



Addis Ababa University

Addis Ababa Institute of Technology

(AAiT) School of Electrical and Computer

Engineering

Optimizing Traffic Network around Grade Crossing for the Case of AALRT

By

Tibebu Tiruneh

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University in partial fulfillment of the requirement for the Degree of Master
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Advisors

Dr. Yalemzewd Negash

Mr. Abi Abate

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Addis Ababa University
Addis Ababa Institute of Technology (AAIT)
School of Electrical and Computer Engineering

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By

Tibebu Tiruneh

Electrical and Computer Engineering Department

Approval by Board Examiners

Chairman, Department Graduate
Committee

Signature

Date

Dr. Yalemzewd Negash
Advisor

Signature

Date

Mr. Abi Abate
Advisor

Signature

Date

Internal Examiner

Signature

Date

External Examiner

Signature

Date

Declaration

I certify that research work titled “**Optimizing Traffic Network Around grade crossing for the case of AALRT**” is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged / referred.

Name: Tibebu Tiruneh

Signature: _____

Place: Addis Ababa

Date of Submission: _____

This thesis work has been submitted for examination with my approval as a university advisor.

1. Dr. Yalemzewd Negash
Advisor

Signature

Date

2. Mr. Abi Abate
Advisor

Signature

Date

Abstract

The existing public transport system in Addis Ababa is critically insufficient to provide service for the existing travel demand. Public transportation is one and the most important means of easing traffic congestion for it makes roads work better by reducing the number of vehicles on the road. This shows that a great concern should go towards the expansion of high- capacity public transportation system like introduction of light rail, heavy rail, road bus transit, and high occupancy vehicles lanes, which coupled with better management of the existing road network and traffic management. We need therefore to have a clearly defined transport management technology to challenge the mobility issues of the city. Grade Crossing is a location where a public highway, road, street, or private roadway, including associated sidewalks, and pathways, crosses railroad tracks at grade (same level as the street). The aim of this thesis is to encourage grade crossing safety and reduce highway traffic delay. The safety of grade crossing can be promoted by removing those vehicles detected on the railroad tracks before the arrival of trains using CCTV camera by image processing technology. Reduce highway traffic delay by proper managing the phase sequence of the intersection. A system model is proposed and developing with the system. The optimization will be implemented into two steps. The first step, the delay function is approximated and represented by artificial neural network. Secondly optimization will be applied based on Levenberg-Marquardt optimization.

We use different approach, instead of protecting grade crossing manually and showing the hostility to the highway drivers, we could develop an advanced traffic management system smart enough to control the traffic near grade crossings. In such a system, we could incorporate grade crossing information into traffic control and prevent the queue from backing onto the railroad tracks. Preemption of the traffic signal at/near a grade crossing is such an alternative to target safety improvement. Artificial neural network is design for both train arrival time at grade crossing and forecasting of traffic signal phase length at intersection. MATLAB programing is applied for the designs simulation. From the simulation result the network is optimized by decreasing MSE of train arrival time and traffic signal phase length prediction by 2.2696×10^{-19} and 8.338×10^{-9} respectively. Image processing is applied for obstacle detections on grade crossing by the concept of image segmented in matrix form.

Key Words: Bistatic radar, artificial neural network, transition preemptions strategy, image processing, MSE, CCTV and grade crossing

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Table of Contents

Abstract	i
List of Figure.....	vi
List of Table	viii
Acronyms	ix
Chapter One	1
1. Introduction.....	1
1.1 Motivation and Back Ground.....	1
1.2 Statement of the Problem.....	3
1.3. Objectives	4
1.3.1 General Objective.....	4
1. 3.2 Specific Objectives.....	4
1.4 Methodology	4
1.4.1 Literature Review	4
1.4.2 Data Collection.....	4
1.4.3 System Designing.....	5
1.4.4 Simulation	5
1.5 Literature Review.....	5
1.6 Thesis Limitation	7
1.7 Thesis Organization	7
Chapter Two.....	9
2. Grade Crossing System Technology.....	9
2.1. Train Detector Technologies.....	9
2.1.1 First Generation Technologies.....	10
2.1.1.2 Conventional Detection Systems	10
2.1.1.3 Inductive Loop Detectors	10
2.1.2 Second Generation Technologies	10
2.1.2.1 Sonic.....	10
2.1.1.2 Radar	11
2.1.1.2.1 Classification of Radar.....	11
2.1.1.2.2 The Characteristics of the Radar System.....	13
2.1.3 Third Generation Technologies	14

2.1.3.1 AVI/Radio Frequency	14
2.1.3.2 Gps	14
2.2. Forecasting Train Arrival Time	15
2.2.1 Historical Average.....	15
2.2.2 Regression Models	15
2.2.3 Kalman Filtering Models	15
2.2.4 Machine Learning Models	16
2.3 Grade (level) Crossing (LC)	16
2.3.1 What is Obstacle/Target Detection?	19
2.4 Closed-Circuit Television (CCTV) for Obstacle Detection.....	20
2.4.1 Wireless Camera Systems.....	21
2.5. Transition Preemption Strategy (TPS).....	21
2.6 Over View of AALRT.	23
Chapter Three.....	25
3 System Modeling	25
3.1 Chapter Overview	25
3.2 Grade Crossing Obstacle Detection System Using CCTV Surveillance	26
3.3.1 Obstacle Detection Using Image Processing	29
3.3.2 Monitoring Equipment	29
3.3.3 VMS (Variable Message Signs) and Preemption Signal Control Unit.....	29
3.4. Algorithm and Methodology for Obstacle Detection Using Image Segmentation	30
3.5. Methodology for Image processing	30
3.6. Radar Design for Train Detection.....	35
3.6.1 Radar Detector	35
3.6.2 Bistatic radar	36
3.6.3 Mathematical Modeling for Bistatic Radar for Train Detection.....	36
3.6.4 Bistatic Radar Range Equations.....	38
3.6.5 Bistatic Doppler Shift	41
3.6.6 Radar Cross Section (RCS).....	43
3.7 Arrival Time Prediction Using Artificial Neural Network.....	47
3.7.1 Network Architecture.....	48
3.7.1.1 Feed forward Networks.....	49

3.7.1.2 Feedback (Recurrent) Networks.....	49
3.7.2 Optimization of Neural Network for Error Minimization	50
3.7.2.1 Levenberg-Marquardt Optimization	51
3.7.3 ANN Design for Arrival Time Prediction	53
3.8 Transitions Preemptions Strategy Algorithm.....	55
3.8.1 Preemption Sequence	56
3.8.2. Timing of track clearance.....	57
3.9 Traffic Signal Design.....	62
3.9.1 Phase design for Adey Ababa Intersection	62
Chapter Four	79
4. Results and Discussion	79
4.1 Simulation of Artificial Neural Network	79
4.1.1 Simulation of Artificial Neural Network for Train Arrival Time Prediction.....	79
4.1.2 Simulation of Artificial Neural Network for Traffic Signal Phase Length Prediction	91
4.2 Simulation of Image Processing	98
4.3Simulation of Radar	105
Chapter five.....	106
Conclusion and Recommendation	106
5.1. Conclusion	106
5.2. Recommendation	107
Reference	108
Annex	112

List of Figure

Figure 2.1 Obstacle Detection Systems without Barrier [27]	19
Figure 3.1 Show the High Level Map of the Grade crossing system	25
Figure 3.2 Shows System Architecture that Employs Level Crossing System at Grade Crossings	26
Figure 3.3 Flow Chart Detections of Obstacles	32
Figure 3.4 show Flow Chart Monitoring train	34
Figure 3.5 Shows Geometry Bistatic Radar.....	39
Figure 3.6 Shows Direct Path and Reflected Path Channel.....	45
Figure 3.7 Passive Radar Signal Processing Scheme for Target Detection.....	46
Figure 3.8 Artificial Neural Networks Architecture	48
Figure 3.9 Input Output Relationship of ANN	49
Figure 3.10 Design of Artificial Neural Network.....	54
Figure 3.11 flow chart of ANN.....	55
Figure 3.12 Transition Preemption Variables	56
Figure 3.13 Flow Chart of TPS Algorithm	57
Figure 3.14 Advance Preemptions	59
Figure 3.15 Geometry of Adey Ababa Grade Crossing.....	60
Figure 3.16 Show Grade Crossing and Station are Near Each other for Adey Ababa Intersection	61
Figure 3. 17 Show Multistatic Radar Setup	61
Figure 3.18 From Sarisabo to Kadiso and Saris Adisu Sefre and Left Turn	63
Figure 3.19 From Nifasilk to Saris Abo, Behre Tsiga and Left Turn.....	63
Figure 3.20 From Behre Tsiga to Kadiso, Sarise Adisu Sefre and Sarise abo	63
Figure 3.21 From Sarise Adisu Sefre to Behre Tsiga, Kadiso and to Saris Abo	63
Figure 3.22 Traffic Signal Phase Sequence at Adey Ababa Grade Crossing	64
Figure 3.23 Traffic Saturation [45].....	67
Figure 3.24 Shows Hardware System Diagram.....	78
Figure 4. 1 Simulation Results for ANN Input	81
Figure 4.2 Simulation Results for ANN for Train Arrival Target	81
Figure 4.3 Creating Networks for 10 Numbers of Neuron	82
Figure 4.4 Input-Output Structure of Artificial Neural Network Model	83
Figure 4.5 Simulation Result of Initial Weights Value for Ten Number Neural.....	83
Figure 4.6 Initial Weight Value before Training Start for Layer One	84
Figure 4.7 Initial Bias Values before Training Start for Layer Two	84
Figure 4.8 Simulation Result of Bias for Layer Two.....	85
Figure 4.11 Simulation Result of Weight Value after a Network is Trained for Layer One.....	85
Figure 4.12 Simulation Result of Weight Value after a Network is Trained for Layer Two	85
Figure 4.13 Simulation Result of Bias Value after a Network is Trained for Layer One	86
Figure 4.14 Simulation Result of Bias Value after a Network is Trained for Layer Two.....	86
Figure 4.9 Simulation Results for Performances Validation	87

