	12	1	26	36	38	80	0	0	26	1	2
29	35	52	3	-1	-2	15	1	20	61	12	70	5	1	13	1	3
58	71	11	6	8	0	75	1	31	18	11	80	-1	4	36	13	4
92	66	12	2	-1	2	10	0	52	22	11	40	0	0	36	19	7
60	90	77	7	-4	3	12	0	30	25	98	40	5	0	7	3	4
30	61	67	2	-	3	75	0	26	31	32	80	-1	4	39	22	2
27	98	74	8	-1	2	12	1	31	46	10	50	4	0	34	21	6

85	30	10	7	0	3	75	0	28	51	10	70	0	1	31	1	5
75	12	12	7	5	3	85	0	55	38	51	80	1	1	14	20	3
1	69	81	6	3	-2	75	0	32	18	23	40	-1	1	7	5	1
33	72	55	1	-	0	85	0	57	42	11	70	4	2	24	16	7
29	7	11	2	-	-2	15	0	40	62	47	50	3	0	11	13	2
88	55	12	3	9	-1	75	0	61	45	47	70	2	2	20	9	2
99	4	98	1	-7	2	85	1	47	41	28	80	-1	1	27	0	4
60	2	13	6	-5	2	15	1	25	41	70	70	5	1	32	19	4
13	17	55	3	1	3	10	1	33	58	11	50	4	0	25	15	7
93	44	95	6	2	-1	12	0	24	28	10	80	3	0	14	2	5
26	48	13	3	10	-2	10	1	21	63	10	60	1	1	35	0	1
44	36	82	8	-2	3	85	0	41	50	88	70	3	3	27	5	1
93	13	11	6	9	-1	75	1	45	34	22	70	4	4	38	21	4
67	92	11	8	5	1	15	0	43	41	10	50	1	1	9	4	3
35	75	80	4	-1	-2	85	0	63	44	43	50	4	3	28	17	1
3	72	96	3	-9	1	12	0	38	58	53	60	0	0	34	12	3
57	22	10	2	-9	3	10	1	58	20	72	80	4	3	7	12	2
21	44	11	1	-	-1	85	1	22	29	12	70	4	2	17	17	3
18	46	65	9	7	3	75	1	35	41	70	60	3	0	12	20	7
90	42	12	4	-4	-2	85	0	22	48	71	80	-1	3	8	2	4
54	62	82	3	-5	1	15	1	57	54	11	60	2	0	30	20	6
53	94	13	9	5	0	12	1	55	29	80	60	0	4	16	10	2
57	60	96	7	0	3	85	1	47	30	55	70	3	2	31	2	3
9	20	70	5	5	-2	10	0	46	35	24	40	2	4	23	22	2
55	13	81	1	10	-2	15	0	26	27	83	40	-1	3	33	10	7
78	15	69	7	6	0	75	0	66	41	41	70	-1	1	32	17	3
95	62	11	2	-	-2	10	0	46	65	10	50	2	3	12	12	4
9	39	11	5	4	2	85	1	66	48	65	60	-1	4	32	7	5
76	20	11	8	3	-2	15	1	28	41	51	80	2	4	39	5	4
30	42	51	9	-8	3	10	0	24	40	35	70	2	0	4	0	6
86	3	12	7	-3	-1	75	1	43	28	11	80	2	3	20	5	4
51	38	76	7	0	-1	85	0	44	47	70	70	4	1	14	21	6
98	95	88	8	8	-2	12	1	51	52	76	60	3	3	29	12	7
64	63	11	1	-6	2	10	0	61	53	87	50	4	4	27	21	6
77	49	12	8	2	-1	10	1	60	45	95	80	5	4	31	4	6
67	66	66	7	3	-1	12	0	18	35	45	70	5	3	35	13	7
92	22	11	2	-	0	85	0	40	27	10	60	-1	4	35	0	7
24	1	11	1	-	-1	12	0	48	63	37	40	5	3	34	7	7
95	55	93	7	2	-1	12	0	28	66	28	40	5	2	17	16	7

The following table shows the results of the accidents (Target array of the neural network):

Table 4-6: section pedestrian NN Targets

The driver possible mistake	Accident possible loses (degree of danger)
11	2
7	1
6	3
1	1
8	1
12	1
9	2
11	3
4	1
8	3
3	1
3	2
12	2
10	2
6	1
9	1
6	1
9	2
11	3
3	1
1	1
13	1
4	1
11	3
10	1
2	1
10	1
6	1
6	1
3	1
7	1
8	1
2	1

5	1
2	1
3	1
13	1
10	2
10	3
6	3
12	1
4	1
5	1
8	3
10	2
13	1
8	1
2	1
6	1
8	2
1	1
10	1
2	1
6	1
10	1
5	1
4	1
11	3
9	2
11	2
13	2
3	2
7	1
11	3
11	3
10	1
13	2
5	1
2	1
12	1
11	1
3	2
3	1
11	1

9	1
6	1
13	1
10	2
8	1
11	1
11	1
13	1
7	1
13	1
5	1
7	1
9	2
1	1
4	1
5	2
6	3
11	2
3	3
13	1
1	3
13	3
3	3
11	3
13	1
1	3
1	1
7	2
13	3
3	3
9	2
5	2
12	1
8	2
2	2
12	2
6	3
7	2
4	2
7	3
4	1

3	1
3	1
6	1
7	2
5	1
9	1
8	3
5	1
1	2
5	1
10	1
2	1
5	1
11	3
4	1
4	1
8	1
6	1
4	1
12	1
6	3
4	2
1	2
2	1
4	3
8	3
6	1
7	3
2	3
2	1
5	2
1	3
4	1
7	1
13	1

The column on the left is the driver mistake number and the column to the right is the loses of the accident (1 means slight injuries, 2 means serious injuries and 3 means fatalities).

The following are the results of training the network with 10 hidden layers:



Figure 4-31: section pedestrian NN result (10 nodes hidden layer)

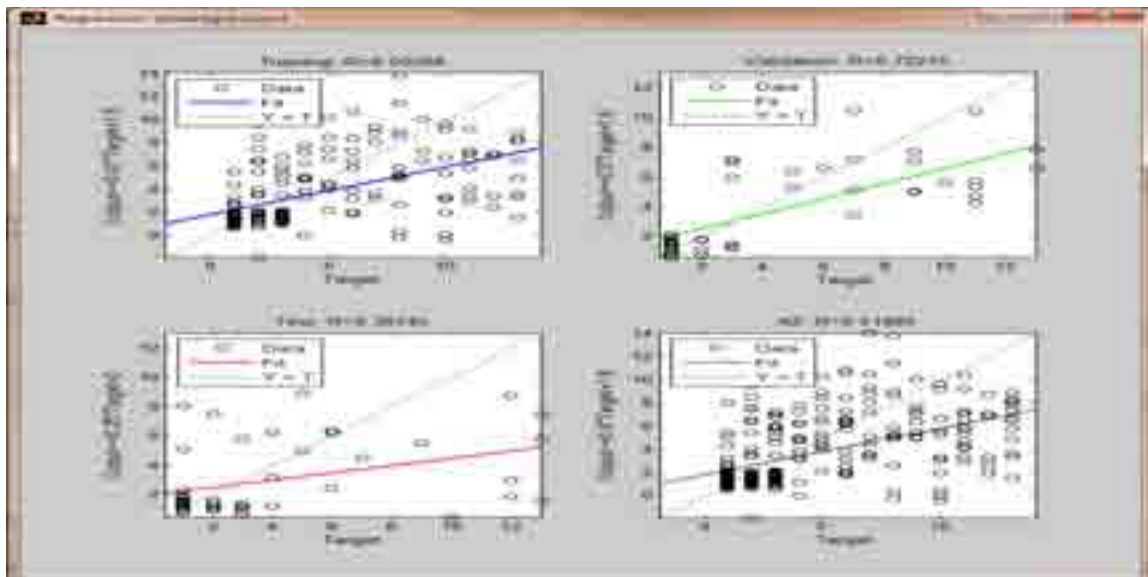


Figure 4-32: section pedestrian NN Regression plot (10 nodes hidden layer)

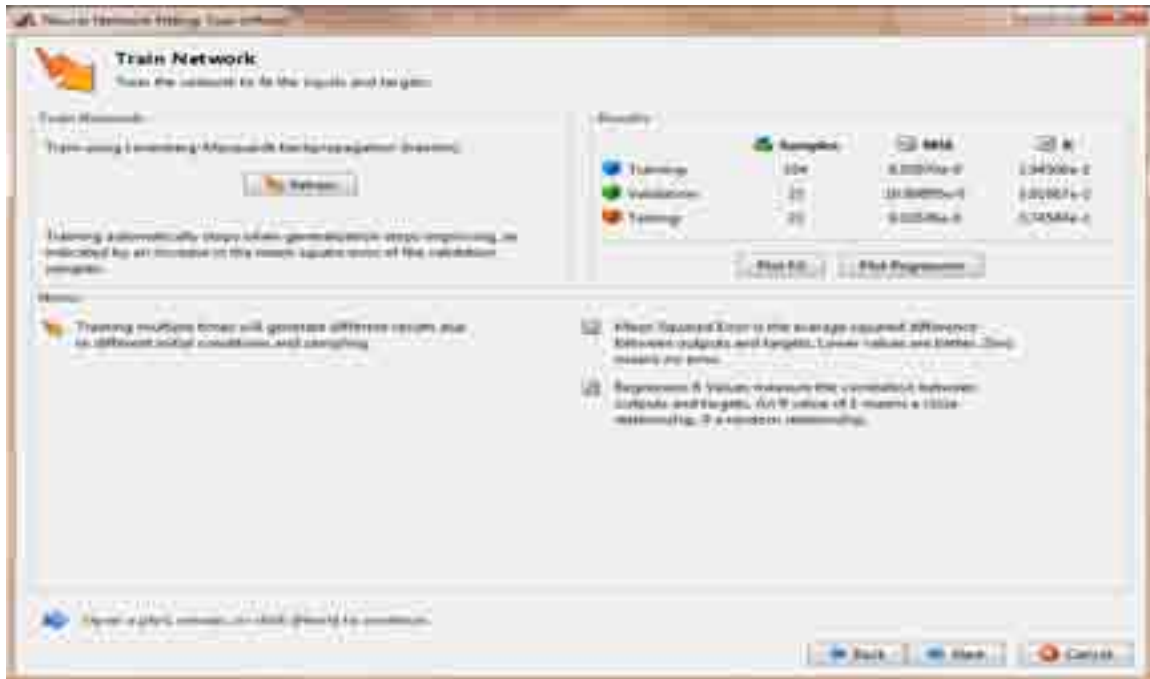


Figure 4-33: section pedestrian NN Regression result (15 nodes hidden layer)

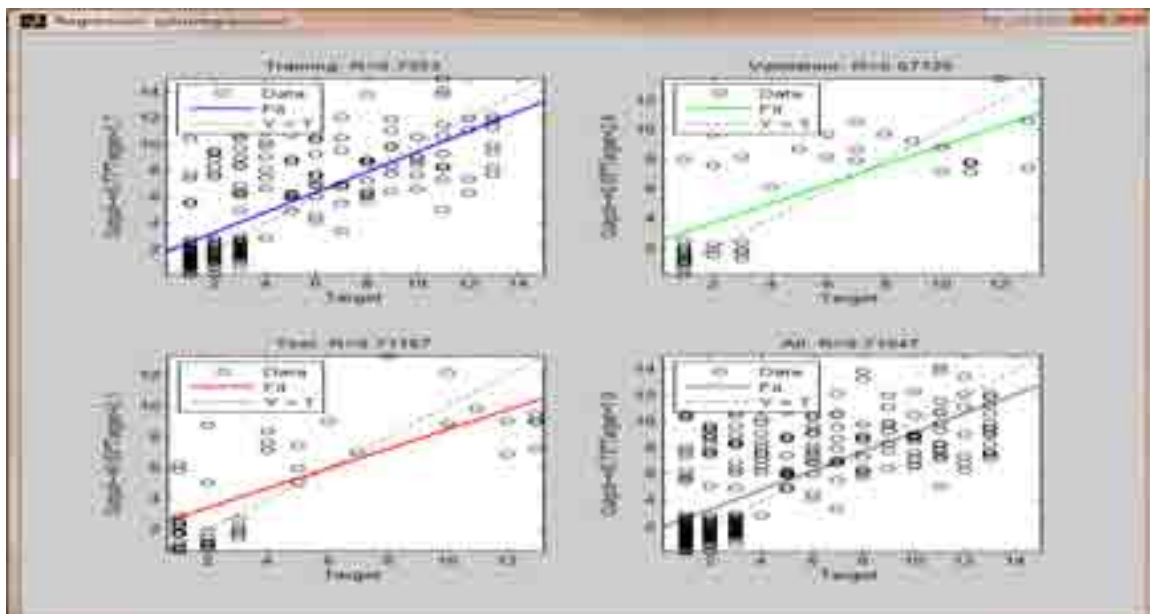


Figure 4-34: section pedestrian NN Regression result (15 nodes hidden layer)



Figure 4-35: section pedestrian NN Regression result (20 nodes hidden layer)

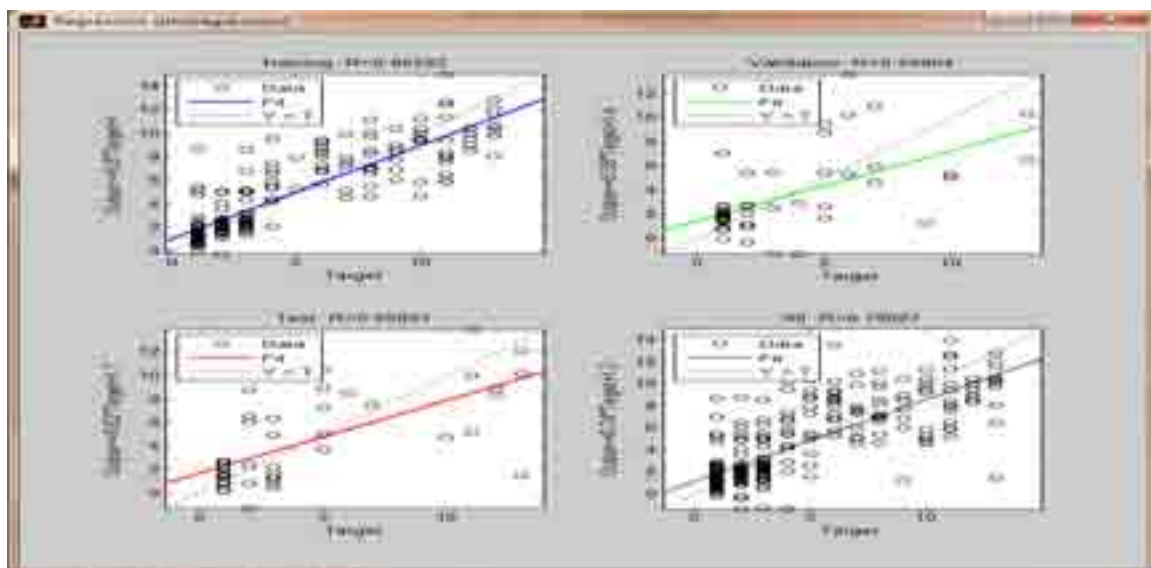


Figure 4-36: section pedestrian NN Regression plot (20 nodes hidden layer)

The following Table contains 150 examples of intersections collision accidents record information that are used in the process of learning the neural network (the intersections collision NN):

Table 4-7: intersections collision NN inputs

Vehicle1 hot spot progress	Vehicle2 hot spot progress	Vehicle1 speed	Vehicle2 speed	Vehicle1 acceleration	Vehicle2 acceleration	Vehicle1 weight	Vehicle2 weight	Vehicle1 ABS	Vehicle 2 ABS	Vehicle 1 intersection leg	Vehicle 2 intersection leg	Driver1 age	Driver 2 age	Hot spot speed limit	Root1 defects	Root2 defects	Weather status	Temperature	Time of day	Day of week
7	5	13	66	-5	-13	750	850	1	1	1	2	3	4	7	3	2	0	3	3	7
7	9	10	73	8	-2	750	850	0	1	1	1	4	3	4	3	0	2	2	2	4
9	3	11	11	-12	-11	100	1000	0	0	3	1	5	2	7	1	5	2	2	0	7
5	2	65	67	6	-7	100	750	0	1	0	0	3	5	7	5	3	4	1	1	6
3	5	82	52	6	-9	100	850	0	0	0	0	4	3	4	3	2	1	3	2	3
8	3	11	81	-3	-5	120	1000	0	1	0	1	2	4	7	4	0	4	6	0	6
9	6	63	13	4	-5	100	850	0	1	2	2	3	2	5	3	3	1	3	1	6
9	4	13	10	-5	6	850	1500	0	0	3	3	4	5	7	2	1	3	3	9	2
2	1	10	12	6	-4	100	750	0	1	0	1	1	2	5	0	1	1	2	5	4
8	3	11	11	6	-6	100	750	0	1	3	0	4	5	6	1	4	2	1	2	5
8	6	98	86	-1	6	100	850	0	0	1	0	5	3	7	5	-	0	6	2	1
2	9	83	78	-3	-5	150	1200	1	1	0	1	5	6	7	0	1	1	2	2	6
1	3	88	50	8	-7	150	850	1	1	1	3	4	4	7	0	-	0	2	1	4
5	5	77	12	7	-3	750	1500	1	1	2	3	2	2	7	5	1	2	6	0	4
8	2	11	84	-8	-3	120	750	0	0	0	1	3	4	7	-	0	0	3	1	5
8	8	12	70	-4	-1	750	850	1	1	1	2	6	5	5	2	1	3	4	5	6
5	5	92	79	8	-2	120	1200	0	0	1	1	6	6	6	5	0	4	3	1	6
4	6	10	11	-3	8	100	1000	1	0	3	1	6	3	5	1	5	2	4	6	3
6	1	63	80	-13	4	150	1000	0	1	0	1	6	2	8	4	3	2	2	6	2
2	5	91	13	9	2	750	1500	0	0	3	1	3	5	6	2	1	2	9	1	1
5	6	11	13	10	-6	850	1000	0	0	1	3	2	3	4	3	1	0	6	1	7
1	4	68	52	0	-8	100	850	0	0	1	2	2	5	6	4	-	4	1	1	1
9	3	93	94	-9	-4	100	1200	0	0	0	0	1	4	4	2	5	2	5	2	2

9	9	13	89	10	3	150	1200	0	0	2	3	6	2	4	4	2	2	3	0	4
1	7	81	83	-9	-9	850	850	0	1	1	3	5	6	5	2	-	0	3	1	7
6	1	82	86	-10	-1	750	1500	0	0	0	3	5	6	5	3	-	3	2	8	5
1	6	89	12	-12	-9	150	850	0	0	0	0	4	4	6	5	5	0	2	4	4
7	4	57	50	-12	10	750	1200	1	0	0	1	3	4	6	5	2	0	1	7	4
8	8	59	10	-8	-4	150	1500	0	1	3	0	2	3	4	1	4	0	1	1	3
4	7	12	12	-8	10	750	750	0	0	1	3	6	6	7	5	1	4	2	1	2
9	7	87	69	-8	-10	850	1000	1	0	0	3	3	3	4	0	4	0	2	1	4
6	7	91	77	-11	-2	100	850	0	0	2	0	1	4	4	2	3	4	3	1	4
7	9	71	61	4	-1	150	1500	1	1	0	0	5	2	8	5	5	0	2	2	2
2	8	90	11	-8	6	120	1500	0	0	2	3	1	6	7	0	0	1	3	1	5
9	4	10	51	-7	-5	750	1000	1	1	0	3	3	4	4	4	1	2	2	1	7
3	7	93	68	4	-7	850	1500	1	1	2	0	4	3	6	5	3	4	2	2	3
4	2	92	13	2	-3	150	1000	1	1	0	0	5	4	7	-	4	2	6	1	6
1	2	86	11	7	-7	150	1200	1	1	0	3	5	6	6	-	0	0	3	1	2
9	9	95	13	6	3	150	1200	1	0	1	0	4	3	5	-	0	3	9	1	4
1	3	13	77	-13	2	850	750	1	0	0	1	4	2	4	5	4	0	2	2	1
7	1	12	12	-11	-2	750	1200	1	0	2	1	5	5	6	2	3	3	5	1	6
3	9	65	11	-12	-5	750	750	0	1	2	0	4	3	5	-	2	4	9	2	1
6	1	97	12	5	-8	100	850	0	0	2	1	3	4	5	3	-	0	8	0	6
5	5	60	75	-8	-1	850	1000	0	1	3	1	5	5	7	3	4	1	9	1	6
2	4	51	11	-8	7	120	1000	0	1	0	0	3	2	7	1	3	2	2	4	7
4	3	11	62	1	4	100	750	0	1	3	1	1	3	4	-	2	0	2	8	7
7	4	12	71	-4	3	750	850	0	1	1	1	5	2	4	1	3	3	8	1	3
2	9	55	10	-7	5	100	850	0	1	0	3	6	3	5	4	5	0	6	7	6
9	9	94	55	-9	-12	120	1500	1	0	2	3	4	4	8	4	3	0	3	1	7
2	2	91	98	6	8	150	1000	1	0	0	0	4	2	4	2	3	0	2	1	4
3	1	90	13	-3	7	850	750	0	0	0	2	5	5	7	-	2	1	1	4	2
3	9	97	11	8	-7	120	850	1	0	0	0	3	2	4	-	2	1	5	8	4
3	3	12	91	5	0	850	1000	0	1	2	1	3	5	4	5	0	2	2	1	6
3	4	13	11	-2	-3	100	750	1	1	0	3	5	6	7	3	0	0	2	1	6
9	3	10	10	-11	-1	120	750	0	1	1	3	5	1	5	5	4	1	7	1	4
1	7	87	10	0	5	100	850	0	0	3	0	2	3	7	1	-	1	3	1	7
6	1	10	13	-13	8	850	1500	0	1	2	2	2	5	6	0	-	2	3	8	6
2	4	10	11	2	2	100	1000	1	1	0	0	4	4	7	4	3	2	3	6	4
6	6	72	88	6	1	850	750	0	1	0	1	2	3	7	-	0	1	1	1	2
7	8	91	98	3	-6	120	1000	0	1	3	0	3	4	8	1	0	4	5	8	4
7	1	13	12	-4	-13	120	1500	0	0	2	2	3	6	7	4	5	0	1	7	5
5	8	74	63	7	6	120	1500	1	1	0	1	4	1	7	2	3	1	1	2	6
1	8	79	10	9	4	750	1000	0	1	3	0	6	2	5	3	4	2	1	1	1
3	6	79	67	4	7	750	850	0	1	3	1	5	3	4	5	3	4	6	1	1

6	8	94	77	3	7	100	1500	1	1	0	3	5	5	4	5	1	1	3	0	2
1	8	12	11	-10	4	850	1500	0	1	0	0	6	5	8	4	5	0	4	1	4
2	9	12	89	-10	1	120	1200	0	1	0	3	5	4	8	3	3	2	8	5	1
8	7	13	10	3	-11	850	750	0	0	3	1	5	6	7	5	0	4	8	9	6
8	4	13	90	-10	-8	120	750	0	1	3	1	4	4	4	5	4	2	2	1	6
7	4	84	78	-11	1	750	1200	0	1	3	3	2	6	4	-	0	2	3	1	1
2	6	13	65	-9	-4	150	1200	0	0	2	3	1	2	6	2	-	0	2	1	3
9	9	13	91	-5	-1	750	1200	1	1	2	3	5	4	7	2	0	4	1	8	6
8	1	78	13	-10	7	100	1000	0	0	0	3	5	3	7	-	3	4	3	1	1
9	5	56	13	-7	0	120	750	1	0	1	1	4	2	8	3	2	1	2	1	3
4	5	83	68	-12	-6	120	850	0	0	1	2	5	6	6	0	5	4	1	1	3
1	2	11	83	-8	-8	120	1000	0	1	0	0	5	3	4	3	4	1	1	1	5
5	1	68	12	3	-12	850	850	1	0	1	3	6	3	5	3	4	4	6	1	7
3	4	53	85	-12	0	100	1000	0	1	0	2	5	4	4	2	3	2	9	1	1
4	2	12	70	5	-13	150	750	1	0	0	3	5	3	7	0	1	3	2	1	6
5	7	80	71	-9	7	750	750	0	0	3	1	5	5	5	0	0	1	2	1	4
1	2	12	13	10	-6	100	850	0	1	2	3	3	6	6	2	5	2	1	1	1
7	1	72	87	8	-3	100	1200	0	0	3	0	3	3	6	2	1	1	2	1	5
7	3	77	94	-1	8	150	1500	0	1	1	0	4	3	4	3	2	0	3	0	3
9	6	10	12	10	-2	750	750	1	0	2	3	3	4	8	5	5	1	2	1	3
6	5	10	13	7	-13	100	1200	1	0	2	2	3	2	7	3	3	2	2	1	5
5	4	11	59	-10	5	850	1500	1	1	1	1	2	6	4	5	5	0	1	1	2
8	2	13	79	-13	-1	750	850	0	1	0	0	5	4	4	5	4	3	1	3	2
2	3	79	86	-9	-8	150	1500	1	0	0	0	3	4	4	4	4	0	1	3	4
2	9	75	66	-4	-5	120	750	0	0	0	1	2	5	8	3	5	4	1	1	4
6	3	55	13	-7	8	750	750	0	1	0	0	5	6	5	-	0	3	3	1	5
5	2	12	11	-5	10	850	750	1	0	3	2	6	5	6	0	0	0	2	2	7
5	8	65	86	-6	4	100	1000	1	0	1	2	6	2	5	0	1	4	3	1	1
2	3	54	78	7	-8	120	1200	0	1	1	3	5	4	5	3	0	0	1	1	5
1	1	99	13	10	2	850	1200	1	0	2	0	6	5	6	-	-	2	2	1	6
7	4	13	12	-10	-1	750	1000	0	1	2	0	3	2	4	2	1	4	2	1	6
9	4	13	11	7	3	150	1000	0	1	2	3	5	3	7	3	-	4	8	2	3
9	3	12	52	-2	4	850	1500	1	1	3	0	6	4	4	-	-	1	3	8	1
8	3	13	57	0	2	100	1200	0	0	1	1	4	2	4	-	3	1	3	1	7
4	9	12	12	10	6	150	1000	1	1	1	2	3	2	8	5	5	4	7	1	5
5	6	85	11	-4	-3	120	750	0	1	3	3	2	3	6	-	0	3	3	1	3
2	4	67	11	-10	-11	750	750	1	0	3	2	2	6	5	2	-	2	1	1	4
5	6	89	12	-9	2	100	1200	1	0	1	3	3	3	4	0	5	1	1	2	7
6	4	50	73	9	-1	750	1500	0	0	1	0	6	5	8	4	5	4	2	1	2
8	2	10	10	8	2	750	850	0	0	0	2	4	6	4	2	2	1	8	9	2
5	2	12	12	-5	-1	850	1000	1	0	3	1	4	4	5	1	3	0	3	0	3

9	7	83	89	-5	6	150	850	0	1	1	0	1	4	4	4	4	2	8	2	6
2	9	71	77	9	-5	120	750	1	0	1	1	6	5	6	2	1	4	3	1	1
5	5	95	77	1	-12	850	1000	1	0	2	0	4	5	7	-	-	2	2	1	3
4	5	54	11	-11	7	150	850	0	1	1	1	5	5	6	4	5	1	1	1	4
1	7	10	70	-3	-13	150	850	0	1	1	2	5	2	4	2	2	2	1	1	2
3	9	81	11	4	9	850	1000	0	0	0	0	5	3	7	2	2	3	3	2	1
2	9	59	11	9	2	100	850	0	1	0	0	2	6	8	0	2	3	6	6	7
1	4	58	97	10	5	850	1200	0	1	1	2	2	2	8	0	-	3	1	2	1
7	3	59	57	1	-3	120	850	0	1	3	2	2	2	6	-	0	4	3	3	3
4	9	11	87	-11	5	120	1200	0	1	3	1	5	3	4	5	2	1	1	7	5
9	9	10	13	9	-13	850	850	1	1	1	3	5	3	5	1	3	2	2	0	3
6	1	53	79	-3	4	100	750	1	1	2	3	4	3	4	-	2	0	3	1	6
5	1	79	10	9	-12	150	1500	1	1	2	1	3	3	8	2	3	2	1	2	2
1	2	12	13	-9	8	850	850	0	0	3	1	4	2	8	3	4	2	2	1	3
9	6	13	99	-7	-12	750	1000	1	1	1	2	4	4	8	2	3	3	1	1	3
5	5	11	12	6	-6	120	1200	1	0	2	1	5	2	7	5	1	4	3	2	5
3	7	92	12	-13	0	750	850	0	1	1	0	1	3	4	0	4	2	3	4	6
9	5	12	81	4	-5	750	1000	0	1	1	1	5	2	8	0	5	3	3	2	5
7	3	70	65	5	4	100	1500	1	0	0	3	6	3	4	3	2	1	1	2	6
8	8	56	11	-6	-10	850	1200	1	1	0	1	2	2	4	2	0	4	2	1	6
6	3	79	97	6	6	150	1000	0	0	2	3	5	6	6	0	2	2	2	7	6
8	8	13	10	3	-8	750	750	0	0	2	1	1	2	6	4	0	2	1	1	3
3	2	98	80	-5	-9	150	1000	1	0	0	1	6	5	6	1	5	0	2	1	3
1	6	13	11	6	4	750	1000	0	1	1	3	3	4	7	2	0	1	5	8	6
6	9	10	50	-11	-2	120	1000	0	0	2	3	6	2	4	3	3	2	2	1	7
3	4	11	97	-2	-9	120	1200	1	1	2	1	5	4	4	1	3	3	1	3	1
1	6	96	12	-3	-5	100	1200	1	1	2	3	5	3	6	4	2	2	1	2	4
5	6	69	10	-6	3	750	850	0	1	0	1	6	2	8	0	3	0	3	1	1
4	8	13	97	9	-10	150	1000	0	0	3	0	4	4	4	1	0	0	2	1	4
6	1	84	81	4	-11	100	1500	1	1	1	1	4	4	7	0	-	1	2	7	7
8	6	68	70	-1	3	120	1200	0	1	0	0	4	3	7	2	0	1	5	3	6
3	6	10	11	10	10	850	750	0	1	0	0	4	5	6	0	-	1	1	1	5
4	6	76	90	8	-11	120	1500	1	0	1	0	1	3	4	3	2	2	2	1	7
2	1	13	13	9	2	850	850	0	1	2	1	2	6	8	0	0	0	3	8	3
3	6	11	13	1	-5	100	1000	1	1	2	0	5	2	6	1	2	4	2	1	3
8	1	12	11	8	-3	750	850	0	0	3	0	4	6	6	0	5	1	1	1	6
4	3	12	80	-5	6	100	1200	1	0	1	3	6	4	6	4	0	3	3	1	2
3	2	12	13	-8	-7	750	750	1	1	0	3	4	3	8	-	1	2	2	1	4
5	2	89	85	1	-3	120	1000	1	1	1	1	5	2	4	5	1	0	2	1	7
1	5	74	52	-3	-11	150	1200	1	0	0	3	5	5	8	2	2	2	3	2	5
8	9	11	85	7	-7	120	750	1	0	0	0	4	3	7	0	1	0	1	5	5