Figure 4.10 Simulation Results for Output-Target Relationship of the Network.....	88
Figure 4.15 Input-Output Structure of Artificial Neural Network Model for Twenty Networks.	88
Figure 4.16 Simulation Results for ANN Performance after training	89
Figure 4.17 Simulation Results for Output-Target Relationship of the Network for Twenty Neural.....	89
Figure 4.18 Input-Output Structure of Artificial Neural Network Model for Thirty Networks ...	90
Figure 4. 19 shows Performance and output-target relation for 30 Networks.....	91
Figure 4.20 Inputs for Volume of Vehicles	92
Figure 4.21 Target Value for Traffic Signal Phase Length Predicted Network	92
Figure 4.22 Input-Output Structure of Artificial Neural Network Model	92
Figure 4.23 Shows Mean Square Error of the Network	96
Figure 4.24 Simulation Results of Network Performances	97
Figure 4.25 Show Performance of Network for Traffic Signal Phase Length Forecasting	97
Figure 4.26 Show Flow Chart of Image Processing	98
Figure 4.27 Show RGB Image without Obstacle.....	98
Figure 4.28 Show the Gray Image without Obstacle.....	99
Figure 4.29 Show the RGB with Obstacle.....	101
Figure 4.30 Show Gray Image without Obstacle.....	102
Figure 4.31 PD vs. SNR Simulation Result with Diff PFA.....	105
Figure 5.1 Show Grade Crossing and Road Intersection Interconnected Each Other	107

List of Table

Table 2. 1 radar frequency band	12
Table 2. 2 Simultaneous Preemptions.....	22
Table 2. 3 Advance Preemptions	23
Table 3.1 Bistatic Radar Specification.....	47
Table 3.2 Volumes of Vehicles for Adey Ababa Intersection	67
Table 3. 3 Traffic Volumes per Hour at Adey Ababa Intersection.....	70
Table 3. 4 Shows Cycle Distributions for Phases	71
Table 4. 1 Train Speed Profile from Nifasilk on to Adey Ababa [47].....	80

Acronyms

AALRT	Addis Ababa Light Railway Transit
ANN	Artificial Neural Networks
APWT	Advance Preemption Warning Time
AVI	Automatic Vehicle Identification
CUT	Coordinated Universal Time
CCTV	Closed Circuit Television Cameras
ETA	Estimated Time of Arrival
ERA	European Railway Agency
HRGC	Highway-railroad Grade Crossings
IHRGCs	Intersections near Highway-railroad Grade Crossings
LC	Levy Crossing
LOD	Grade Crossing Obstacle Detection
LOS	Level of Service
LRT	Light Railway Transit
MSE	Mean Square Error
MOV	Measure of Effectiveness
MUTCD	Manual on Uniform Traffic Control Devices
TPS	Transitional Preemption Strategy
NP	Next Phase
N2P	Next two Phase
VC	Vehicle Call

Chapter One

1. Introduction

1.1 Motivation and Back Ground

In Africa, vehicle traffic congestion is a new phenomenon [1]. It has an economic cost on the productivity of the cities' communities and economy. Despite the lower car ownership levels, traffic is congestion becoming more serious problems in a day to day activity of all people in all parts of the Addis Ababa city, specifically, in morning and evening peak hours.

The main reason for traffic congestion is the outcome of insufficient traffic management in the city. Insufficient capacity of the roads, inadequate public transport, fixed working time and illegal on-street parking habit are also the major problems that lead to vehicles traffic congestion in the city [1]. In addition, long travel time or delay to reach destination that affect business users time productivity, increasing fuel consumption, are main impact of vehicles congestion around intersection. It is generally believed that real-time systems respond automatically to the normal traffic conditions are potentially more efficient than clock-based fixed-time.

Transportation structures are very important as significant drive for the growth of both economy and society of any country around the world [1]. The current standard and condition of the Addis Ababa road network is a limitation to the development of an efficient road transport system. The government of Ethiopia starts to implement public transport system to mitigate traffic congestion. Railway transport one of newly constructed public transport system. It had been used as a major freight and passenger transport to the eastern part of Ethiopia from 1917 to 2010. The system comes to existence during the reign of Emperor Menelik II and covers a total of 781km powered by diesel engine and jointly owned by Ethiopia and Djibouti. Great improvement of road network is fundamental in Ethiopia, but with limited connectivity, high cost of transportation and poor quality of service. The mobility need of the country population and the development of transportation system are far from compatibility. Therefore; the country is in need of modern, economic, time saving and long lasting transportation which will ease import export system and result fast development. To this end, the government of Ethiopia has gone on

board on railway system. The main reasons for the renewed interest in the railway are environmental, economical, and safety related issues [2].

But Grade crossings have been identified as a particular weak point in road and railway infrastructure, seriously affecting their safety and traffic congestion. In road and railway infrastructure grade crossing systems requires for high level of safety. Modern Grade crossings have come a long way from the early days of human railway employees waving red flags and shining lanterns to clear railroad tracks of vehicles and pedestrian traffic for oncoming trains. Road users must follow road rules and signs and pay attention to the road environment when approaching rail crossings [2].

Due to the ever growing of transportation, congestions are the main problem of the city. This congestion is expected to be complicated due to introduction of rail way infrastructure in the city. Traffic congestions around grade crossing expected to complicate with the train preemption interrupting regular traffic operations, delay and queue are expected to increase at intersections adjacent to grade crossings [3]. In the signaling design of the Addis Ababa LRT, there is no system of detecting an obstacle to prevent an accident and to control traffic congestion at grade crossing; the responsibility is fallen to the train operator who is driving on sight [4]. But what if an obstacle is there on the Grade crossing, what if he couldn't see farther because it is foggy, night or geomorphic restriction etc. To solve this problem a CCTV camera is installed on the Grade crossing to monitor the states of the intersection. The multilayer perception neural network, bistatic radar for train detection systems are implemented to optimization grade crossing performance. The system is going to be designed and analyzed for its detection performance, reliability, and cost effectiveness. The safety and congestion problems arising from traveler at-grade highway railroad crossings are the focus of the research and means of motivation.

1.2 Statement of the Problem

In the signaling design of Addis Ababa LRT project, manual driving mode is adopted to control the running speed of the train and the crossing signaling system will be set with barriers [21][46]. This shows that the only way of protecting cars from getting into the Grade crossing is the coordinated traffic lights with barriers and there is no way of informing to the train operator if there is an obstacle in the Grade crossing. This may lead to a fatal accident, long highway traffic and also to a low performance of train speed operation due to the different aspects of vehicle and pedestrians driver errors. Currently there is no mechanism to coordinate railway signaling system with road traffic signaling system for grade crossing intersection.

Another problem of the current traffic control system around the Grade crossing system is the neighboring intersection is not coordinated each other. Due to this the movements at adjacent intersections can be blocked. In that case, an elongated queue will not only block the traffic at nearby intersections, but also will result in the slowdown or full termination of the mobility of the intersection, or even the entire roadway network in proximity to the railroad. Severe congestion and consequential delay may cause a failure of roadway system operations and increase negative environmental impacts.

To overcome these limits, this thesis proposes better Grade crossing system technology signaling system to balance the above disadvantages of existing system and make persons (train or vehicle drivers, pedestrians, and etc.) more secure. The proposed level cross signaling system informs vehicle drivers and pedestrian that train is approaching and can provide better highway traffic management. The other important feature of this system is that it also inform train driver about the status of Grade crossing by CCTV camera.

1.3. Objectives

1.3.1 General Objective

In general, the objective of this thesis is to investigate grade crossing safety and reduce highway traffic delay around grade crossing based on optimization technique.

1.3.2 Specific Objectives

Specifically; the aim of this thesis is to:-

- 1) Investigate weakness and strength of the current AALRT level cross signaling system.
- 2) Investigate and determine a proper preemption phase sequence to promote highway, rail grade crossing (HRGC) safety
- 3) Avoiding congestion on highway sides based on appropriate arrival time prediction. Safety promoted by de-queuing those vehicles detected on the railroad tracks before the arrival of trains.
- 4) Detection of any obstacle in the Grade crossing Using CCTV surveillance.
- 5) Propose on how to optimize traffic and ensure safety at Grade crossing.
- 6) Evaluate and compare the performance of proposed system with existing one.

1.4 Methodology

1.4.1 Literature Review

In this study different related research works review, this includes browsing internet, reading book, publications and journals related to Optimizing Traffic Network around Railroad Grade Crossing and related works, having brief understanding of the problem, collection of necessary information which is essential to achieve the objective of this thesis work.

1.4.2 Data Collection

Collecting the information on the intersection (record the road width, road properties, signal timing, queue length, traffic flow in various directions and time delay through surveying), then the collecting data inputting into the artificial neural network traffic management system or MATLAB to establish the objective of the work.

Data collection is a vital element of the traffic signal timing process, therefore it is important to develop a data collection plan. The data should include, but is not limited to:

- Intersection geometry
- am peak hour
- pm peak hour
- Off peak period or any other special traffic period and existing traffic signal system. This information can be used to determine the phasing/timing capabilities at a selected railroad intersection.

1.4.3 System Designing

It involves using artificial neural network, bistatic radar, traffic signal system and TPS algorithm the Grade crossing system and study for their component relationship.

1.4.4 Simulation:

To satisfy the objective of this thesis MATLAB will be used for radar, CCTV camera and artificial neural network for evaluation purpose.

1.5 Literature Review

In the investigation for literature, we have read different thesis. Some of the researches conducted on the area of train-to-ground communication architecture and associated service and related to this work are briefly reviewed below.

Pankaj Jain, Dr. Mohan Awasthy [7].They implements Automatic Obstacle Detection using Image Segmentation. This thesis contribution for the system aims at the path detection problems for the mobile system or robot system. The obstacle is detected for mobile systems is processed by first segment the obstacle containing image and find the obstacle from that obstacle containing image.

Zhanget [8] using GPS detector developed the signal optimization under rail crossing safety constraints (SOURCAO) model for optimizing traffic network signals at Grade crossing. The author used an inference engine to choose a preemption phase sequence that help grade crossing safety. A neural network and Quadratic programming algorithm also used to find the optimized phase length and minimize the total delay. Using the mentioned technique decreased the average network delay by 13.8% and improved safety. But the systems not consider pedestrians safety.

Cho and Rilett. [9] Using Doppler radar for train detection system and modular artificial neural network for arrival time prediction. Based on this he developed an improved transition preemption strategy (ITPS) algorithm to overcome the limitations of standard preemption (SP) and the transition preemption strategy (TPS), such as not considering pedestrian and driver safety or the impact made on intersection operational efficiency by having only one detector with limited prediction capability. The ITPS algorithm as long as more time to the blocked phases during the preemption mode than phases served during the preemption mode, thus improving the intersection performance and reducing clearance phase at the arrival of preemption. This algorithm improved the safety and manage traffic signal phase. The delay is decreased by 5.4%.

Bullock et al. [10] investigated track clearance performance measures from fixed 15-second, fixed 20-second, and extensible track clearance green times at railroad-preempted intersections. This study measured the preemption trap performance by counting how often a track clearance green phase failed to completely clear the link between the tracks and the intersection during a preemption event. The number of opportunities for a preemption trap to occur was reduced from 33 to 3 when the fixed track clearance interval was increased from 15 to 20 seconds. The opportunities for a preemption trap to occur were zero when the extensible track clearance interval was used. This study did not consider the traffic delay, though the delay increased as the track clearance interval increased.

Kimet al. [11] used a GA to determine optimal sensor locations (sensor placement and number of sensor using simulation) for the accurate estimation of travel time on a freeway. The study used a GA with VISSIM, a microscopic simulation model, to estimate travel time from selected sensor locations. This approach estimated average travel time with errors within 10% and performed better than the conventional approach that used fixed point sensors.

Jacobson, M, Venglar, S, and Webb. [12]. Developed transition preemption strategy algorithm by the Texas Transportation Institute (TTI) to serve the purpose of avoiding unnecessary signal interval length. Due to ever growing of the traffic technology TPS was developed for vehicle and pedestrian safety using earlier preemption warning time obtained from a train detection technology to transmit early warning preemption to grade crossing traffic controller for better traffic facility.

1.6 Thesis Limitation

This work is limited to

- 1) AALRT Adey Ababa grade crossing
- 2) Single intersection, not consider inter connected the nearby road intersection
- 3) Radar detector only for train detections.
- 4) Vehicles detector sensor is not consider for this work
- 5) The system is not field tested due to time constraint and cost

There are also limitations on the thesis, mainly on time restriction to collect actual data like traffic density, traffic flow (volume). Therefore, to implement the proposed one have to verify all the collected data and refine the assumptions taken. Assumptions adapted on this thesis are the state of vehicle condition; road parameters and drivers behavior remains constant. Additionally the proposed systems not consider detail designs of the radar.

1.7 Thesis Organization

This thesis work is organized in five chapters. The first chapter includes introduction which provides clear information about the background of the thesis work, statement of the problem, literate review, research method, and limitation of the thesis.

Chapter two is about current technologies of train detection technology, arrival time prediction module technology and TPS technology. This section provides clear understanding of Grade crossing system technology that can provide optimization of traffic network around grade crossing.

Chapter three is about Design of the Grade crossing system technology, System Architecture, System structure, Required Hardware components and Design of the software procedures of the system. In this chapter the design of bistatic radar for train detections, artificial neural network for arrival time prediction and transition preemptions algorithm for traffic signal management and its integration railway signaling system. Chapter four is about MATLAB simulation, after having the simulation result, we discussed what the simulation result is to mean. The final chapter is recommendation and conclusion. Here, conclude the thesis work based on the result obtained and discussed in chapter four. Further recommendation for the development of new

model or improvement of the result in this thesis is suggested. Base on the recommendation interested research group can upgrade this work to more than one step forward.

Chapter Two

2. Grade Crossing System Technology

In the previous chapter, introductions, objective of the work and literature review related to optimization of traffic network around grade crossing were briefly discussed. In this chapter different technology related to this work and over view of AALRT is introduced. In section 2.1 train detector technologies from first generation to third generation is discussed. In section 2.2 forecasting technology like historical average, regression, kalman filtering and machine learning will discussed. The remaining section discuss about grade crossing, CCTV surveillance, TPS and overview of AALRT.

2.1. Train Detector Technologies

Travel time forecasting is an important part of dynamic traffic transportation system. Dynamic traffic data collection is the precondition of forecasting. Many traffic data collection methods have been accepted, such as loop inductive vehicle detector, radar detector, video detector, GPS and so on. In this thesis, we discuss a travel time forecasting method based on Bistatic radar sensor detector technology.

Once a train is detected, the detection system sends an electric signal to the traffic signal controller to activate the preemption sequence. A number of detection technologies have been developed for this task. The most common detector system uses the tracks as part of a circuit. When no trains are present, a uniform signal in the form of white noise is sent to the controller. When a train is present, the circuit is completed and a different signal is sent to the controller. Because these systems send only detection information to the traffic signal controller, they can only measure the presence of a train and are so referred to as first-generation technology. In contrast, second-generation technologies are capable of providing estimated time of arrival (ETA) information in addition to basic detection information. Generally, these systems are not part of the railway operations and are installed adjacent to the railway. Third-generation technologies go one step further to provide continuously updated train information typically acquired using on-board global positioning systems (GPS) [11][13].

2.1.1 First Generation Technologies

2.1.1.2 Conventional Detection Systems

In these systems, the rails are used as conductors of energy supplied by a battery. The relay remains energized as long as no train is present in the circuit. When a train enters the circuit between the battery and the relay, the train axles shunt the circuit, causing the relay to de-energize. When the relay is de-energized, automatic warning devices are activated and the traffic signal controller near the intersection receives the notification that a train is approaching through a separate interconnection circuit [11] [14].

2.1.1.3 Inductive Loop Detectors

Inductive loop detectors are currently being used in a four-quadrant gate system to detect vehicles that may be locked in between the gates. The use of this system is being evaluated as a means of providing a more fail-safe design for four-quadrant gate systems. Loop detectors have also have been applied to detect transit trains. Several tests revealed that burying these detectors under the track ballast leads to a decrease in the effectiveness of the detector. For this reason, a loop detector that can be mounted directly on the tracks was developed. Systems of three or four detectors are often applied to detect a train approaching a HRGC and activate a preemption of the traffic signal at the IHRGC. However, this technology has similar limitations to the conventional track circuitry approach [15].

2.1.2 Second Generation Technologies

2.1.2.1 Sonic

Sonic waveform detectors have been used to detect trains in several train priority systems. Originally these systems were developed to identify the siren from an emergency vehicle so that the traffic signal controller could provide a green signal for that vehicle when it approaches the intersection. These systems have been modified for trains so that a silent emitter is placed in each locomotive to emit sonic waves that the receiver can detect but are undetectable to the human ears. When the wave is detected, a “preemption” call is sent to the traffic signal controller to activate the preemption sequence. The emitter can be disabled by the driver of the train if preemption is not necessary at the intersection. The major disadvantage of this system is that trains can be detected only within a limited distance of a HRGC. Although the detector can be placed farther away from the crossing to provide a longer warning time, the

actual warning time is a function only of the location at which the emitter in the locomotive emits sonic waves [17].

2.1.1.2 Radar

The word radar is an abbreviation for **R**adio **D**etection and **R**anging. In general, radar systems use modulated waveforms and directive antennas to transmit electromagnetic energy into a specific volume in space or an area on the ground to search for targets (Obstacle) [17]. The basic principle of radar operation is transmission of the electromagnetic waves across the monitored area. When an object enters the zone of interest it interrupts the radiation the portion of which is reflected back to the antenna.

2.1.1.2.1 Classification of Radar

Radars can be classified as generally monostatic radar and bistatic radar but specifically ground based, airborne, space borne, or ship based radar systems. They can also further classified into numerous categories based on the specific radar characteristics, such as the frequency band, antenna type, and waveforms utilized. Another classification is concerned with the mission and/or the functionality of the radar. This includes: weather, acquisition and search, tracking, track-while-scan, fire control, over the horizon, terrain following, and early warning radar. Radars are most often classified by the types of waveforms they use, or by their operating frequency. Considering the waveforms first, radars can be Continuous Wave (CW) or Pulsed Radars (PR). CW radars are those that continuously emit electromagnetic energy, and use separate transmit and receive antennas.

Pulsed radars use a train of pulsed waveforms (mainly with modulation). In this category, radar systems can be classified on the basis of the Pulse Repetition Frequency (PRF) as low PRF, medium PRF, and high PRF radars. Low PRF radars are primarily used for ranging where target velocity (Doppler shift) is not of interest. High PRF radars are mainly used to measure target velocity. Continuous wave as well as pulsed radars can measure both target range and radial velocity by utilizing different modulation schemes [16].

The following Table has the radar classifications based on the operating frequency.

Letter Designation	Frequency(GHz)
HF	0.003 - 0.03
VHF	0.03 - 0.3
UHF	0.3 - 1.0
L-band	1.0 - 2.0
S-band	2.0 - 4.0
C-band	4.0 - 8.0
X-band	8.0 - 12.5
Ku-band	12.5 - 18.0
K-band	18.0 - 26.5
Ka-band	26.5 - 40.0
V-band	46-56
W-band	56-110

Table 2. 1 radar frequency band

High Frequency (HF) radars utilize the electromagnetic waves reflection off the ionosphere to detect targets beyond the horizon. Very High Frequency (VHF) and Ultra High Frequency (UHF) bands are used for very long range. Because of the very large wavelength and the sensitivity requirements for very long range measurements, large apertures are needed in such radar systems. Radars in the L-band are primarily ground based and ship based systems that are used in long range military and air traffic control search operations. Most ground and ship based medium range radars operate in the S-band. Most weather detection radar systems are C-band radars. Medium range search and fire control military radars and metric instrumentation radars are also C-band. The X-band is used for radar systems where the size of the antenna constitutes a physical limitation; this includes most military multimode airborne radars. Radar systems that require fine target detection capabilities and yet cannot tolerate the atmospheric attenuation of higher frequency bands may also be X-band. The higher frequency bands (Ku, K, and Ka) suffer severe weather and atmospheric attenuation. Therefore, radars utilizing these frequency bands are limited to short range applications, such as police traffic radar, short range terrain avoidance, and terrain follows radar. Milli-Meter Wave (MMW) radars are mainly limited to very short range Radio Frequency (RF) seekers and experimental radar systems [17][18].

2.1.1.2.2 The Characteristics of the Radar System

1) Ability to Detect Moving and Stopped Vehicles

Among the type of radar system millimeter wave or radar sensors are based on Frequency Modulated Continuous Wave (FMCW) rather than just Continuous Wave (CW) emissions, they do not rely on Doppler-shift detection and are therefore capable of detecting stopped vehicles, fulfilling another important objective of a radar-based solution. Differentiation from objects that are always stationary (poles, buildings, etc.) is accomplished by sophisticated algorithms that continuously 'learn' the sensors' environment and begin to ignore objects that have remained stationary for longer than 15-60 minutes (min). Long Life, High Mean Time between Failures. Calculated Mean Time Between Failures (MTBF) for the radar sensor is greater than 10 year is proven [16] [19].