1	4	68	85	9	-7	750	1000	1	1	3	1	3	3	7	3	3	2	3	2	6
7	7	63	13	-10	-4	850	850	0	0	1	3	6	5	6	2	5	4	3	1	4
1	8	79	11	-7	-11	750	1000	1	1	2	1	6	2	7	-	2	3	3	1	2
7	1	80	91	-5	-2	750	750	1	1	3	0	3	5	8	4	0	4	1	3	5

The following table shows the results of the accidents (Target array of the neural network):

Table 4-8: intersections collision NN Targets

The driver possible mistake	Accident possible loses (degree of danger)
12	1
9	1
3	1
9	2
1	2
10	1
1	3
12	1
11	1
7	1
6	2
7	2
10	1
13	3
9	1
10	1
13	1
13	2
13	1
12	1
13	1
2	2
8	2
13	1
11	1
12	1
9	2

1	2
2	1
4	1
6	1
1	1
9	2
9	3
4	1
4	1
9	1
8	1
8	1
13	1
2	1
4	1
13	2
9	1
4	1
12	1
6	2
10	2
8	1
10	1
11	1
8	2
2	3
8	1
11	1
9	1
2	1
1	1
4	2
3	1
10	1
6	1
1	1
9	1
9	1
3	2
7	3
8	1

8	1
3	1
12	2
11	1
2	1
10	2
10	1
3	3
10	2
5	3
11	1
11	3
1	1
9	3
1	3
6	1
5	1
10	1
7	1
4	1
4	2
6	2
10	1
2	3
13	1
12	1
7	1
1	1
8	2
2	1
10	1
1	1
7	2
3	2
10	1
5	1
4	1
7	1
9	2
13	3
8	2

10	3
2	2
10	2
2	1
4	1
12	1
10	1
4	1
8	1
13	2
7	3
12	1
9	1
5	1
12	1
8	1
8	1
5	1
1	1
9	3
6	2
1	2
12	1
3	1
4	2
2	1
13	3
12	1
11	3
12	1
2	2
4	1
6	2
7	2
11	1
4	1
8	1
2	3
9	2
4	1
5	1

The column on the left is the driver mistake number and the column to the right is the loses of the accident (1 means slight injuries, 2 means serious injuries and 3 means fatalities).

The following are the results of training the network with 10 hidden layers:

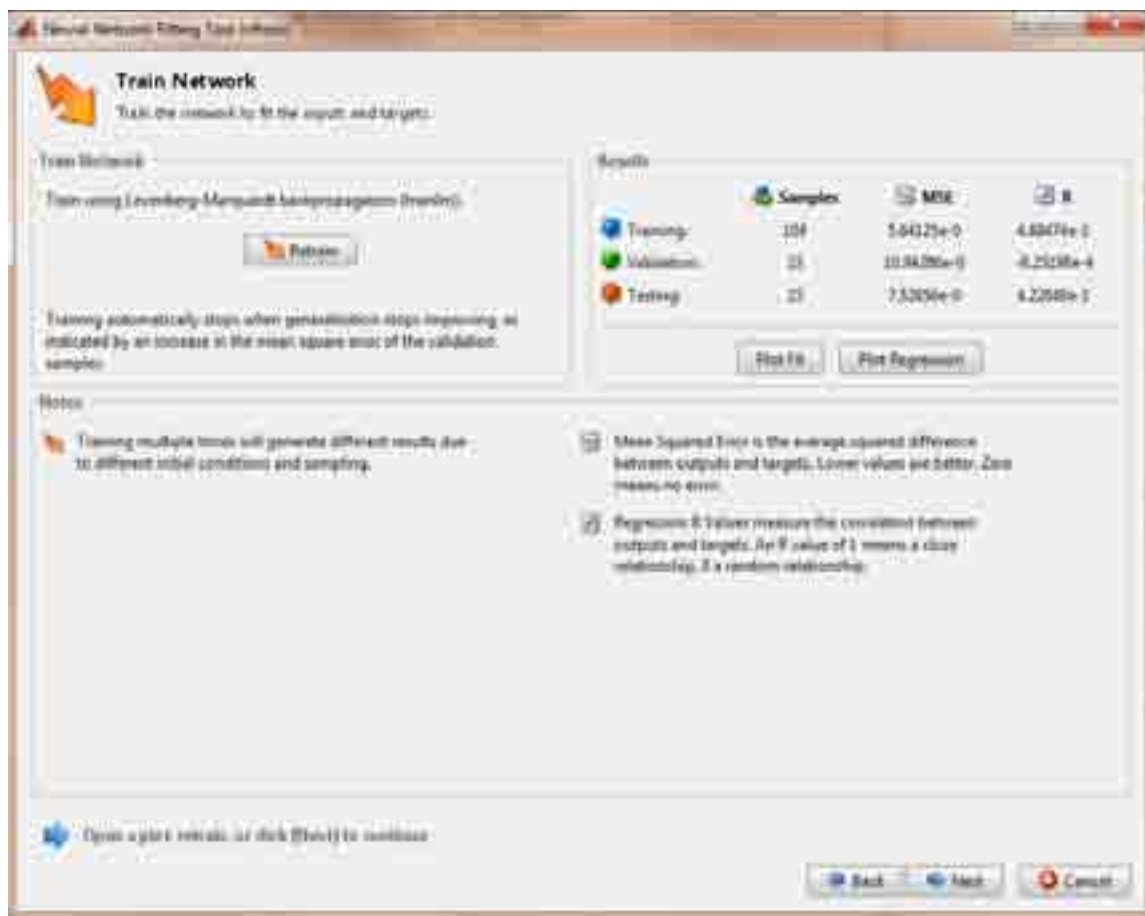


Figure 4-37: intersections collision NN Regression result (10 nodes hidden layer)

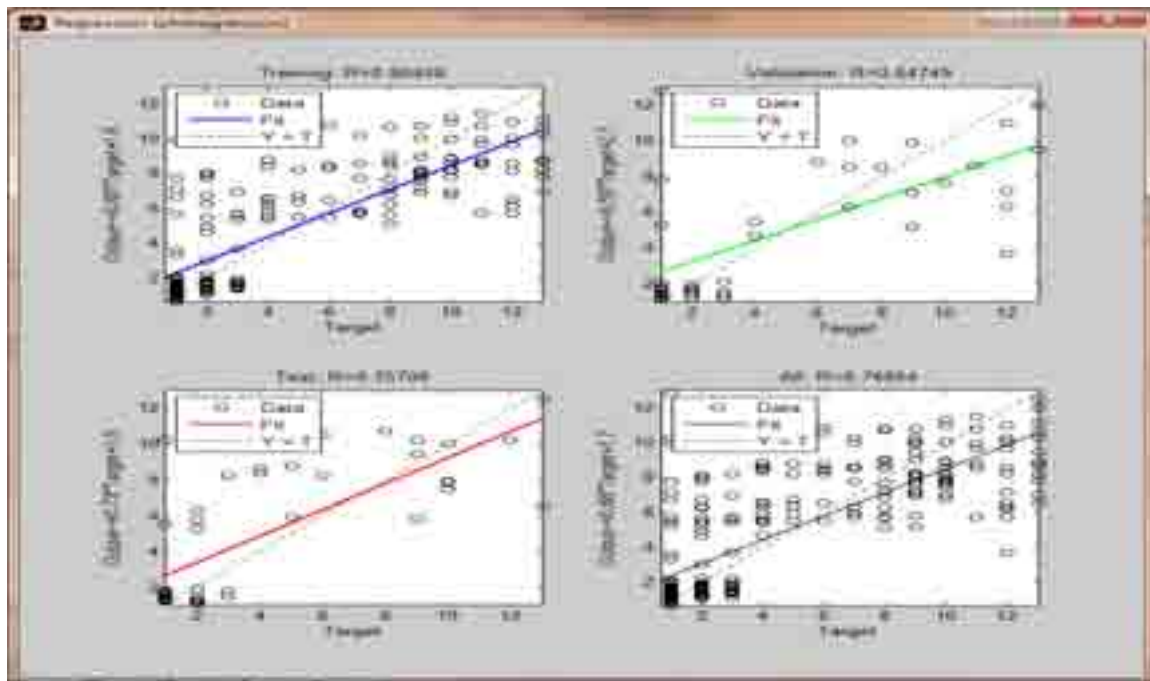


Figure 4-38: intersections collision NN Regression plot (10 nodes hidden layer)

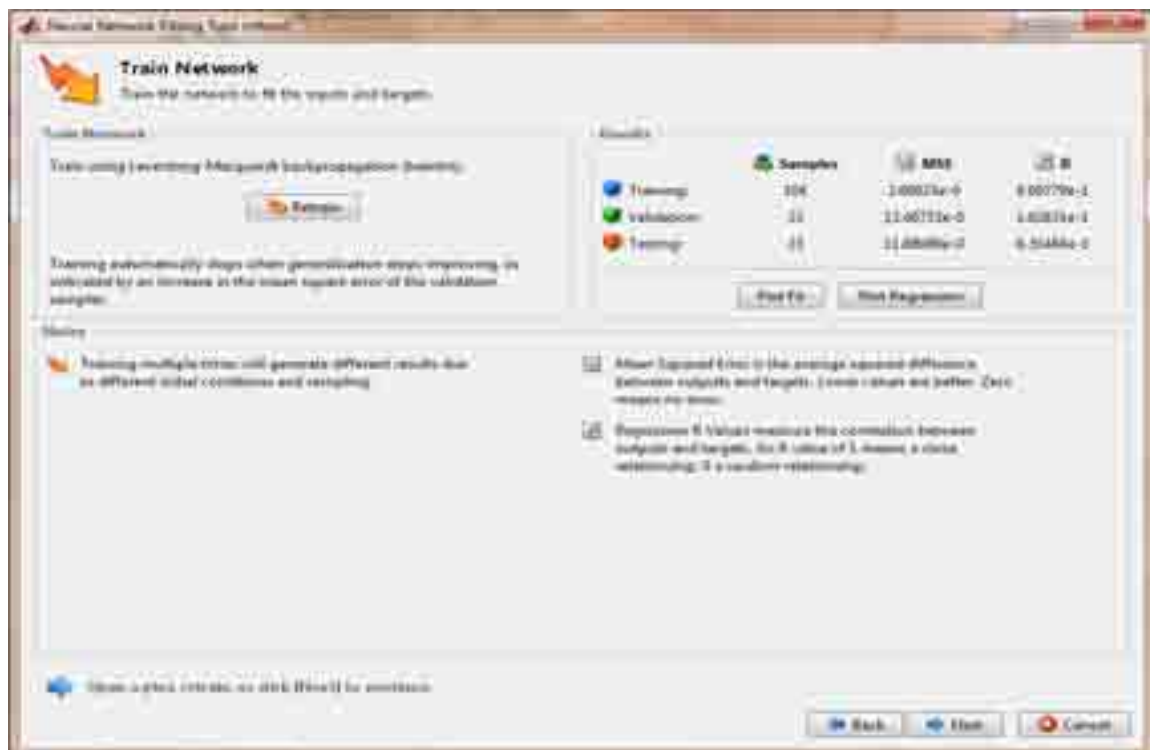


Figure 4-39: intersections collision NN Regression result (15 nodes hidden layer).

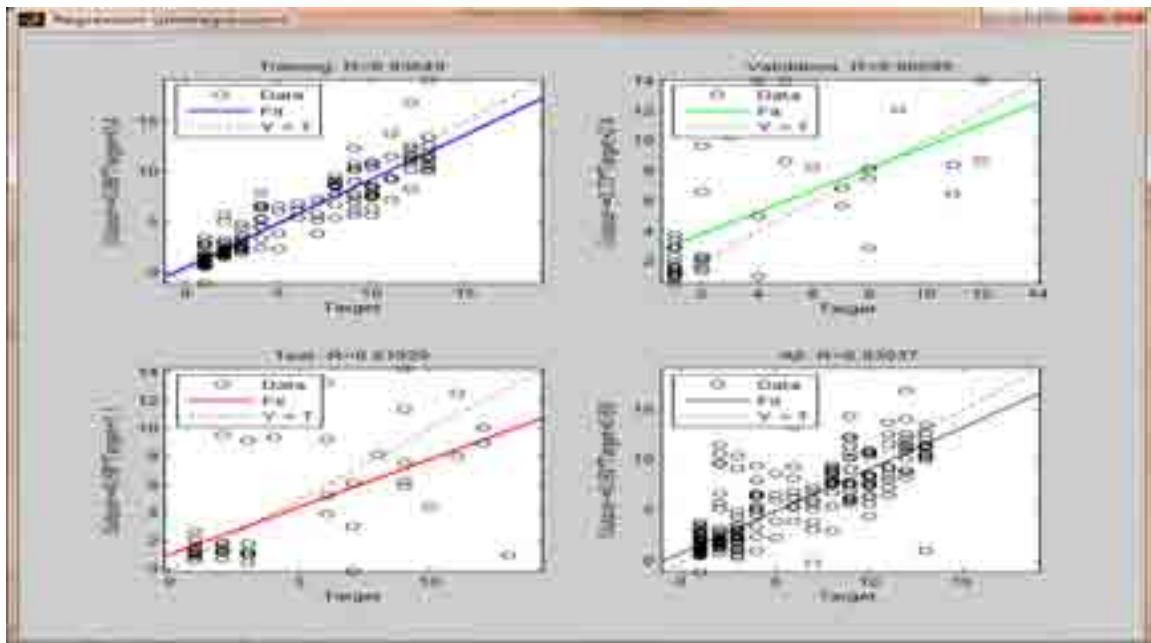


Figure 4-40: intersections collision NN Regression plot (15 nodes hidden layer)



Figure 4-41: intersections collision NN Regression result (20 nodes hidden layer)

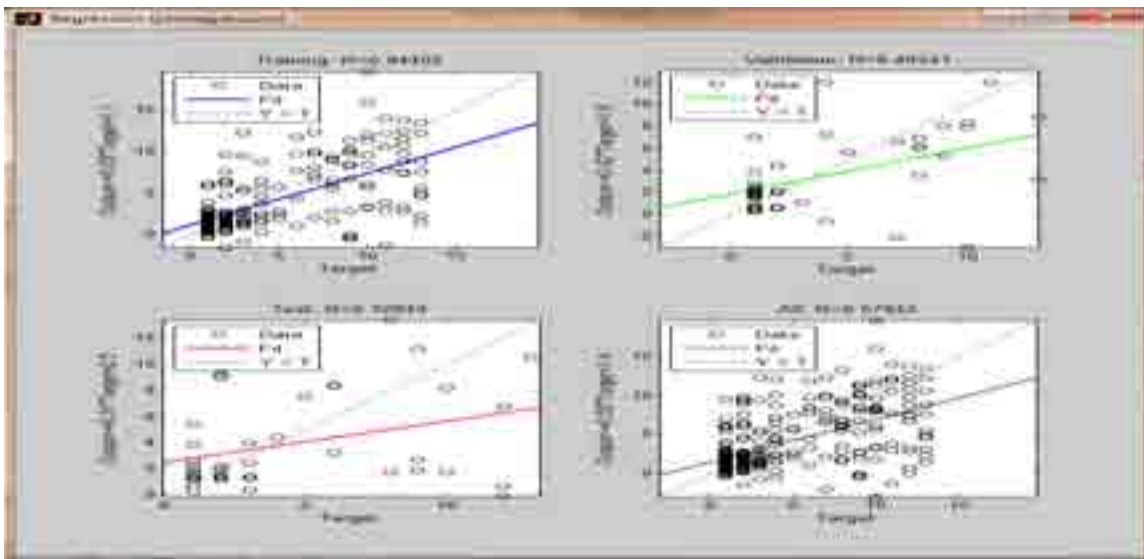


Figure 4-42: intersections collision NN Regression plot (20 nodes hidden layer)