The main advantages of the MMW range are:

Short wavelength: the component sizes are reduced compared to those in the microwave band. This makes them suitable for mobile platforms such as aircrafts, helicopters, cars or even small robotic platforms. It is also possible to achieve lower beam width which results in better resolution. Wide bandwidth: Investigating atmospheric absorption for horizontal propagation over 300 GHz of bandwidth including the Milli-Meter Wave (MMW) radars band represents that the principal windows exist at 35, 94, 140 and 220 GHz with extremely large available bandwidths around each [16]. This has a number of advantages:

- High data rate for communication systems,
- High resistance to jamming since wide bandwidth is available,
- Very high range resolution for tracking and target detection,

Increased recognition capability of slowly moving target due to the high Doppler frequency Low sensitivity to environmental characteristics. Atmospheric absorption and attenuation due to inclement weather condition such as fog, dust or smoke are much lower Compared to optical and IR frequencies [16].

Radar-Based Detection System Cost

Because of the non-embedded nature of the radar vehicle detection system, installation time and labor is considerably less than for an inductive loop system.

New Radar Detection System Cost Estimate

The cost of a new inductive loop detection system for a dual-track, six-loop system is estimated to be \$36,680. In contrast, installation of a dual radar system to detect vehicles within the same type of crossing is estimated to be \$27,500, or 25 percent less than the cost for a loop based system. Compared to the mentioned technology CCTV is a very cheap technology for obstacle detections, estimated to be \$1200[33]. For this thesis work proposed radar (bistatic) for train detections and CCTV for obstacle detections for the selected site.

2.1.3 Third Generation Technologies

2.1.3.1 AVI/Radio Frequency

Automatic vehicle identification (AVI) systems have been applied in a number of train applications. An electronic “identification tag” containing information about the train is installed in all or a subset of the vehicles on the train. AVI readers, which are typically radio frequency antenna, are located at various locations along the train right of way. As the train passes the readers, the information from the identification tags is read. Therefore, this system provides more precise train position information than the systems discussed previously. However, because the train information is collected only at discrete locations, only space mean speed between the receiver locations can be calculated. Thus, speed change may not be accurately accounted for when predicting train arrival time, especially when the distance between the receiver locations is long [17] [20].

2.1.3.2 Gps

A global positioning system uses satellites orbiting the earth to collect information on the train as it approaches the HRGC. The GPS device is located on the lead locomotive. Using this device and the satellites, the train’s position on the tracks, direction of travel, and train speed at any point along the approach to the HRGC is obtained. Because the information is updated continuously, the forecast train arrival time can be updated continuously. Even though this

system is superior to any other system for collecting more accurate train information, there are a number of issues. For example, the safety and operation of the system is entirely dependent on

- 1) Access to U.S. military GPS satellite information

- 2) The ability of GPS receivers on trains to remain in relatively constant radio communication with satellites this may not be possible [21]. Since GPS technology cannot manage locally due to this reason rise security issue to apply this technology.

2.2. Forecasting Train Arrival Time

Better forecasting of train arrival time is essential if improved IHRGC preemption strategies are to be developed. The transition preemption methodology requires a forecast of the train arrival time that must occur sooner than required under the normal preemption strategy. To provide the earlier forecast train arrival time, forecasting arrival time tools has to be designed in thesis. The most widely-used train travel time prediction technology models can be classified into four categories, which are discussed below [22].

2.2.1 Historical Average

Historic data-based average prediction models give the current and future travel time from the historical train travel time of previous journeys, and the current traffic condition is assumed to remain stationary. Therefore, a model of this kind is reliable constant train speed are consider. For variable train speed profile cannot be implemented [22].

2.2.2 Regression Models

Regression models predict and explain a dependent variable with a linear function formed by a set of independent variables. Unlike historical data-based prediction models, these are able to work satisfactorily under unstable traffic condition. Regression models are unstable and complex as the number data is increasing [39].

2.2.3 Kalman Filtering Models

Karman filtering models has sophisticated mathematical representations (e.g., linear state-space equation) and the potential to adequately accommodate speed fluctuation with time-dependent parameters. These models have been used extensively for predicting bus arrival time. Their basic function is to provide estimates of the current state of the system, but they also serve as the basis

for predicting future values or for improving estimates of variables at earlier times. This model has limitation when data become large [22] [39].

2.2.4 Machine Learning Models

Machine learning methods such as Artificial Neural Networks (ANN) can deal with complex relationships between predictors that can arise within large amounts of data, process non-linear relationships between predictors, and process complex and noise data. These models can be used for prediction of travel time without explicitly addressing the (physical) traffic processes. The ANN method is classified under this category. ANNs recently have been gaining popularity in predicting train arrival time because of their ability to solve complex non-linear relationships [31].

Artificial Neural Networks have the following potential advantages for intelligent control:

- ❖ They learn from experience rather than by programming.
- ❖ They have the ability to generalize from given training data to unseen data.
- ❖ They are fast, and can be implemented in real-time.

Additionally ANNs have advantages over many other techniques since they are able to simulate non-linearity in a system. They can also effectively distinguish relevant from irrelevant data characteristics. Moreover, they are a non-parametric technique, which means that ANN models do not necessarily require the assumption or enforcement of constraints [31]. A disadvantage of ANNs, however, is that the optimal form or value of most network design parameters (such as the number of neural in the hidden layer) can differ for each application and cannot be theoretically defined, which is why they are commonly determined using trial-and-error approaches [32]. This is explained in result and discussion part of this thesis work.

Due to the mentioned advantage Artificial Neural Networks is implemented for this thesis work for train arrival time and traffic signal phase length forecasting at Adey Ababa intersection.

2.3 Grade (level) Crossing (LC)

The definition of grade crossings is "an intersection of a road and a railway on the same level, where roads and rail include different operator and responsibilities". As a result, Grade crossing protection is the common task of all those involved in the operation and oversight of roads and

railways. Grade crossings come under the purview of laws, regulations, administrative provisions and directives.

ERA (European Railway Agency) classified LCs into two groups: active LCs (group A) and passive LCs (group B) (Fig.2.1).

In the case of an automatic active LC (A.1 in Fig.2.1), these devices are activated by the approaching train. Manual active LCs (A.2) is activated by humans when there is no railway signal interlocked with control train movements. In the case of passive LC (B in Fig.2.1) there is no warning system and/ or protection system showing when it is unsafe for the user to cross the LC. Select project carried out an analysis of accident statistics by comparing operational risk according to the different LC types. As a basis for comparison, seven basic LC types as defined per ERA were taken into account. The individual risk for road LC user was compared as per the different LC types. As basis for operational risk comparison, the seven Grade crossing types defined by ERA have been taken. However, only five of these types could be identified (the A1.1 and A2.2 were not clearly identified) when analyzing the 66 collected national Grade crossing types of countries involved in SELCAT project. Risk considering the accidents (Acc), fatalities (Fat) or injuries (In) at LC of a particular type are covered deeply [33].

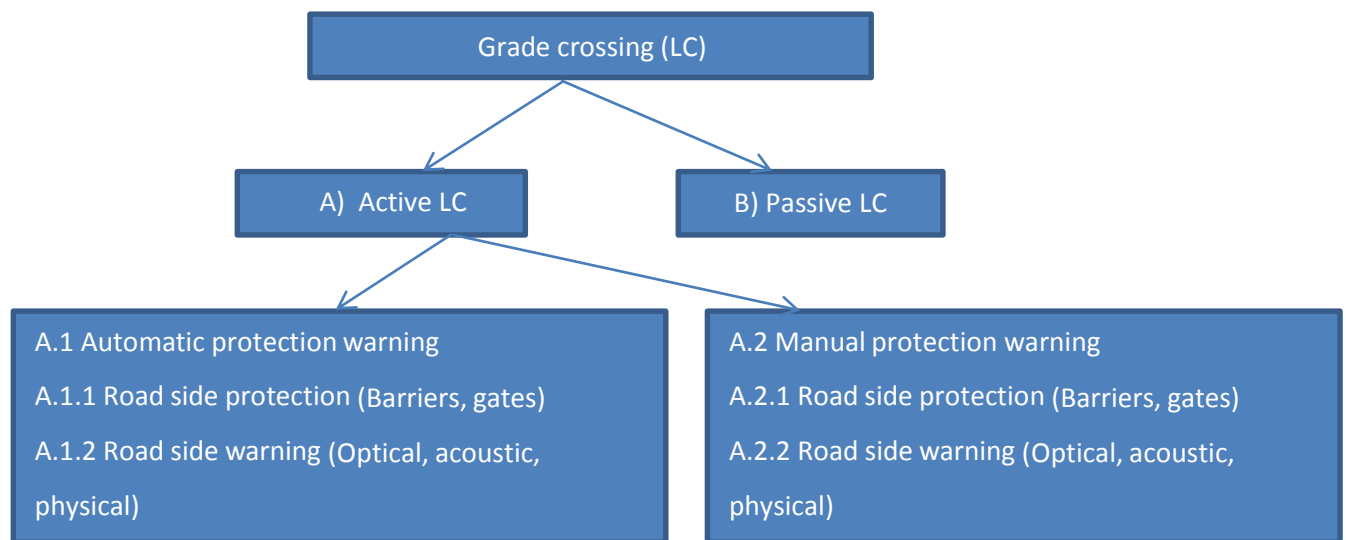


Figure 2.2 Grade Crossing (LC) Types Classified by ERA

For the European countries involved in Safer European Level Crossing Appraisal and Technology (SELCAT), the highest risk applies to LCs with warning lights (A 1.2), followed by

the automatic LC with warning lights and barriers (A 1.3). Therefore, the main conclusions drawn from the statistics analysis by the European Conference of Transport Research Institutes (ECTRI) in 2008 are as follows:

Safety at LCs is a definite problem for rail companies as they have no control over actions of road vehicle drivers and pedestrians at LCs and as it represents 29% of total accidents in a rail system compared to the road sector which represents 0.9% of total accidents. Clearly, while LCs represents a significant risk area for the safe operation of a rail network, this is in fact only a small element of the overall road safety issue.

The highest operational risk in Europe is attributed to automatic LCs fitted with warning lights but without barriers. The second highest risk is attributed to automatic LCs with warning lights and with barriers.

The results of investigations into causes of LC accidents have identified inappropriate or inadequate human behavior as the main source of the problem. Human factors play an important role for both the road and the rail. Violations of traffic regulations, disregard of warning signals, and trespassing by road vehicle drivers and pedestrians contribute to most of the fatalities. In terms of rail, staff with safety related responsibilities (i.e. manually operated LCs, warnings given by train drivers, supervision, and fallback operations) are particularly vulnerable to human errors [33]. Therefore, design of new technological solutions which will help increase people's awareness of risk at LCs, the operational speed of the train and it will minimize the impact of intentional and unintentional hazardous human behavior. The solution suggested for these problems on the LC is to use the active and automatic warning system in addition to the automatic train braking system. Since LC is a risky part of rail transportation system, it has got to be protected using reliable, fast and cost-effective means of technology to prevent accident before happening or to minimize the risk. In this thesis the proposed means of accident prevention on the LC of Addis Ababa LRT is Active LC with Automatic warning system and automatic train braking system using the CCTV camera to detect obstacle and the train. This system connects both the train control system and the highway traffic signal system. It would control the traffic signals and provide information to motorists on roadside variable message signs. Then Obstacle detection systems appear as a breakthrough solution to improve LC safety and lower the number of fatalities.

2.3.1 What is Obstacle/Target Detection?

It is important to understand what is meant here by ‘obstacle/target detection’: in this context it is a means of identifying the presence of an object on a Grade crossing as the train approaches and/or the presence of train which is approaching to the LC. So that by providing information to guide a suitable response collision can be avoided or the consequences minimized. Obstacle/target detection is not just about the type or technology of the detector; what is done with the output is also critical for an effective system. At present there are no obstacle detection systems in operation at grade crossings in Ethiopia. However, there is growing use of these systems in other countries. Ideally, an obstacle detection system would:

- ❖ Improve safety at Grade crossings for all users (road and rail)
- ❖ Cause no or minimal delays for both train and road users
- ❖ Be reasonable in terms of costs to install, operate and maintain
- ❖ Be practical to use and maintain

Given the definition used at the start of this section for obstacle detection, there are three main components (see Fig.2.2) that can be used to describe the configuration of such a system at grade crossings:

- ❖ Detection: determining whether or not the crossing is clear
- ❖ Communication: a means of informing a person or system the need to take action
- ❖ Response: the action taken to mitigate collision [27]

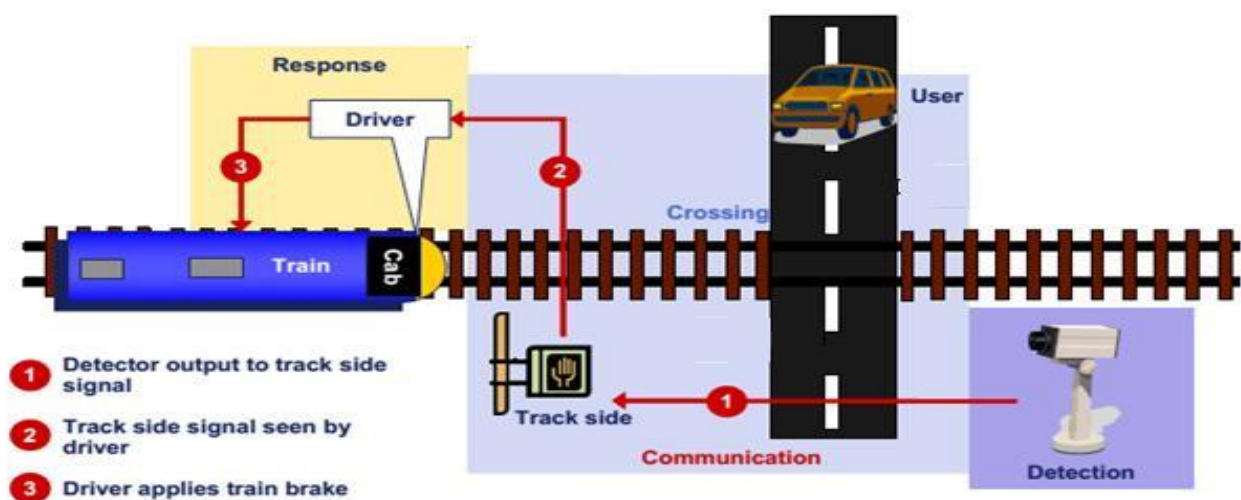


Figure 2.1 Obstacle Detection Systems without Barrier [27]

The detection of vehicles, pedestrians or other obstacles approaching a LC requires the setting up of detectors. Object detection technologies have been developed and implemented, with varying degrees of success and satisfaction. These have included technologies that utilize infrared light, video analytics, microwave or bistatic radar, and buried (embedded) technologies such as magnetometers and inductive loops. The technology is discussed before train detector technology during the discussion in the previous section.

Obstacle detectors can be divided into two major categories: conventional and advanced. Conventional obstacle detection has been used to prevent crashes between trains and vehicles (optical beam, sonic detection, inductive loop). Obstacle detection systems under advanced category are Radar Method and video imaging (CCTV) [28]. CCTV surveillance is applying for Grade crossing obstacles detections.

The technology discussed in the section 2.2.1. And 2.1.1.2 for train detection technology can apply directly to obstacle detections for prevention of accident on LC. But for this work a CCTV camera is applied for obstacle detection.

2.4 Closed-Circuit Television (CCTV) for Obstacle Detection

Closed-circuit television (CCTV), also known as video surveillance, is the use of video cameras to transmit a signal to a specific place, on a limited set of monitors. It differs from broadcast television in that the signal is not openly transmitted; it may employ point to point (P2P), point to multipoint, or mesh wireless links. Though almost all video cameras fit this definition, the term is most often applied to those used for surveillance in areas that may need monitoring such as banks, traffic monitoring, airports, military camp, and Grade crossing monitoring [27].

In industrial plants, CCTV equipment may be used to observe parts of a process from a central control room, for example when the environment is not suitable for humans. CCTV systems may operate continuously or only as required to monitor a particular event. A more advanced form of CCTV, utilizing digital video recorders (DVRs), provides recording for possibly many years, with a variety of quality and performance [17][27].

2.4.1 Wireless Camera Systems

Wireless security cameras consist of wireless transmitter and receiver antennas and allow closed circuit cameras or IP security cameras to transmit a wireless signal using a 5.8 GHz signal up to 4 miles. These systems are used in situations where cable searching is not practical or is cost prohibitive [29].

2.5. Transition Preemption Strategy (TPS)

The Manual on Uniform Traffic Control Devices (MUTCD) states that “On tracks where trains operate at speeds of 20 mph or higher, circuits controlling automatic flashing light signals shall provide for a minimum operation of 20 seconds before arrival of any train on such track” [30]. The Association of American Railroads (AAR) Signal Manual states that “warning time devices shall operate for a minimum of 20 seconds before a train operating at maximum speed enters the crossing” [8].

To provide the appropriate warning time, the location of the train detector is critical. In North America, the detector location is based on a minimum warning time (MWT). The recommended value from the MUTCD and the AAR Signal Manual is 20 seconds. The product of the fastest train expected and the minimum warning time is used to identify detector location as shown in Equation 2.1 [33].

$$D = V \times W \quad (2.1)$$

Where;

D = Detector location from the crossing (m);

V = Average train speed for the track (m/s); and

W = Minimum warning time provided to crossing users (s).

For our case the average speed of the train near intersection is 20km/hrs. Or 5.55m/sec
Therefore the $W= 180$ second. This is arrival time of the train to travel 1km length. If we apply the constant warning system using the existing technology the train will arrived after 3 minute. It is late. To manage this delay to reasonable value the proposed system design TPS algorithm with radar detector.

Two types of preemption are commonly used in practice: 1) simultaneous preemption, and 2) advance preemption. Under simultaneous preemption, the traffic signal controller starts the preemption sequence at the same time that the railroad crossing warning devices activate, providing at least the minimum warning time. Under advance preemption, the traffic signal controller starts the preemption sequence before the railroad crossing devices activate. Advance preemption is required if the time available under simultaneous preemption is not enough to clear the tracks safely [19].

The time difference between when the traffic signal controller starts the preemption sequence and when the railroad crossing warning devices activate is called the advance preemption time. The highway authority usually requests advance preemption time if the minimum warning time is not enough to clear traffic safely off the tracks. The advance preemption time is zero for simultaneous preemption [17] [8].

The relationship between each element of preemption during simultaneous preemption is shown in Table 2-2, while Table 2-3 shows the same for advance preemption. After the traffic signal controller receives the preempt notification, the right of way must be transferred to traffic in the approach to the intersection crossing the tracks. The required wait time prior to the track clearance phase is termed the right-of-way transfer time. The right-of-way transfer time depends on the controller state. Once the right of way is transferred, the track clearance phase is active. The track clearance green should be provided at least equal to the queue clearance time, which is the time it requires a vehicle stopped on the track to start up and move off the tracks [17].

Railroad warning time			
Warning lights flashing			
Delay(3sec)	Gate descending	Gates horizontal	
Right of way transfer time	Track green	Yellow	Dwell

Table 2. 2 Simultaneous Preemptions

Actual advance preemptions time	Railroad warning time		
Lights	Warning lights flashing		
Gate	Delay(3sec)	Gate descending	Gates horizontal
Right Of Way Transfer Time	Track green	Yellow	Dwell

Table 2. 3 Advance Preemptions

2.6 Over View of AALRT.

Addis Ababa light railway is one of the newly constructing railway transport sector. The LRT Project in Addis Ababa consists of the East-west Line and the South-north Line. The total length of lines is approximately 31km; wherein, the length of shared track section is approximately 2.662km. The main line of N-S line is 16.689km in full length, with the starting point mileage of YCK1+745 and terminal point mileage of YCK18+418. It has the subgrade section about 10.057km in length, the elevated section about 5.977km in length (including a common rail section 2.662km in length), and the underground section about 0.655km in length. There are 22 LRT stations and five of them are shared with East-West corridor. The minimum separation distance between stations is 435 meter; the maximum separation is 1972 meter and the average interval is 775 meter [7] [5].

The full length of main line of the East-west Line is approximately 16.998km. There are 12 Grade crossings between the line of this project and urban roads. The axle counter is arranged at the main track and depot for inspection of position of the train. ACS2000 (a type of axle counter implemented LRT) axle counter is divided into the indoor and outdoor equipment; a wheel sensor is arranged respectively at the starting point and ending point of the track section. It is determining the occupied status of a block is using devices located at its beginning and end that count the number of axles entering and leaving. If the same number of wheels leaves the block as enter it, the block is assumed to be clear. Axle counters can provide similar functionality to track circuits; they also exhibit a few other characteristics [21].