The following is the full system model:

1- Initialization Phase

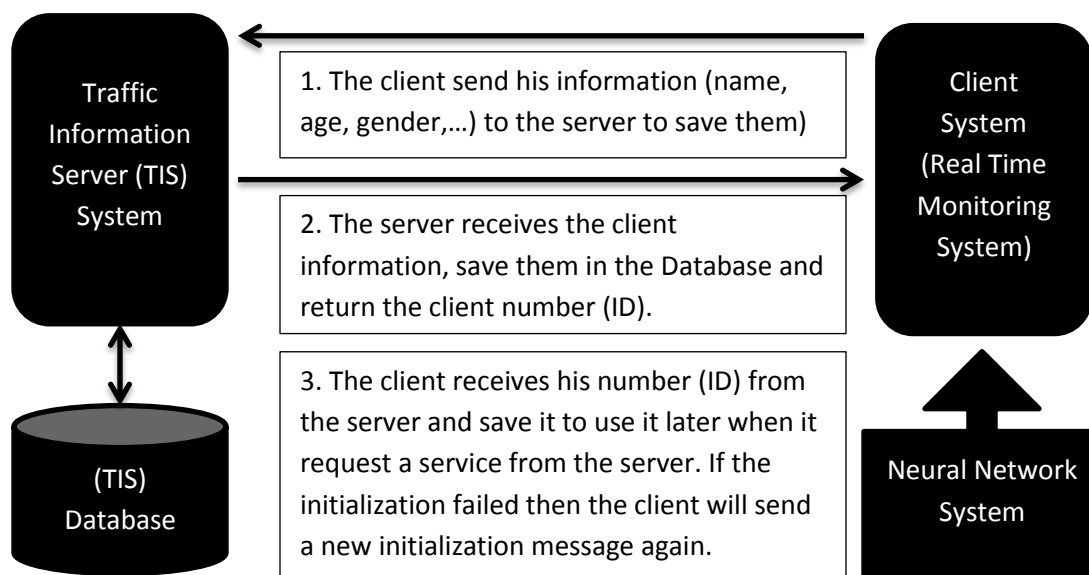


Figure 4-43: Navigation Phase system model

2- Navigation Phase

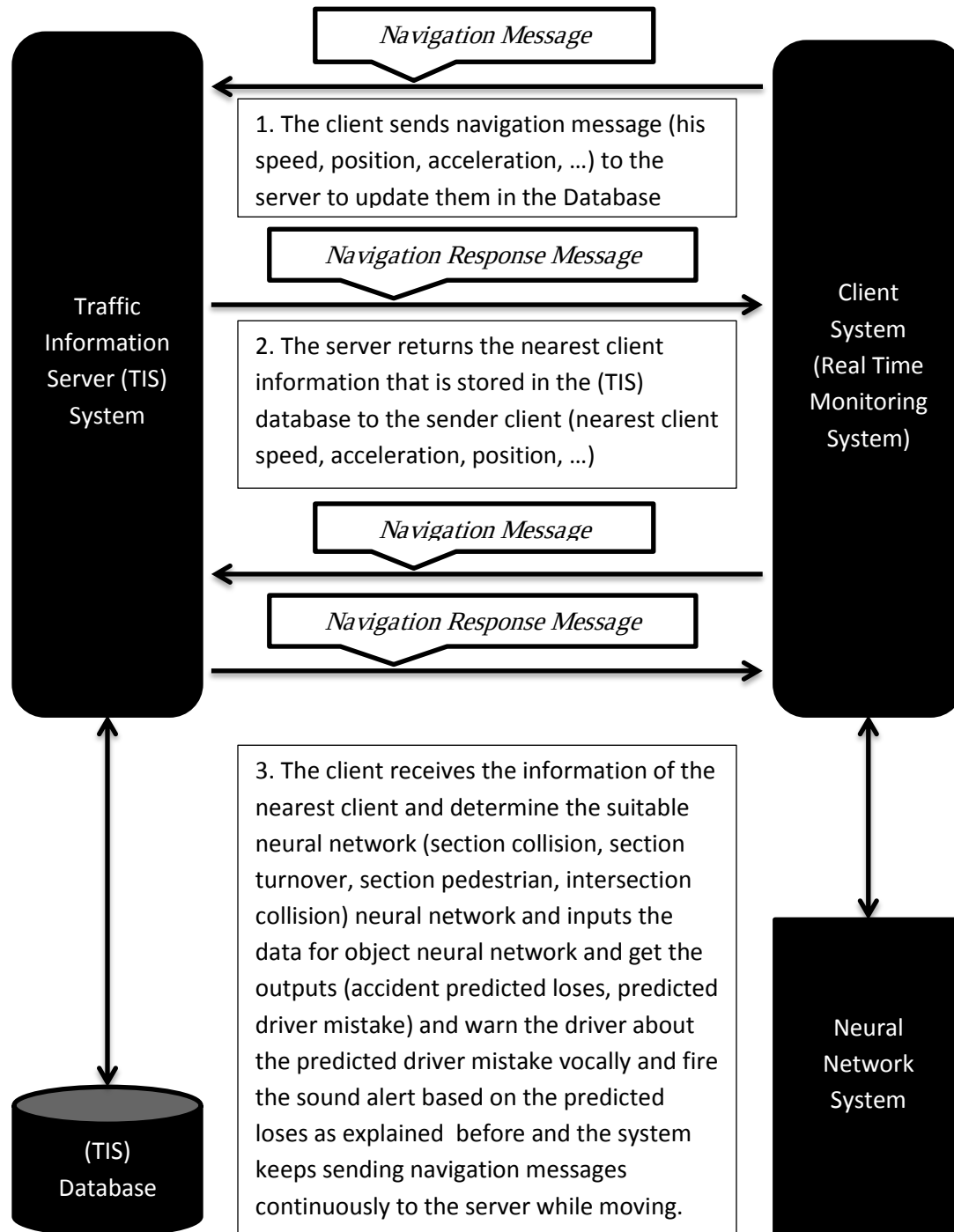


Figure 04-44: Navigation Phase system model

Chapter Five

5 Conclusion & Future Work

5.1 Summary and Conclusion

The road accidents are distributed over all the road, but there is a some areas that called (hot spot) witnesses a higher rate of accidents duo to some vehicle, weather, road and driver issues. These conditions can influent the road accidents and its severity; this research built a system model to predict the accidents by analyzing the previous accidents conditions and influentials utilizing one of the strongest artificial intelligence techniques the neural networks.

The first task was to extensively review the previous accidents statistics and conditions and study the various techniques employed in this field. And benefit from these methods to choose the suitable way to build an accident prediction system. The neural network model has chosen because of their various advantage, such as their ability to perform non-linear operations very efficiently, their capability of learning, and their ability to produce reasonable results by adapting to new inputs not encountered during training.

The next step consisted of collecting the data needed to perform the analysis and build the database of accidents that is used for training. In order to predict the accidents, the multilayer perceptron (MLP) neural network model was used to develop the system and

test the data in the database. The Root Mean Squared Error (RMSE) for the models was checked To minimize the error in the prediction values.

The next phase of the research was to learn the MLP with different hidden layers (10, 15, 20) hidden layer to predict the accident loses and driver mistakes with the lowest possible error. And a model for client and server system structure was developed to manage the relations and data flow between the clients and the server to achieve the system goal.

5.2 Future Work

Further studies can be carried out to extend and improve the system and models can be developed to classify the accidents and its results using the Neural Network Trees and studying the effects of different traffic variables, geometric and driver characteristics on the injury types and other loses of accidents. The results obtained can be compared to the results of other statistical models and other NN types can be applied and modified to enhance the system outputs.

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Appendix: Data Collection and Classification

The General Directorate of Jordan Civil Defense has classified traffic accidents based on its main factors as follows:

1- Type of accident:

Turnover accident, pedestrian accident and collision accident.

The following table shows the accidents and its types and results based on the month for the year 2011:

Table A-1: Accidents and its types and results based on the month for the year 2011

Month	Accidents	Accident Type			Loses and injuries		
		Collision	Pedestrian	Turnover	Fatality	Serious	Slight
January	10918	10599	231	88	34	170	1015
February	10160	9907	93	60	49	142	950
March	11655	11364	219	72	49	190	1214
April	11642	11305	232	105	72	231	1267
May	12088	11719	272	97	47	208	1322
June	12386	11949	317	120	49	255	1392
July	14936	14386	344	206	69	265	1698
August	15197	14936	320	190	87	218	1559
September	13043	12557	313	173	59	225	1519
October	11099	10675	286	138	62	229	1375
November	9478	9128	231	119	64	157	1125
December	9986	9613	265	108	53	166	1230
Total	142588	136889	3223	1476	694	2456	15666

2- Based on the month:

January, February, March, April, May, June, July, August, September, October, November and December.

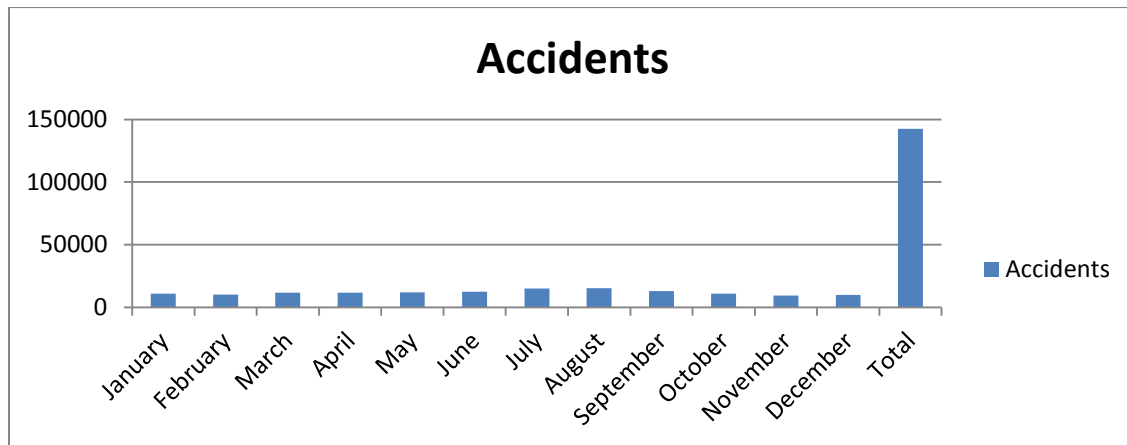


Figure A-1: Total number of accidents for each month

The following chart previews the collision accident compared with total number of accidents for each month:

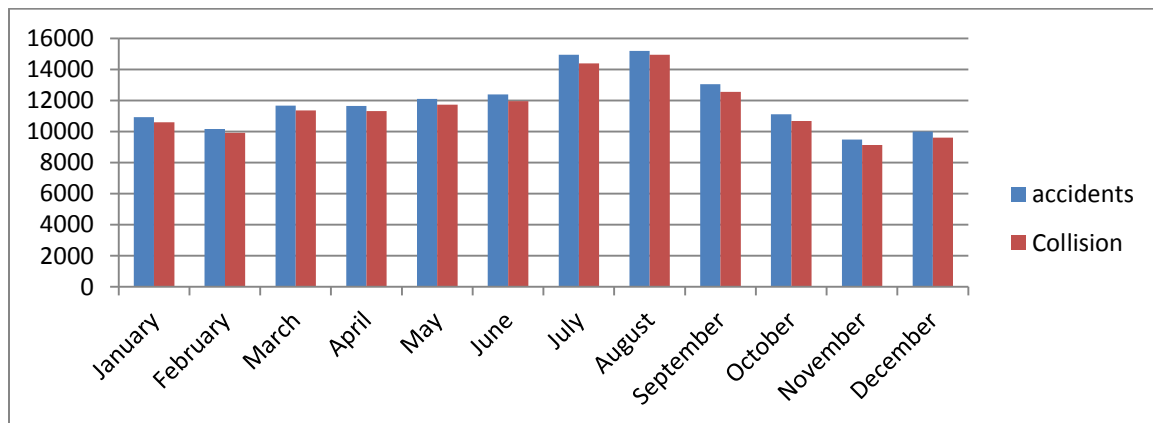


Figure A-2: Comparison between the collision accidents and the total number of accidents

We note the collision accidents have high portion of the accidents. The highest number of total accidents and collision accidents was in August where it formed 10.7% of all the months.

The following diagram shows the pedestrian and turnover accidents.

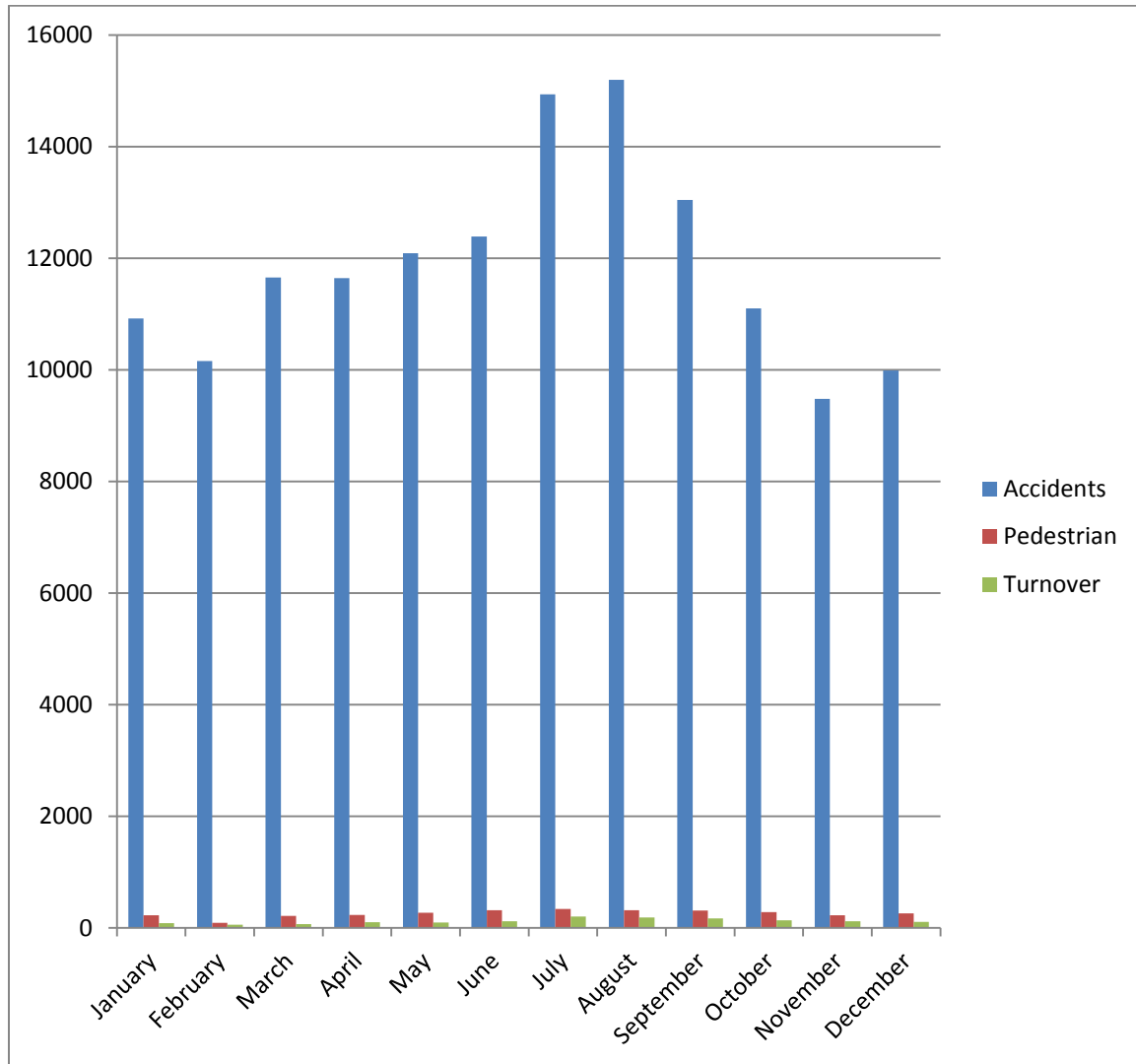


Figure A-3: Pedestrians and turnover accidents distributed over the months of the year

The following diagram shows fatalities distribution on the months.

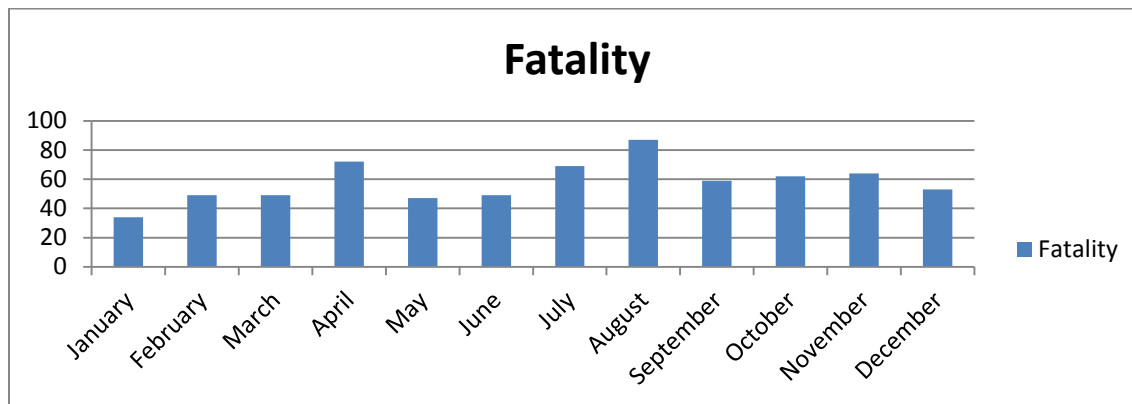


Figure A-4: Fatalities distributed over the months of the year

August has the highest number of fatalities (12.5%) from the total number of fatalities.

The following diagram shows the number of injuries (slight and serious) for each month.

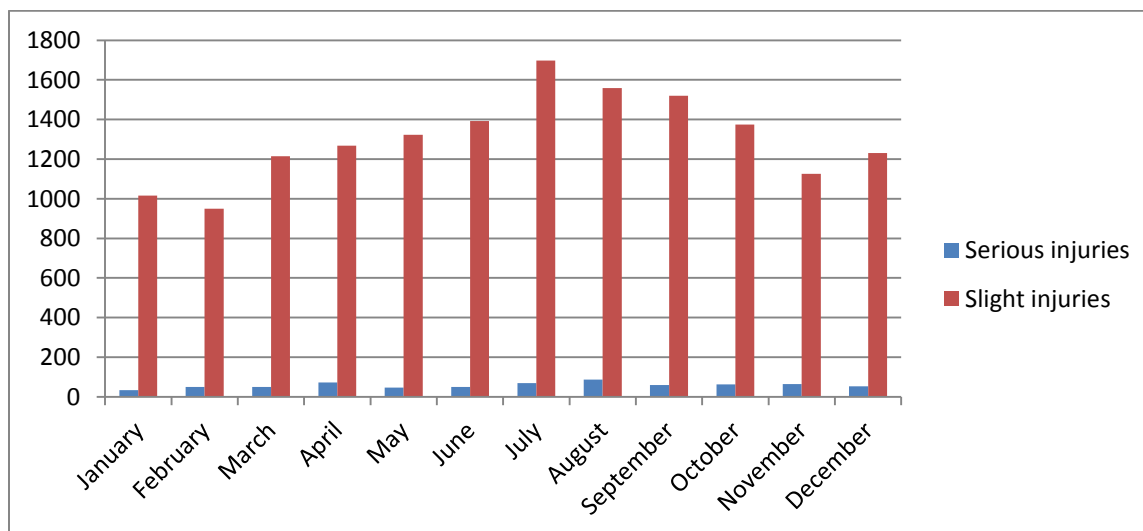


Figure A-5: Injuries types distributed over the months of the year

August has the highest number of injuries for both slight and serious injuries (10.8%) of the total number of injuries.

3- Based on the day of week:

Saturday, Sunday, Monday, Tuesday, Wednesday, Thursday and Friday.

Table A-2: Accidents, injuries and fatalities distribution over the days of the week

Day	Accidents	Accident Type			Loses and injuries		
		Collision	Pedestrian	Turnover	Fatality	Serious	Slight
Saturday	19617	18960	433	224	84	317	2088
Sunday	21905	21209	468	228	86	310	2239
Monday	21444	20798	447	199	102	330	2068
Tuesday	20597	19926	470	201	102	354	2309
Wednesday	20798	20170	439	189	109	337	2157
Thursday	24151	23393	557	201	106	376	2535
Friday	14076	13433	409	234	105	432	2270
Total	142588	137889	3223	1476	694	2456	15666

The following diagram shows accident distribution on the days of week.

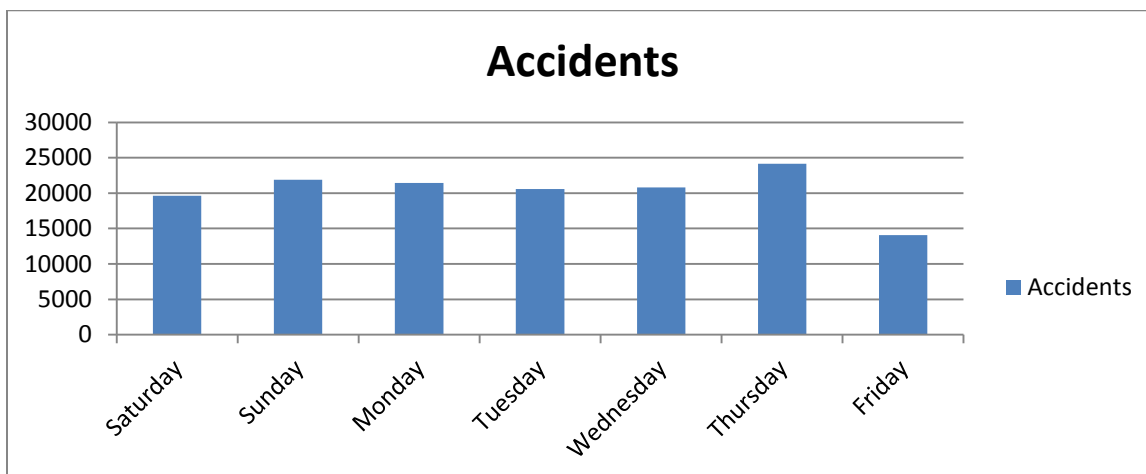


Figure A-6: Total of road accidents distributed over the days of the week

Thursday has witnessed the highest number of accidents (16.9%) of the total number of accidents.

The following diagram shows the number of collision accidents for the week days.

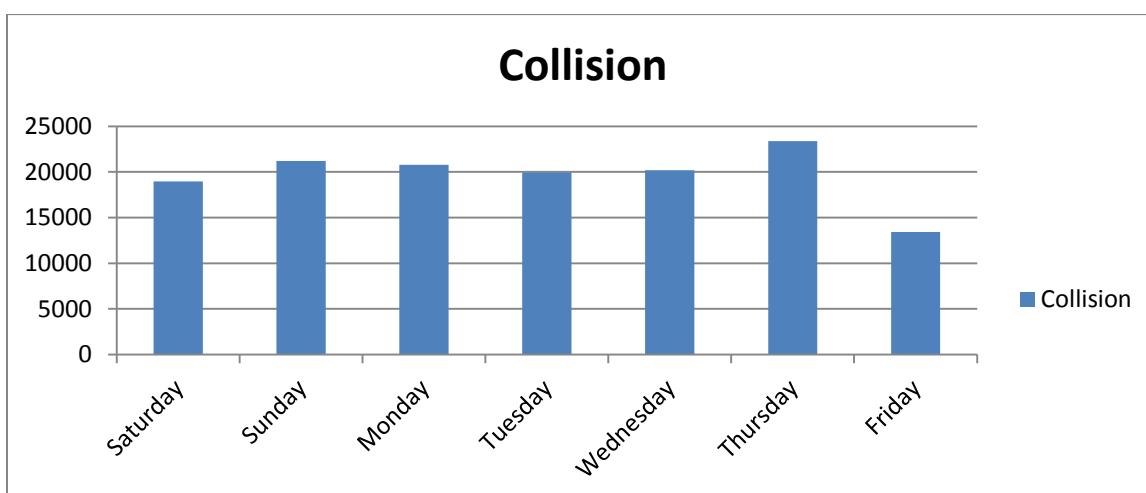


Figure A-7: Collision accidents distribution over the days of the week

Thursday has registered the highest number off collision accidents too (17.0%) from the total number of collision accidents.

The following diagram shows the number of pedestrians and turn over accidents.

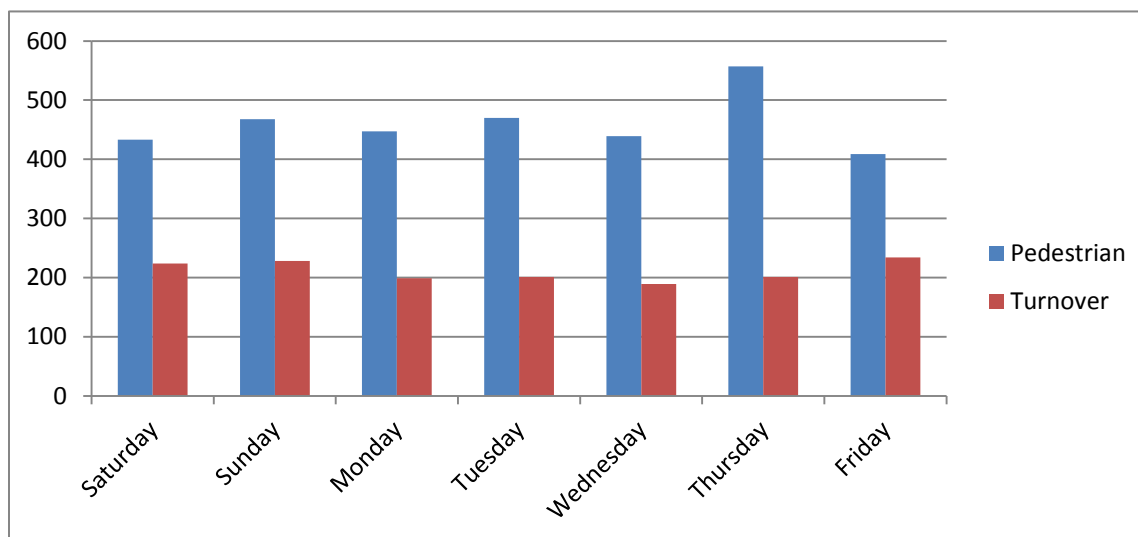


Figure A-8: Pedestrian and turn over accidents distribution over the days of the week

Thursday get the highest pedestrian accidents (17.3%) of the total number of pedestrian accidents, and the turn over accidents got the highest value in Friday with (15.8%) of the total number of turn over accidents.

The following diagram shows the accidents fatalities distribution by day of week.

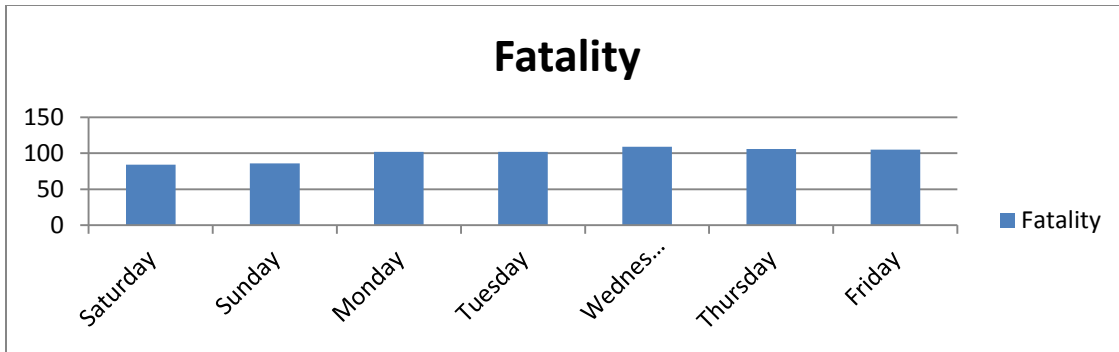


Figure A-9: Fatalities distribution over the days of the week

Wednesday fatalities are the highest of all days of week with (15.7%) of the total number of all the days.

The next is the count of the injuries and its distribution across the days of the week.

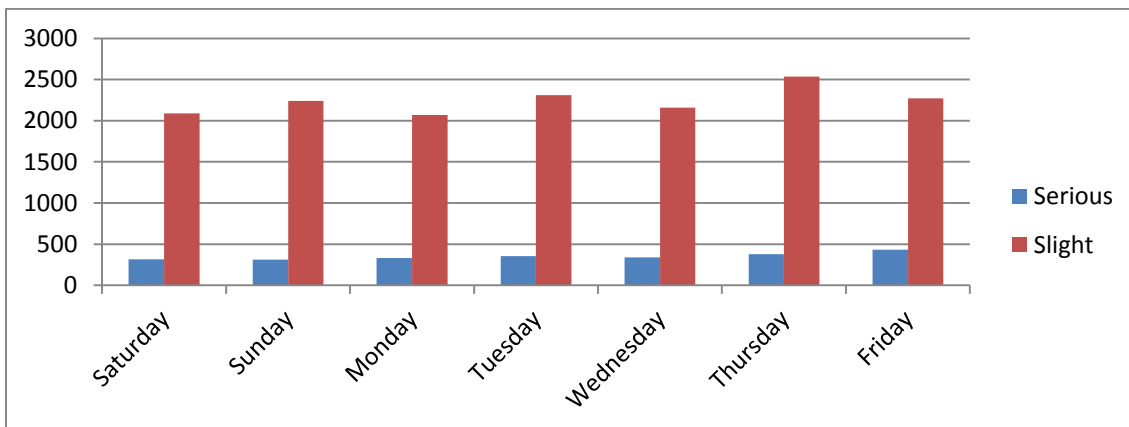


Figure A-10: Injuries distribution over the days of the week

Slight injuries for Thursday are the highest percentage with (16.2%) of the total slight injuries, and Friday is the highest percentage of serious Accidents injuries.

4- Based on time

The times off accidents are segmented into 24 time zones as follows.