One of Grade crossing equipment is barrier and Barrier Control Box. The Barrier Control Box is used for the Crossing operator to control the barrier. Two sets (Set A and Set B) of lifting/lowering buttons are arranged in each Barrier Control Box and one set of lifting/lowering

buttons may be shared by two opposite barriers for simultaneous lifting and lowering control. The lowering of barrier is control by manual system but lifting of the barrier is automatic [22].

In Addis Ababa, no traffic light control system is available at the grade crossing between the line of the Project and the public roads. This is the reason why traffic conflict is a main issue around Grade crossing.

We understand the following weakness.

The current Ethiopian railway corporation uses an axle counter to detect the passing of a train between two points on a track. The problem of this system is if in case of a power failure, axle counters May 'forget' how many axles are in a section, the loss of signal power may destroy the “memory” circuits in charge of “remembering” that a train has entered a block. This implies that a wrong message passing to grade crossing traffic controller can case safety and delay problems.

1. Reset Requirements – If for any reason there is a failure (possibly a loss of power during a train movement), axle counters must be manually reset (the default startup mode is to create an occupied block). This cause reliability issues.
2. The other weakness of the current system is lowering of gate control is controlled by manual, by observing the approaching of the train by eye site.
3. There is no obstacle detection on grade crossing
4. Since Axle counter is fixed blocking system, once train enter in to the section weather the train stop, accelerate or decelerate there is no way to inform grade crossing controller. This may cause delay or accident.

To overcome these limits, this thesis proposes smart grade crossing signaling system to balance the above disadvantages of existing system. The next chapter discuss about the design of the new system that gives solution for existing problem of grade crossing control system.

Chapter Three

3 System Modeling

In the previous chapter, efforts are made to introduce different technology related to grade crossing. The strength and weakness of the technologies were discussed. Based on the strength of the technology a base line is set for the proposed system. In this chapter System Architecture, mathematical models and algorithms are design for the work.

3.1 Chapter Overview

Once the thesis is proposed and functional specifications are ready, a baseline is set for the development work to begin. Design emphasizes a conceptual solution that fulfills to decrease delay and avoid accident.

From the data that is taken from radar sensor, inform the approaching of the train to grade crossing and this initiate the preemption controller. Based on radar data the train arrival time is predicting using artificial neural network. Once arrival time of the train is determined the action of the preemptions will start. The following high level map shows the overall view of the proposed system.

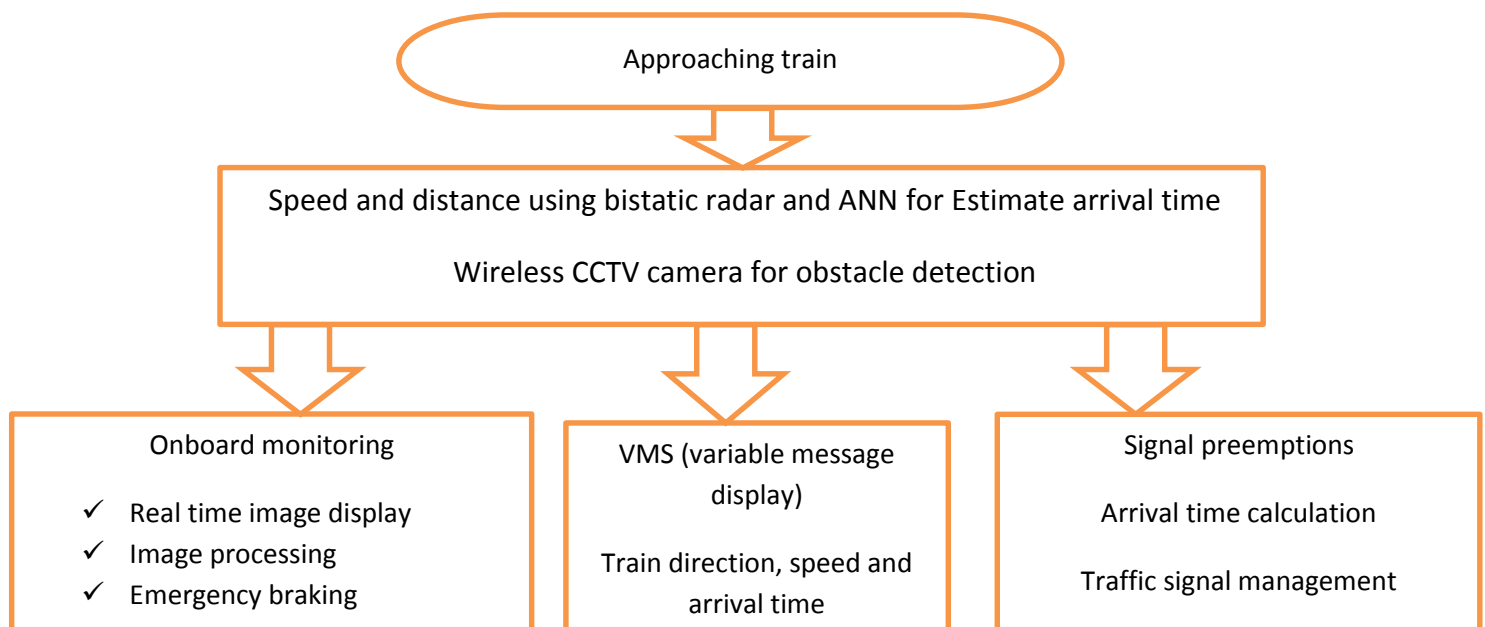


Figure 3.1 Show the High Level Map of the Grade crossing system

- 1) On board monitoring. The CCTV camera that is installed on Grade crossing pass message to the driver of the train inside the cab. If there is obstacle in Grade crossing and the driver will not react, the system take braking action by itself.
- 2) Variable message displays (VMS) is prepared for road side user to inform the speed, direction of the train and arrival time of the train.
- 3) Signal preemption prepares to stop the vehicles and ready for the train.

The following Figure 3.2 show the detail of Grade crossing system technology architecture.

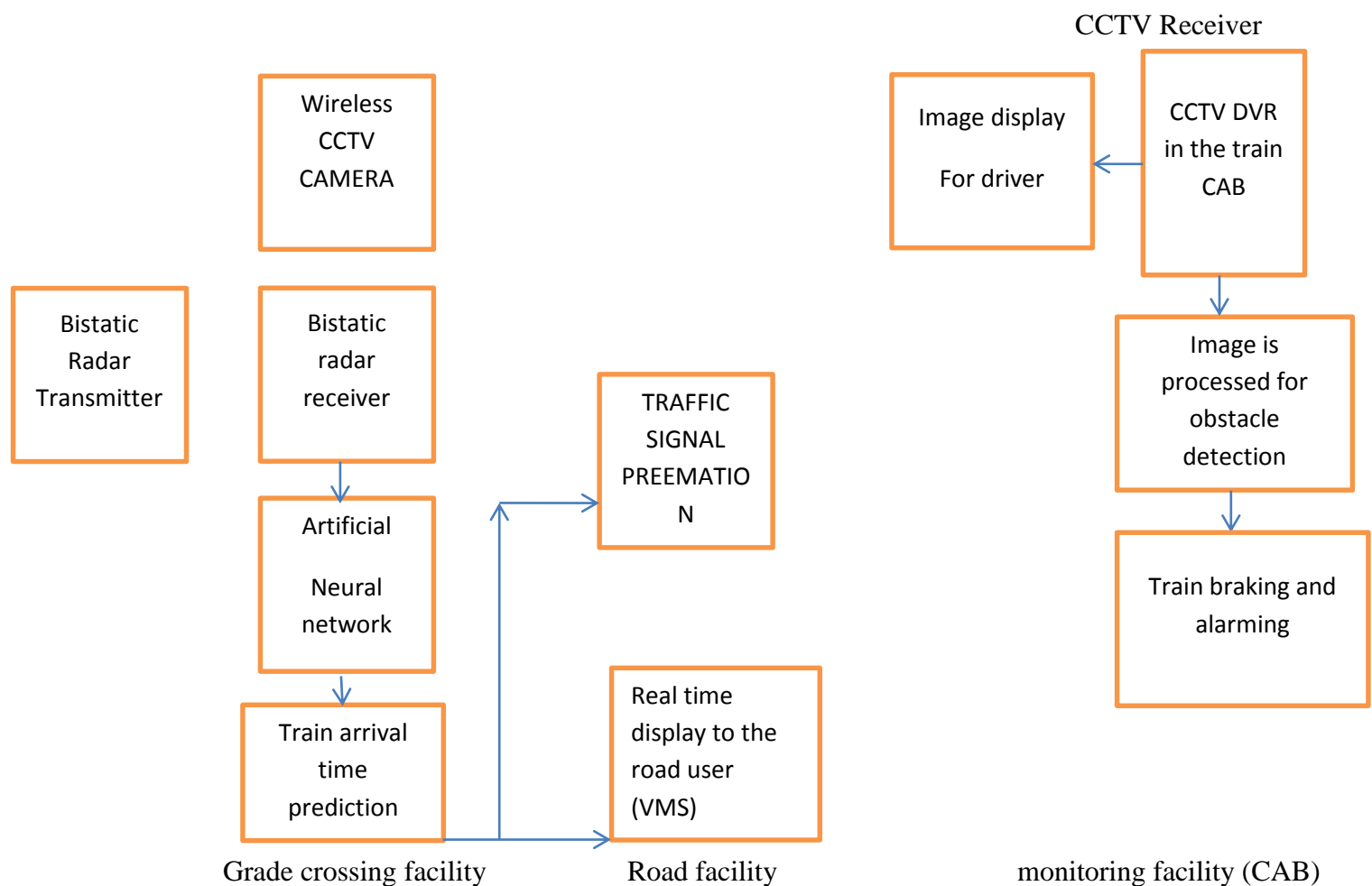


Figure 3.3 Shows System Architecture that Employs Level Crossing System at Grade Crossings

3.2 Grade Crossing Obstacle Detection System Using CCTV Surveillance

Accidents at Grade crossing has large portion on train accidents, and causes economical loss by train delay and operational interruption. Various safety equipment employed to reduce the

accident at Grade crossing. But existing warning device and crossing barrier are simple train-oriented protection equipment's. In this thesis, better railway Grade crossing system technology is proposed to prevent and reduce accidents using CCTV surveillance camera. For train driver's quick action, image of Grade crossing and obstacle warning message are continuously provided to train driver through wireless communication from grade crossing. Obstacle warning messages, which are extracted by MATLAB using computer processing of captured image at Grade crossing by CCTV camera that is installed at grade crossing(for this work Adey Ababa grade crossing), are recognized by train driver through message color, flickering and warning sound. It helps train driver to decide how to take an action. Meanwhile, for vehicle driver's attention, location and speed of approaching train are given to roadside equipment's using variable message display around grade crossing [31][25].