00:00 to 00:59, 01:00 to 01:59, 02:00 to 02:59, 03:00 to 03:59, 04:00 to 04:59, 05:00 to 05:59, 06:00 to 06:59, 07:00 to 07:59, 08:00 to 08:59, 09:00 to 09:59, 10:00 to 10:59, 11:00 to 11:59, 12:00 to 12:59, 13:00 to 13:59, 14:00 to 14:59, 15:00 to 15:59, 16:00 to 16:59, 17:00 to 17:59, 18:00 to 18:59, 19:00 to 19:59, 20:00 to 20:59, 21:00 to 21:59, 22:00 to 22:59 and from 23:00 to 23:59.

Table A-3: Accidents, injuries and fatalities distribution over the hours of the day

Time	Accidents	Accident Type			Loses and injuries		
		Collision	Pedestrian	Turnover	Fatality	Serious	Slight
00:00-00:59	824	781	21	12	4	19	123
01:00-01:59	2348	2259	48	41	17	45	269
02:00-02:59	2229	2172	36	21	14	25	270
03:00-03:59	1249	1208	17	24	11	26	220
04:00-04:59	1030	994	17	19	9	27	147
05:00-05:59	873	815	20	38	12	29	131
06:00-06:59	1240	1175	38	27	22	64	269
07:00-07:59	3926	3709	168	49	17	58	593
08:00-08:59	5800	5643	81	76	20	70	566
09:00-09:59	5825	5571	169	85	29	67	571
10:00-10:59	7037	6801	162	74	42	122	731
11:00-11:59	9528	9191	224	113	40	146	941

12:00-12:59	11011	10605	286	120	60	202	1236
13:00-13:59	10468	10118	248	102	44	173	1036
14:00-14:59	12290	11952	230	108	47	167	1138
15:00-15:59	11808	11501	216	91	42	174	1167
16:00-16:59	10706	10386	233	87	57	163	1164
17:00-17:59	9618	9275	254	89	42	170	982
18:00-18:59	9683	9353	248	82	39	164	942
19:00-19:59	7371	7111	199	61	34	109	820
20:00-20:59	4794	4610	140	44	27	108	636
21:00-21:59	5357	5171	139	47	25	117	704
22:00-22:59	3922	3787	94	41	29	71	497
23:00-23:59	3671	3552	70	49	11	71	536
Total	142608	137740	3358	1500	694	2387	15689

The following diagram shows the accident based on the time of occurrence for 2011.

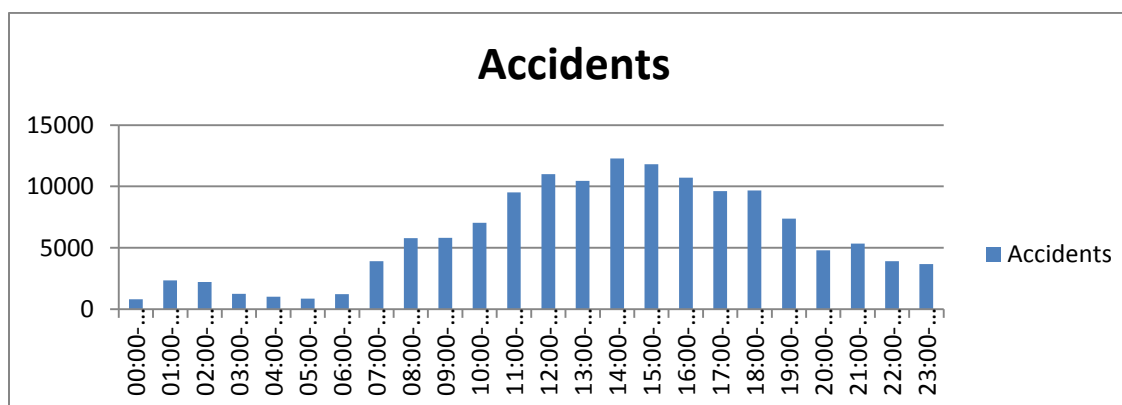


Figure A-11: Accidents distribution over the hours of the day

The period from (14:00 to 14:59) has registered the highest number of accidents with 8.6 from the total percentage value of accidents.

The following diagram views the collision accidents distributed on the day hours for the year 2011 compared with all the types of accidents for the same period.

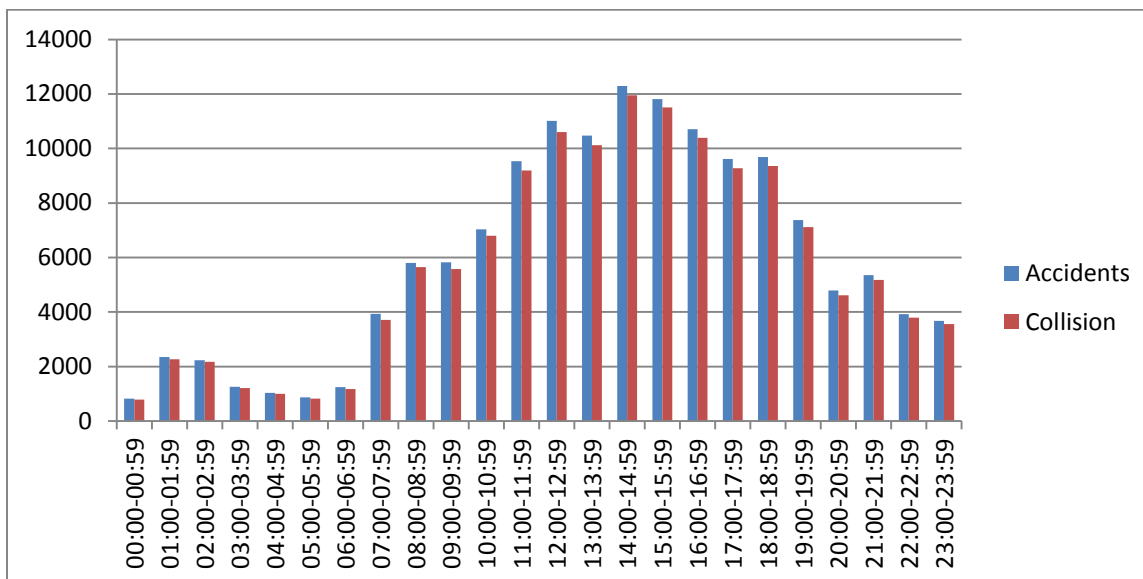


Figure A-12: Comparison between the collision accidents and the total road accident based on the hours of the day

Collision accidents have formed 8.7 of all the accidents for the period (from 14:00 to 14:59).

The following diagram shows the pedestrian and turnover accidents distributed on the hours of the day.

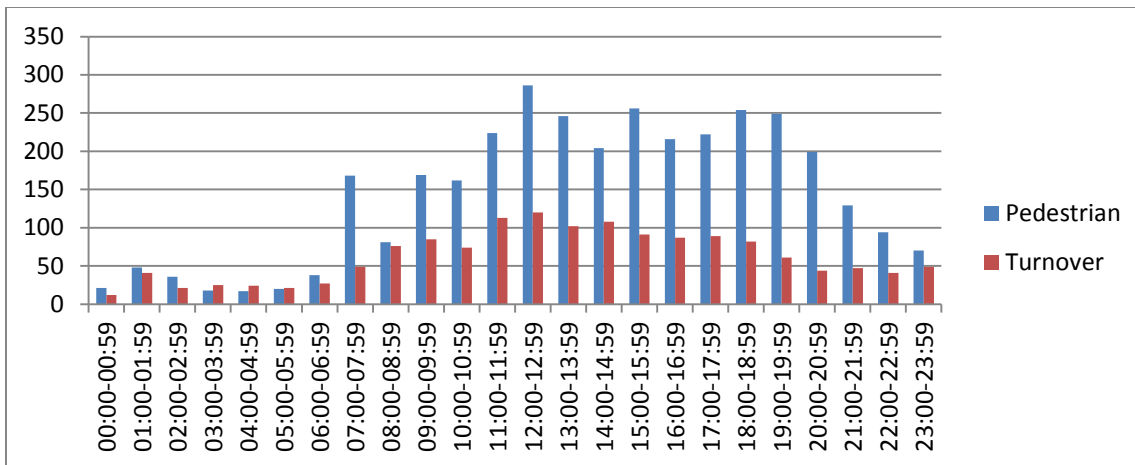


Figure A-13: pedestrian and turnover accidents distributed on the hours of the day

The period from 12:00 to 12:59 has got the highest proportion of the pedestrian and turnover accidents with 7.1% of the summation of both the pedestrian and turn over accidents.

The following diagram shows the distribution of fatalities on the hours of day.

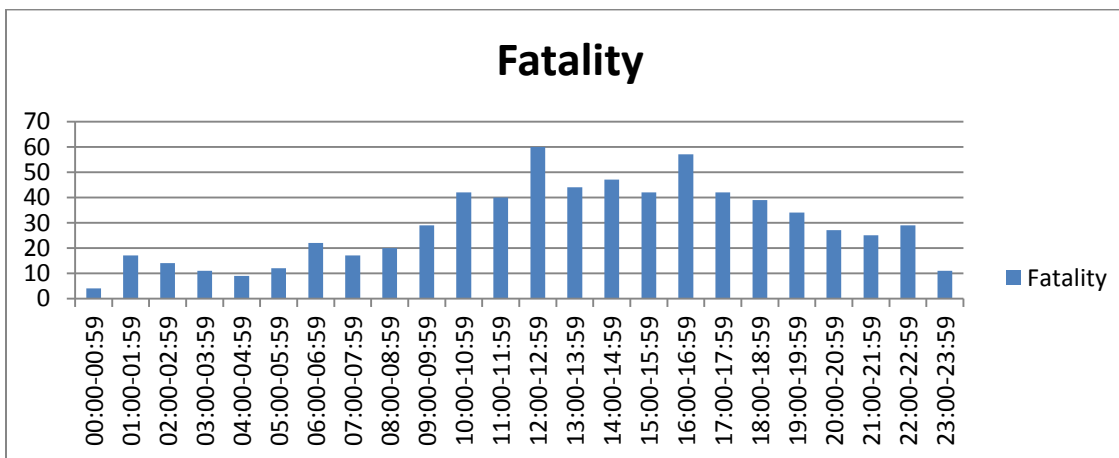


Figure A-14: Fatalities of road accidents distributed on the hours of the day

The period from 12:00 to 12:59 has the highest proportion of fatalities formed 8.6 percent of the total number of fatalities.

The following diagram shows both serious and slight injuries of the accidents.

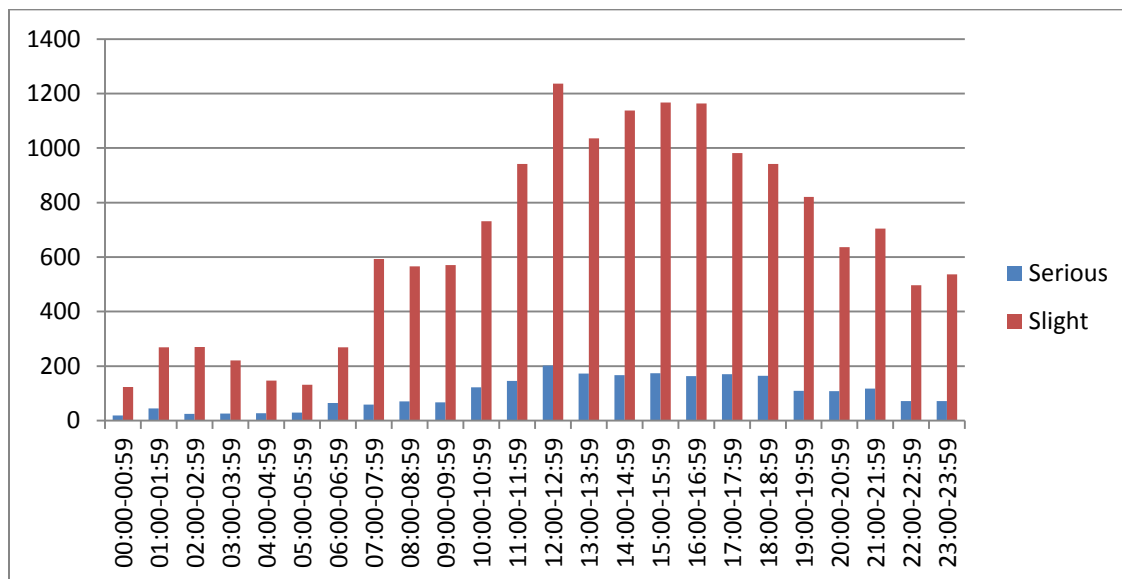


Figure A-15: Serious and slight injuries of the accidents distributed on the hours of the day

Slight and serious injuries of accidents for the period (12:00 to 12:59) have the highest value of the total number of slight and serious injuries with (7.9% and 8.2) respectively.

5- Based on lighting conditions

Daylight, night with enough lighting, night with bad lighting, night, Sunrise and sunset.

The following table shows the distribution of accidents based on lighting conditions.

Table A-4: distribution of accidents based on lighting conditions

Lighting	Accidents	Accident Type			Loses and injuries		
		Collision	Pedestrian	Turnover	Fatality	Serious	Slight
Daylight	127093	122705	3047	1341	640	2263	14652
night with	9643	9519	82	42	21	72	411
night with bad	145	121	16	8	6	16	77
night	1169	1107	37	25	13	46	274
Sunrise	3858	3817	9	32	3	14	112
Sunset	680	620	32	28	11	45	140
Total	142588	137889	3223	1476	694	2456	15666

Collision accidents during the daylight have the highest value with 89% of the total collision accidents.

92% of the total number of fatalities have registered in the daylight.

And the following is the accident injures based on the lighting.

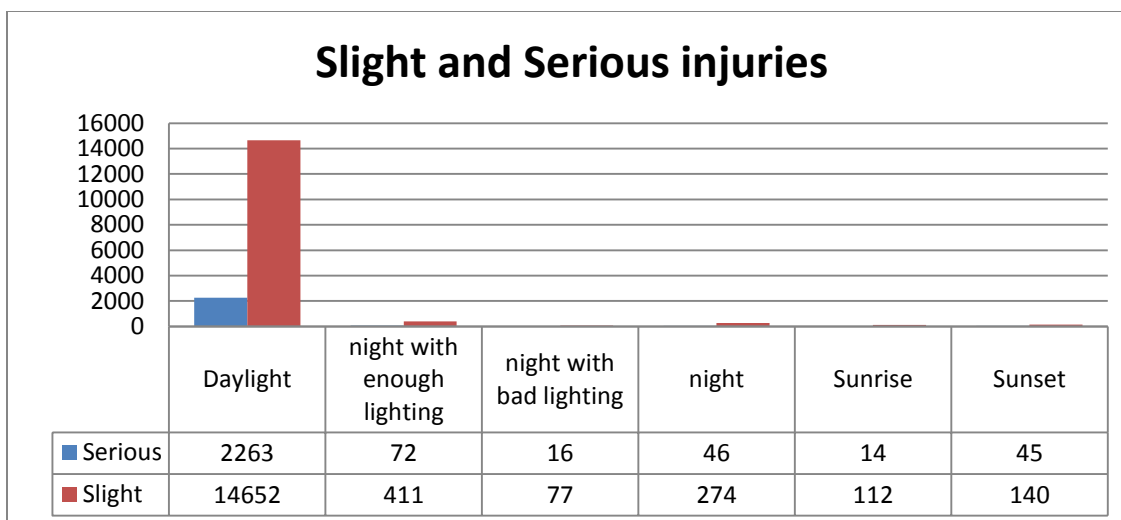


Figure A-16: Accident injures based on the lighting

Also the daylight got the highest number of slight and serious injuries.

6- Based on the weather conditions

Clear, fuggy, rainy, snowy, windy and dusty.

The following table shows some information about accidents, loses and injuries distribution over different weather conditions.

Table A-5: Accidents and loses distribution over different weather conditions

Lighting	Accidents	Accident Type			Loses and injuries		
		Collision	Pedestrian	Turnover	Fatality	Serious	Slight

Clear	132837	128270	3176	1391	681	2403	15226
fuggy	7338	7262	17	59	3	18	192
rainy	2256	2225	13	18	5	20	96
snowy	84	77	5	2	3	11	84
windy	27	21	3	3	1	2	27
dusty	46	34	9	3	1	2	41
Total	142588	137889	3223	1476	694	2456	15666

The following diagram shows the distribution of accident over the weather conditions for the year 2011.

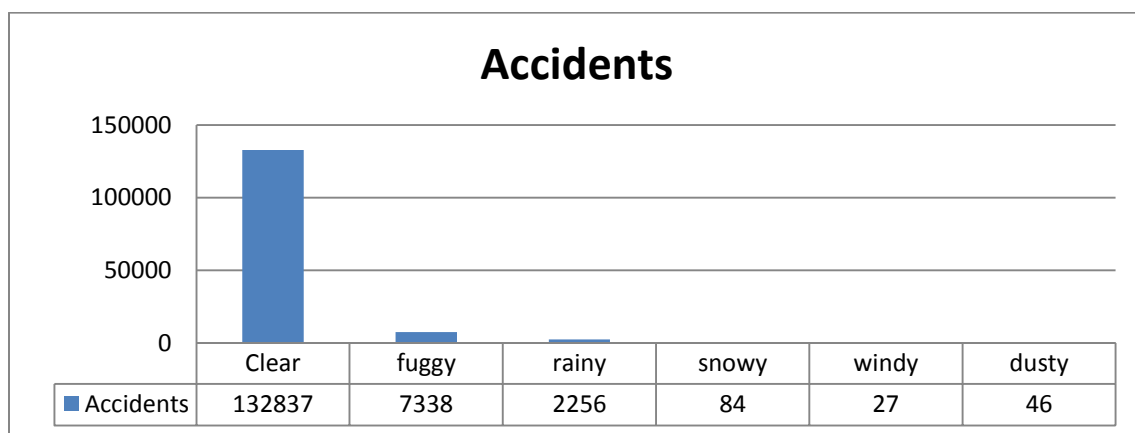


Figure A-17: the distribution of accident over the weather conditions

93% of the total accidents have occurred in the clear weather.

The following diagram shows a comparison between the different accident types based on the weather conditions.

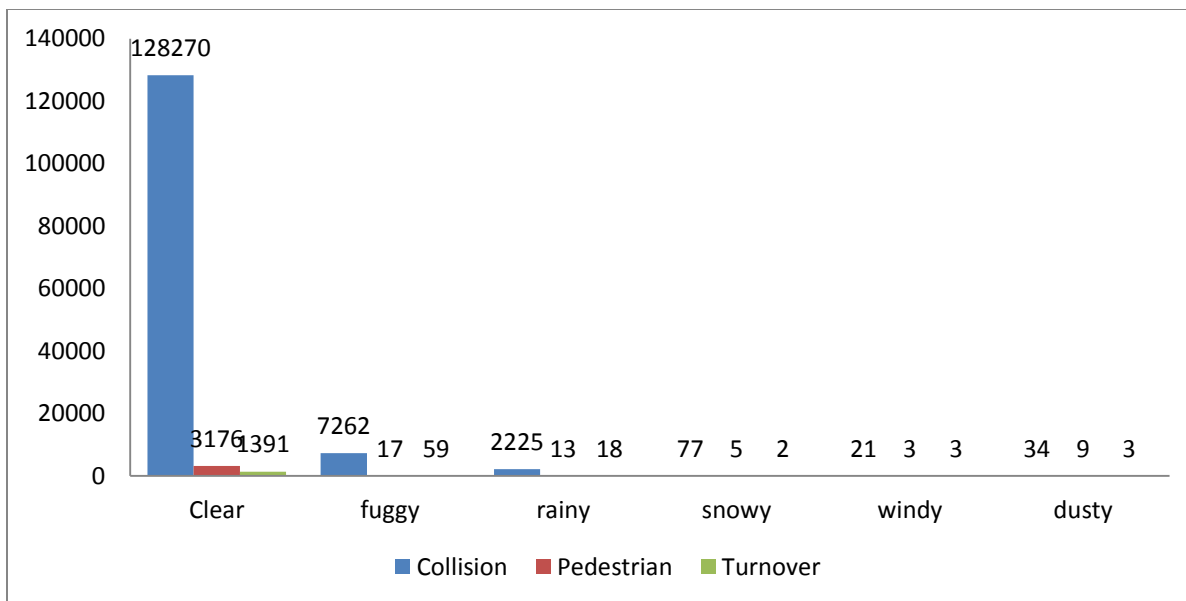


Figure A-18: Accident types based on the weather conditions

The following chart summarizes the accidents, injuries and fatalities based on the weather conditions.

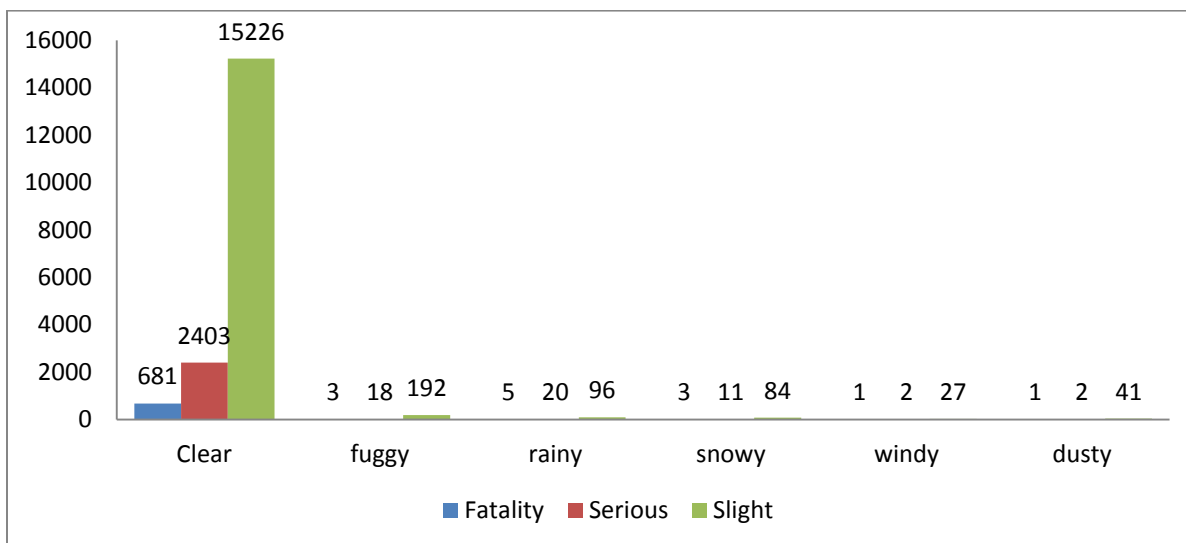


Figure A-19: The accidents, injuries and fatalities based on the weather conditions

The highest of all injuries and fatalities are in the clear weather conditions.

7- Based the road surface

Dry, wet, snow, frost, mud, oil, sand.

Table A-6: The relation between road surface and accident types, loses and injuries

Lighting	Accidents	Accident Type			Loses and injuries		
		Collision	Pedestrian	Turnover	Fatality	Serious	Slight
Dry	127084	122698	3047	1339	671	2319	14650
Wet	3858	3817	9	32	19	127	943
Snow	9509	9385	82	42	1	7	57
Frost	1169	1107	37	25	1	3	1
Mud	680	620	32	28	0	0	2
Oil	279	255	16	8	0	0	4
Sand	9	7	0	2	2	0	9
Total	142588	137889	3223	1476	694	2456	15666

The following chart shows the accidents distribution based on the road surface state.

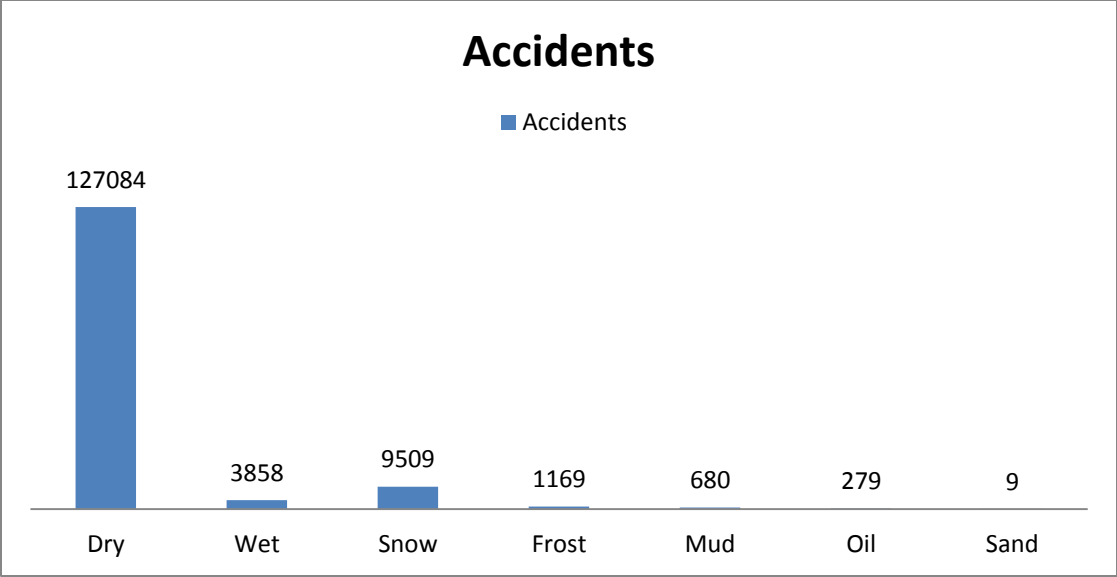


Figure A-20: Accidents and road surface

The following chart shows the different accident types distribution on the different road surface states.

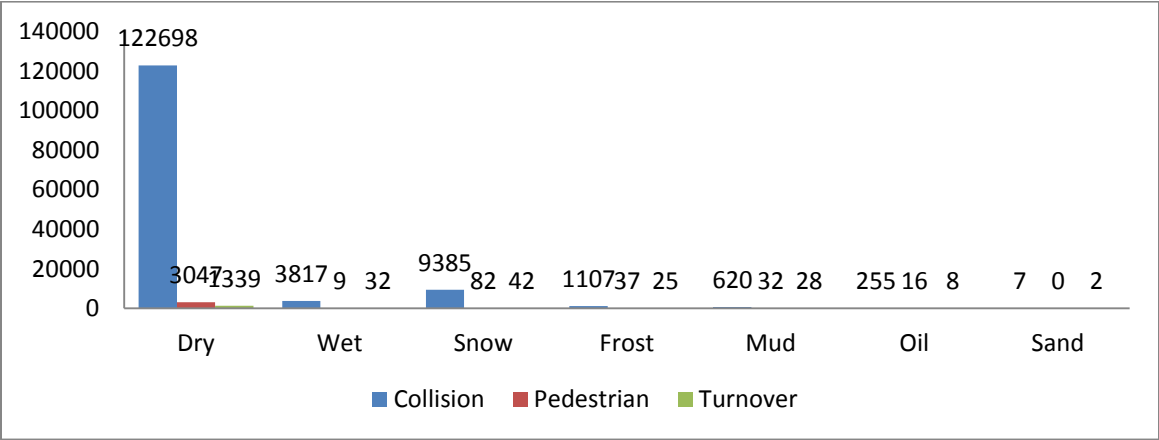


Figure A-21: Accident types and road surface

For the collision pedestrian and turnover accidents the highest value was on a dry road surface with (89% for collision accidents, 94.5% for pedestrian accidents and 90.7% for turnover accidents).

The following diagram shows the relation between the road surface and human injuries and fatalities.

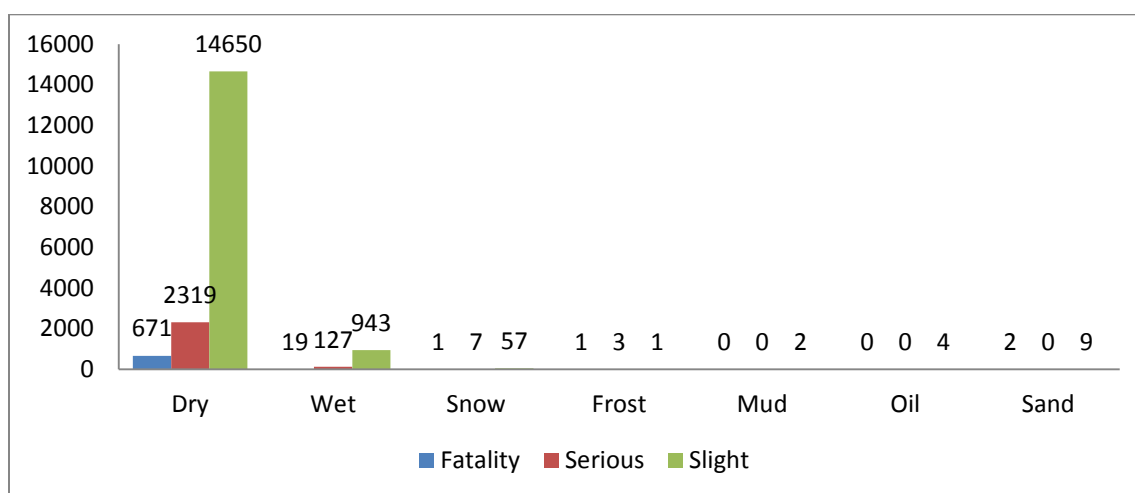


Figure A-22: The relation between the road surface and human injuries and fatalities

8- Based on the road defects.

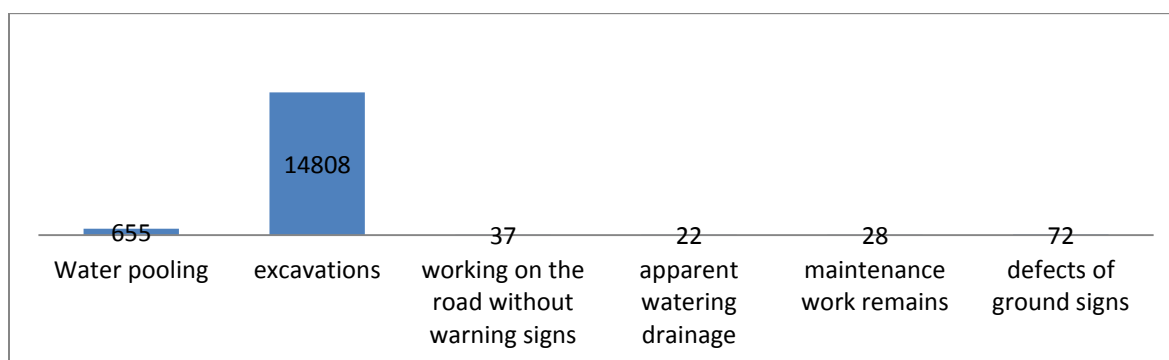
Water pooling, excavations, working on the road without warning signs, apparent watering drainage, maintenance work remains and defects of ground signs.