The Grade crossing Obstacle Detection System named LOD, OR CCTV scans the crossing area immediately after the barriers are closed to detect the presence of any obstacles that potentially cause accident.

The detection is made through one or more CCTV camera sensing units, depending on the size of the Grade crossing. Control unit collects the information received by the wireless CCTV camera sensing units and generates alarms based on high-level thresholds (minimum obstacle dimensions). Most European Railway Company use CCTV surveillance due to ease of installation, flexible configuration, and integration [33].

The idea is now to find solutions to improve safety on the Grade crossing. While rail remains the safest form of land transport from a road user point of view. Because major cause crashes and accidents is the road user behavior rather than malfunctioning of technical equipment .This is largely attributable to driver's distraction, risk taking or disobeying the road rules. Consequently, most of the countries are working on the problematic of safety at Grade crossing and propose new sophisticated technologies for barriers, road sign in order to enhance security. But in order to check human's behavior, the most appropriate solution has to be based on surveillance. Nowadays, engineers are creating new technologies more and more specialized in terms of surveillance. From radar, to lidar (laser range finder) technology, through video cameras, the choice of a specific system for a specific problem is not always easy

In our case, we would like to find a system which is easy to install on our LC, easy to maintain and easy to use for operators. With these constraints, we cannot keep solutions like inductive loop, which need important work of installation. In a same way, solution like radar or lidar seems very expensive.

Among the other existing technologies, the one which catches our attention is a solution based on CCTV video camera for obstacle detections due to the following reason [33]

- ✦ Ease of installation and adaptation to the area morphology
- ✦ Number of sensing units per installation reduced to the minimum compared to other technological solutions, e.g. micro-wave radar monitoring systems
- ✦ Simple configuration for the specific geometry of Grade crossing
- ✦ Easy to maintenance and replacement
- ✦ Integration with Grade crossing protections systems and communication to the Interlocking System (inputs from voltage-free contacts, voltage-free contact outputs, 24V DC vital outputs)
- ✦ Closed-circuit television system for visual check of the status of the area.

The number of vehicles on the road continues to rise dramatically. This has led to heavy traffic congestion which is responsible for a growing number of car accidents. Particularly serious accidents can occur because of violations of Grade crossing regulations. Many researchers have proposed schemes to prevent Grade crossing accidents. However, more Grade crossing management technology is required to prevent accidents at Grade crossings.

The management Grade crossing system provides warning information to train and roadside traffic adjacent to a Grade crossing, using a wireless communication link, for the purpose of preventing accidents and reducing damage.

Grade crossing events (like warning messages) and video information about obstacles trapped on the crossing gate (vehicles and pedestrians, etc.) are transmitted to a train from the Grade crossing, and information related to the train (direction, velocity, estimated time of arrival) is sent to the Grade crossing based on bistatic radar and artificial neural network. The video information transmitted from the Grade crossing is displayed on the monitoring equipment of the train cab so that the train driver can stop the train before approaching the Grade crossing. ANN estimates the time of arrival using information from the train (bistatic radar) and provides this

arrival time to roadside display units and to the road traffic signal control equipment of the intersection adjacent to the Grade crossing. This information makes drivers and pedestrian informed of the approaching train, and encourages them to clear the Grade crossing quickly.

The main components and functions of the Grade crossing system are as follows.

3.3.1 Obstacle Detection Using Image Processing

This diagnoses the condition of crossing gates, detects any trapped obstacles, and tracks the movements of obstacles in real time [33]. Obstacle detection detects obstacle at Grade crossing area through image process and it determines whether obstacle exists by checking entry of object, dwell time at Grade crossing area.

3.3.2 Monitoring Equipment

This subsystem is installed in the cab of the train. Warning messages and real-time video of any obstacles are provided to help the train driver notice obstacles and stop the train before the Grade crossing. If the train driver fails to react appropriately, this system is designed to immediately deploy the emergency brake.

3.3.3 VMS (Variable Message Signs) and Preemption Signal Control Unit

An LED visual display device is installed between the Grade crossing and the adjacent road intersection to tell vehicle driver and road side user to provide information about approaching trains such as, The VMS indicates the presence of vehicles on the Grade crossing and the approach of trains in real time to vehicle drivers for the purpose of reducing accidents on the Grade crossing.

In urban areas, long lines of vehicles on road intersections adjacent to Grade crossings can occupy Grade crossing and cause accidents. If a Grade crossing is near a road intersection, the vehicles leaving the Grade crossing for the road intersection shall be given priority for the traffic signal. In other words, when a train is approaching, it is necessary to stop vehicles attempting to enter the Grade crossing and to allow vehicles already on the Grade crossing to quickly exit the Grade crossing. In this way, accidents can be prevented. Preemption signal control will discuss in detail in section 3.8

3.4. Algorithm and Methodology for Obstacle Detection Using Image Segmentation

This thesis presents an algorithm for Obstacle Detection using image processing method. This method is divided into two parts

1. Segment the obstacle containing image
2. Find the obstacle from those obstacles containing image.

Obstacle detection is one of the most popular problems within the subfield object detection in terms of the amount of research it has attracted and it has number of uses too. A good obstacle detection system must be capable of the following.

1. To detect obstacles on a given space in good time
2. To detect and identify correct obstacles
3. To identify and ignore ground features that may appear as obstacles by setting proper threshold value.

Performing reliable object detection is an important task as it is one of the key requirements for realizing fully autonomous, general purpose obstacle detection.

3.5. Methodology for Image processing

The methodology involve for image processing is the back ground subtractions from the image that has obstacle, the image which is having obstacle and background image is dividing into many segments and each segment is processed for the finding the obstacle, then the segments which is having obstacle and segments which is not having any obstacle are find out and further processing is going on these segments. In this method first the image is divided into many segments and numbering is done to each segment in such a way that we can differentiate or compare each segment with segment and these groups of segment give the information of the obstacle. For finding the obstacle from any static image we had to first convert the RGB image to Gray image and then whole process is done on gray image. Now the segmentation of image is done using some specific matrix value. The reason why changing RGB (Red, Green and blue) image to gray, is to avoid background lighting effect and to save the memory of the microcontroller.

Algorithm for obstacle Detection:

1. Get the image containing obstacle.
2. Convert the image into gray image.

Gray Scale Conversion:

The input image is first converted to a gray scale image.

All gray scale algorithms utilize the same basic three-step process:

- a. Get the red, green, and blue values of a pixel
 - b. Use math functions to turn those numbers into a single gray value
 - c. Replace the original red, green, and blue values with the new gray value
3. The image should be resized into a fixed dimension since all the images are not of same size.
 4. Segment the image into fixed matrix of $M \times N$ numbers.
 5. Numbering is done for each segmented images.
 6. Take one of the segmented images and apply the process to find obstacle.

Process is that takes the standard of the image and applies some threshold value (image without obstacle). If the processed value is greater than threshold value than that segment image contain obstacle.

7. Then check the entire segmented image in the process and find the images which contain obstacle.

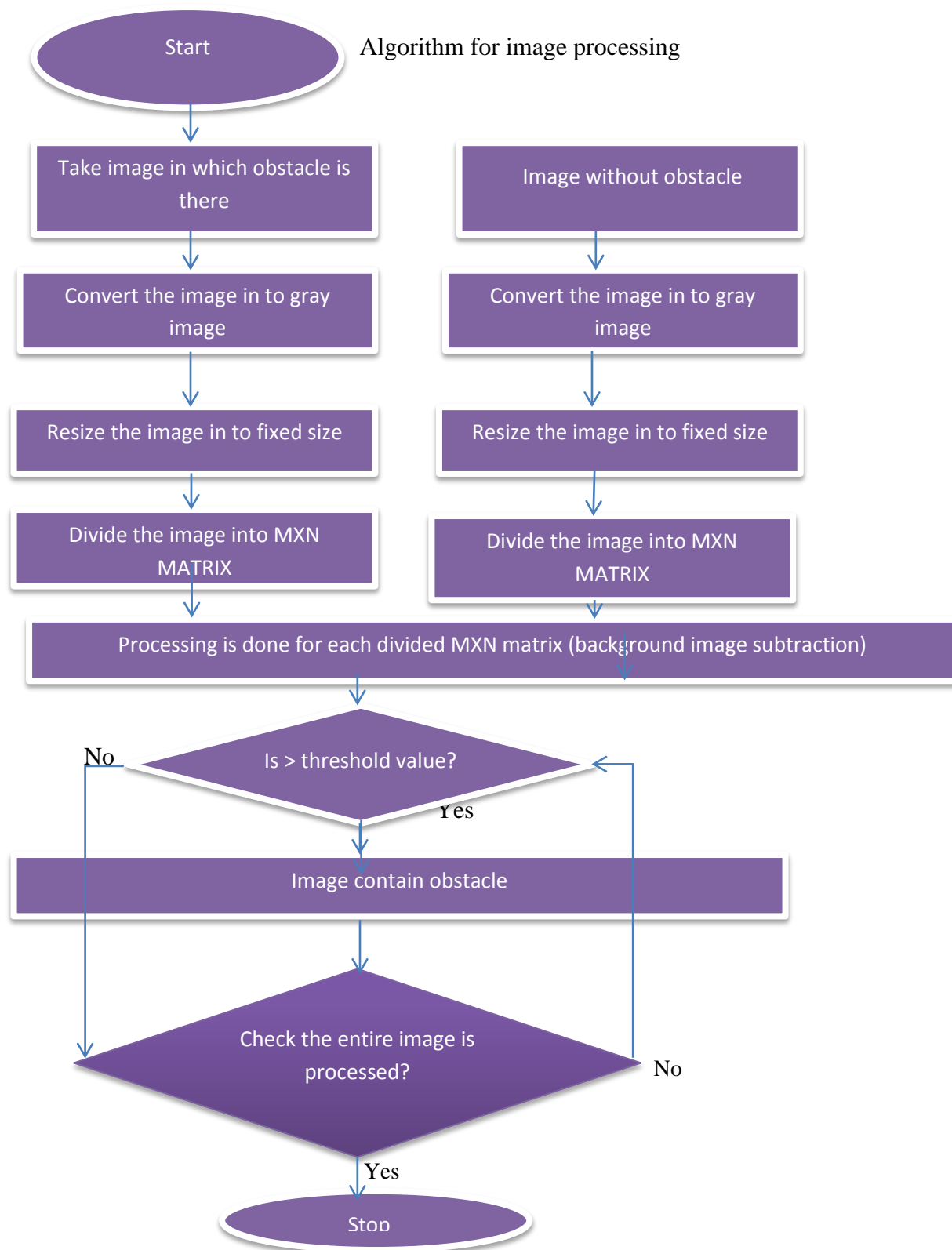


Figure 3.4 Flow Chart Detections of Obstacles

Background Subtraction:

The processed input images are subtracted using the following algorithm.