The following table shows the number of accidents that have occurred as a result of road defects.

Table A-7: the number of accidents and road defects

Road Defect	Number of accidents
Water pooling	655
excavations	14808
working on the road without warning signs	37
apparent watering drainage	22
maintenance work remains	28
defects of ground signs	72
Total	15622

The following diagram shows the relation between the accidents and road defects.

**Figure A-23: the relation between the accidents and road defects**

The main road defect the results accidents is the excavations and leaded into (94.7%) of the total accidents that have occurred as a result from a road defect.

9- Based on the speed limits

Speed limits are segmented to the following speeds

20, 30, 40, 50, 60, 70, 80, 90, 100, 110 and 120.

Table A-8: The road accidents and speed

Speed Limit	Accidents	Accident Type			Loses and injuries		
		Collision	Pedestrian	Turnover	Fatality	Serious	Slight
20	1086	1059	19	8	6	8	43
30	1791	1746	36	9	6	17	122
40	64418	62606	1411	401	166	800	5436
50	35979	34907	862	210	85	437	3148
60	28242	27236	633	373	175	582	3701
70	4545	4332	121	92	51	174	957
80	3572	3291	80	201	114	226	1308
90	876	803	16	57	28	80	360
100	529	458	6	65	34	66	269
110	703	635	14	54	28	52	250
120	847	816	25	6	3	14	72
Total	142588	137889	3223	1476	696	2456	15666

The following chart shows the accidents related with speed.

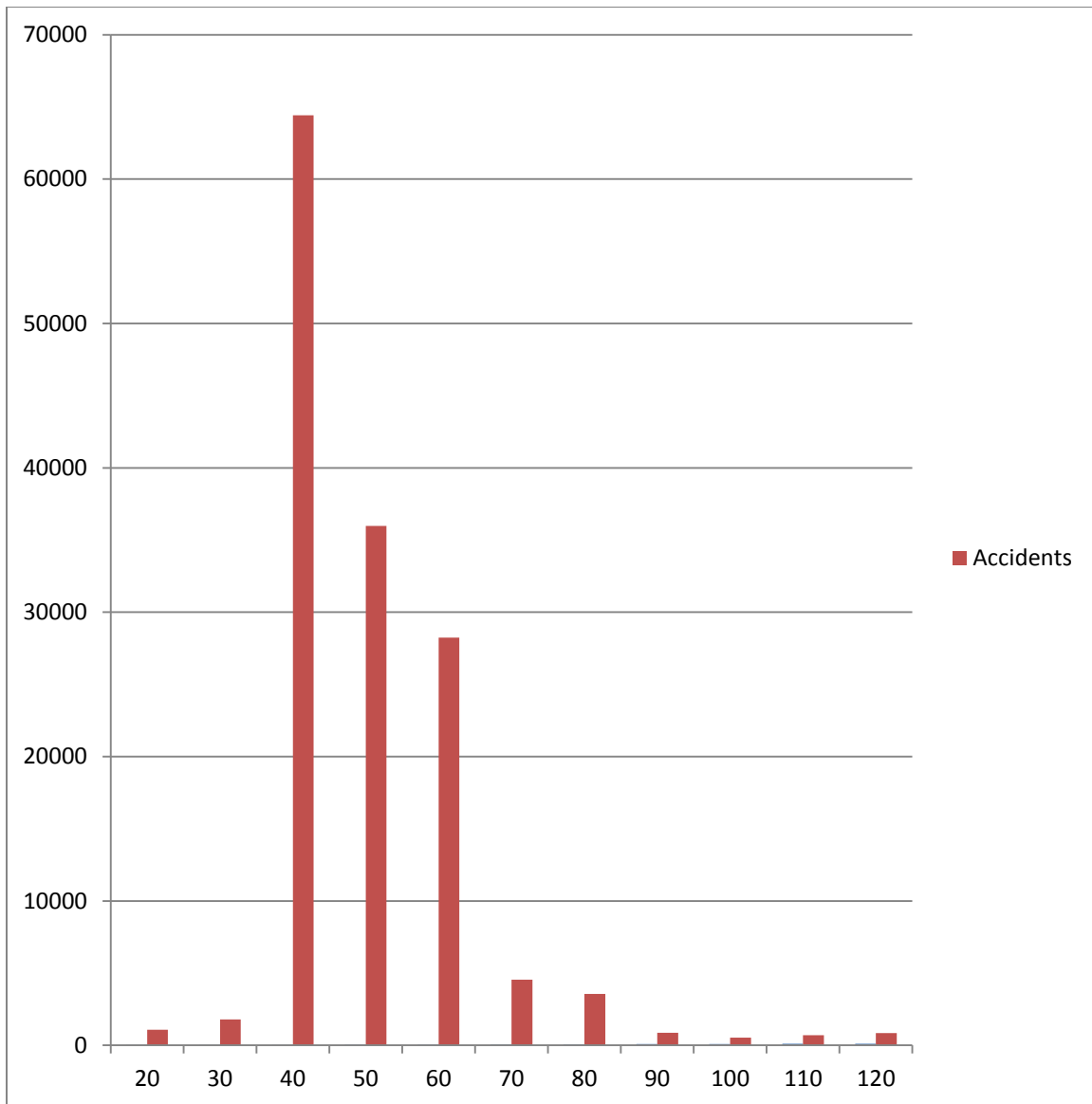


Figure A-24: The relation between the accidents and speed

The streets with speed limit 40 Km/h registered the highest number of accidents with (45.2%) from the total accidents count for the year (2011).

The following chart views the different accident types based on the speed limit of streets.

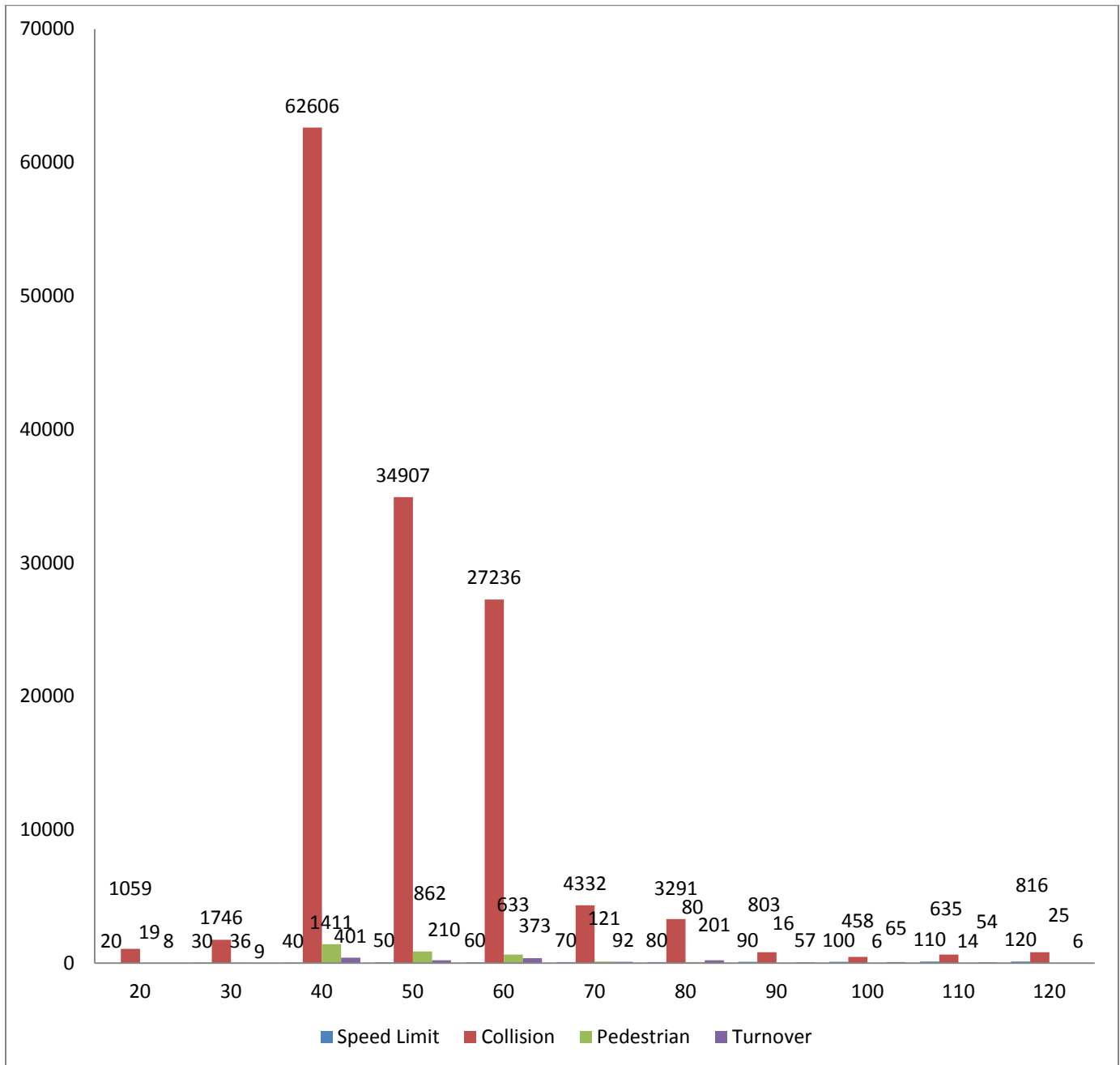


Figure A-25: accident types based on the speed limit of the road

The following chart views fatalities and injuries based on the speed limit.

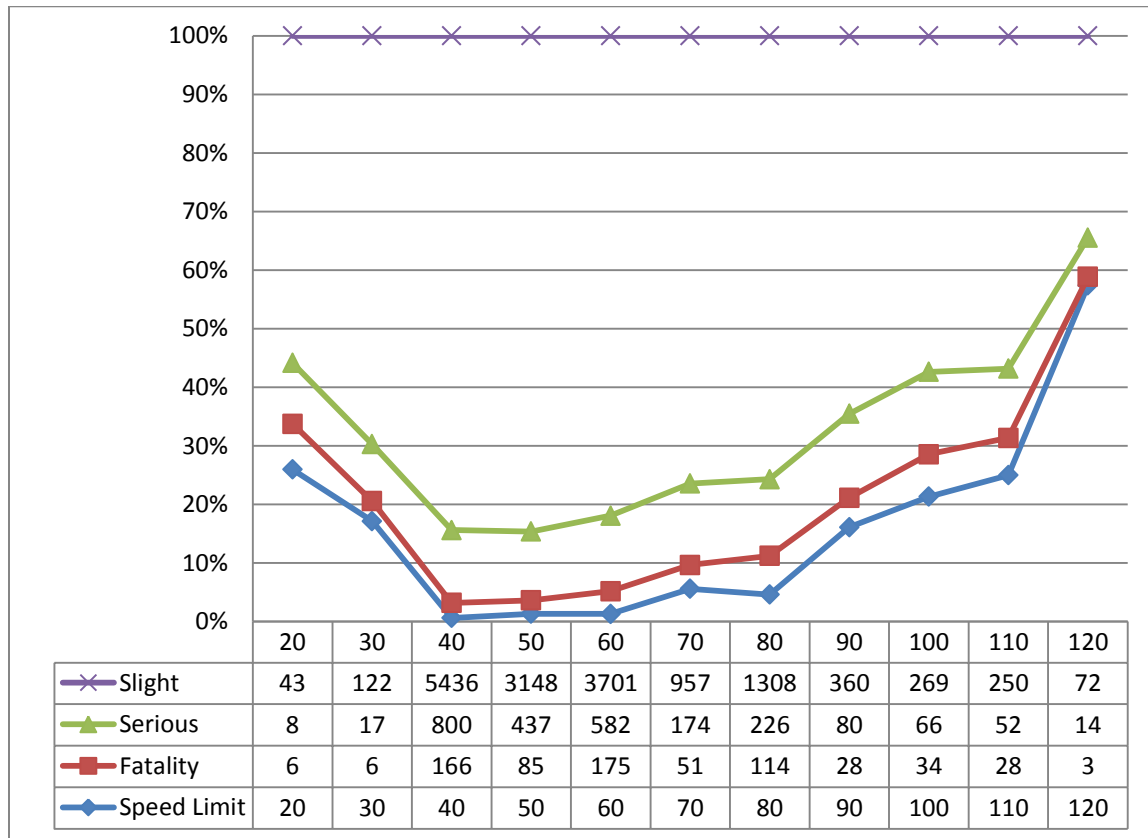


Figure A-26: The fatalities and injuries based on the road speed limit

For both slight and serious injuries and fatalities the highest numbers was in streets with 40Km/h.

10- Based on driver age and gender

The driver ages have segmented into the following groups.

(18<), (18-20) ,(21-23) ,(24-26) ,(27-29) ,(30-32) ,(33-35) ,(36-38) ,(39-41) ,(42-44) ,(45-47) ,(48-50) ,(51-53) ,(54-56) ,(57-59) ,(60+).

Table A-9: The relation between the driver age and the number of accidents

Driver Age	Accidents
18<	12868
18-20	7623
21-23	26094
24-26	28120
27-29	27544
30-32	36116
33-35	21514
36-38	18889
39-41	17606
42-44	16266
45-47	12888
48-50	10300
51-53	7476
54-56	3809
57-59	4029
60>	16414
Total	267556

The following diagram shows the relation between the driver age and the number of accidents.

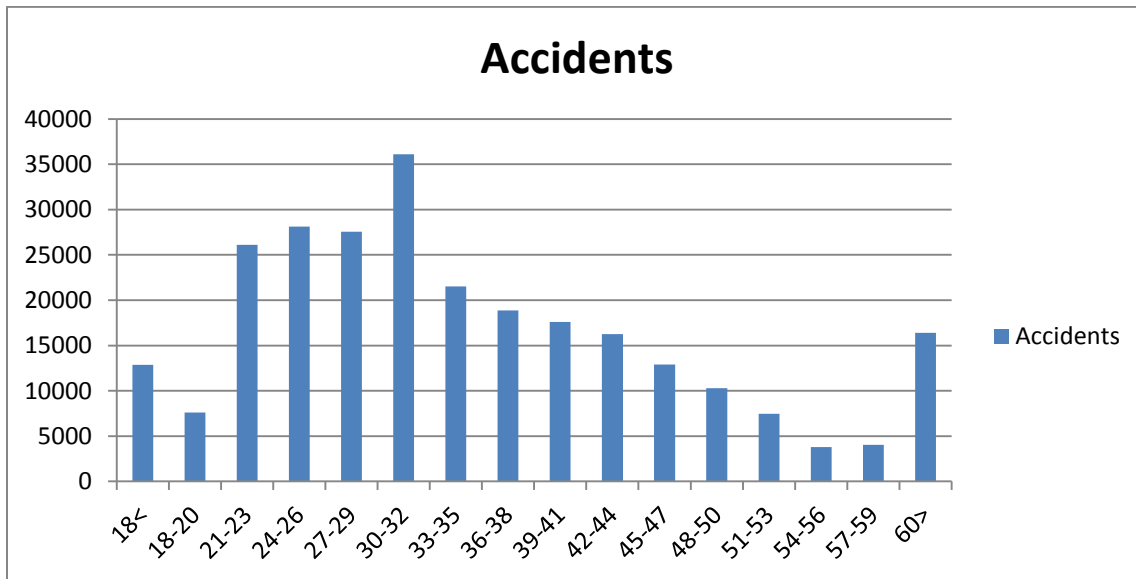


Figure A-27: The relation between the driver age and the number of accidents

The diagram shows that the highest number of participants in the accidents was the drivers with the (30-32) age range.