Background subtraction Algorithm:

$$D_k = 1 \quad \text{if } F_k - B_k > T$$
$$= 0 \quad \text{Otherwise}$$

Where F_k : Current Frame

B_k : Background Image

D_k : Difference Image

T : Set threshold (background image plus some noise)

Our main aim is to detect an obstacle (object) from any image, and from the methodology used in this we can easily and quickly detect the obstacle (object).

The wireless CCTV camera installed on the pole at Adey Ababa crossing. The transmitted image is processed using the above algorithm. Additionally the driver can see the status of the Grade crossing directly by display.

Obstacle detection algorithm

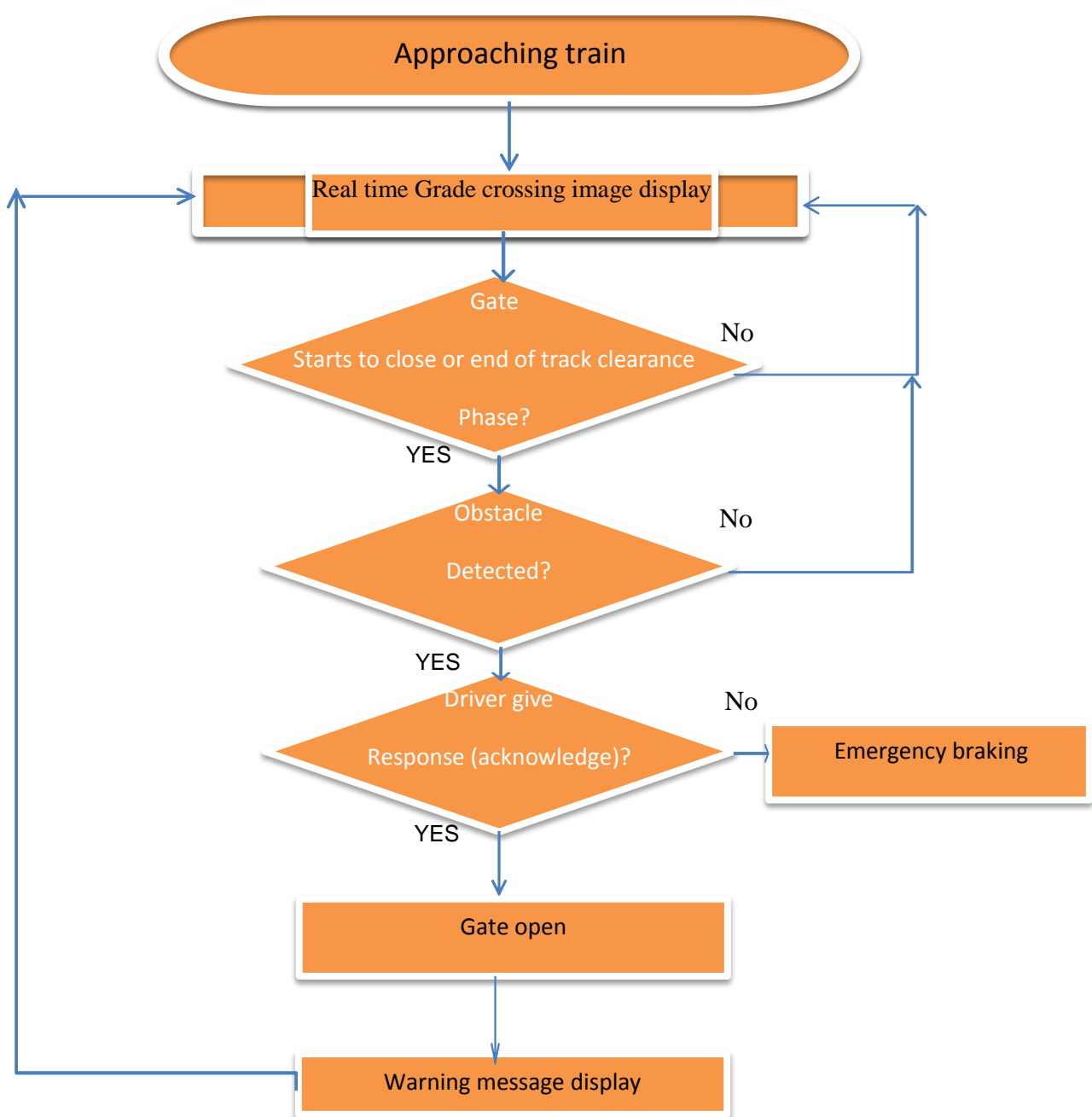


Figure 3.5 show Flow Chart Monitoring train

3.6. Radar Design for Train Detection

3.6.1 Radar Detector

Radar (Radio Detection and Ranging) is an object-detection system that uses radio waves to determine the range, angle, or velocity of objects. It can be used to detect a train, aircraft, ships, spacecraft, guided missiles and motor vehicles. Radar transmits radio waves or microwaves that reflect from any object in their path. A receive radar, which is typically the same system as the transmit radar, receives and processes these reflected waves to determine properties of the object(s) [17].

In this thesis we are discussed about bistatic radar instead of monostatic (the receiver and transmitter are built in common space) for arrival time prediction. Bistatic radar is the name given to a radar system a transmitter and receiver which are separated by a distance that is comparable to the expected target distance the separation distance can be from 100m to 100th kilometer [19].

The working principle of a radar systems use modulated waveforms and directive antennas to transmit electromagnetic energy into a specific volume in space or an area on the ground to search for targets. Objects (targets) within a search volume will reflect portions of this energy (radar returns or echoes) back to the receiver of radar. In this process the frequency of the reflected energy is changed (shifted). This shift in frequency is known as the Doppler Effect. These echoes are then processed by the radar receiver to extract target information such as range, velocity, direction of movement, and other target identifying characteristics.

The system continually measures and records train speed. From the data recorded, train acceleration or deceleration may be estimated. Prediction algorithms also have been developed using the speed, acceleration, and deceleration information. Some of the arrival time prediction algorithms that were developed use the distance of the train and detector from the HRGC along with the train speed.

For this thesis a radar technology (specifically bistatic radar) is selected for train detection at far distance from grade crossing.

Bistati radar is selected for the work, due to the following reason [36] [37]

- ❖ Due to being passive, they are potentially undetectable.
- ❖ They may be lower cost compared to ordinary radar
- ❖ They can update the target positions very fast.
- ❖ They do not need any specific frequency allocations.
- ❖ Possible enhanced Radar Cross Section (RCS) of the target due to geometrical effects.
- ❖ Lower acquisition and operational & maintenance costs due to lack of transmitter and moving parts.
- ❖ Physically small; easily deployed in places where conventional radars cannot be
- ❖ Remote, standalone operation possible Minimized effects from weather conditions
- ❖ Detection of low altitude targets (by diffraction)
- ❖ Rapid updates, typically once a second
- ❖ Secret operation, including no need for frequency allocations
- ❖ Green radar; no EM pollution

3.6.2 Bistatic radar

Bistatic radar employs two sites that are separated by a considerable distance. A transmitter is placed at one site, and the associated receiver is placed at the second site. Target detection is similar to that of monostatic radar: target illuminated by the transmitter and target echoes detected and processed by the receiver [37]. When two or more receive sites with common spatial coverage are employed and target data from each site is combined at a central location, the system is called multistatic radar.

3.6.3 Mathematical Modeling for Bistatic Radar for Train Detection

Bistatic Radar equation

The radar equation represents the physical dependences of the transmit power, that is the wave propagation up to the receiving of the echo-signals. Furthermore one can assess the performance of the radar with the radar equation [37] [36].

A) Receiver power formula

a) PR corresponds to the absence of any attenuation

$$PR = \frac{(PT*GT*GR*C2*\sigma_B)}{(4*\pi^3)*f^2*RT^2*RR^2)} [W] \quad (3.1)$$

b) P_R

In the presence of a real atmosphere, we take attenuation into account.

$$PR = \frac{(PT*GT*GR*C2*\sigma_B)}{(4*\pi^3)*f^2*RT^2*RR^2L)} [W] \quad (3.2)$$

Where

R_T = transmitter-to-target range

R_R = receiver-to-target range

P_T = transmitted power

G_T = gain of the transmitter's antenna

G_R = gain of the receiver's antenna

λ = wavelength

σ_B = bistatic radar target cross section area (target RCS)

F_T = transmitter pattern propagation factor

F_R = receiver pattern propagation factor

k = Boltzmann's constant = 1.38x10⁻²³

T_S = receiver total noise temperature

B_n = receiver noise bandwidth

(S/N) min = signal-to-noise ratio (SNR) needed for detection

L=L_T = L_R = losses in transmitter and receiver (cables, signal processing, etc.)= 1

κ = bistatic maximum range product

3.6.4 Bistatic Radar Range Equations

The range equations for bistatic radar are derived in a manner that exactly the same way in the monostatic radar case. The derivation of these equations can be found in [17]. With this analog, the bistatic radar maximum range equation [37], is shown below

$$(RTRR) 2 MAX = \frac{PT*GT*GR* \lambda^2 * FT2*FR2}{(4\pi)^3 * k * TS * Bn * (s/n)_{min} * LT * LR} = \kappa \quad (3.3)$$

Signal to noise equation

$$S/N = \frac{PT*GT*GR* \lambda^2 * FT2*FR2}{(4\pi)^3 k TS Bn LRT2RR2} \quad (3.4)$$

Or

$$S/N = \frac{K}{RT2RR2} \quad (3.5)$$

Where S/N is the signal- to -noise ratio

$$K = \frac{PTGTGR AR2 FT2FR2}{(4\pi)^3 k TS Bn LRT2RR2} \quad (3.6)$$

The term K is called the bistatic radar constant, and is related to the bistatic maximum range product κ and minimum SNR value. Therefore, the minimum SNR contour can be obtained from the equation 3.7. for 15db SNR = 31.63watt

$$\left(\frac{S}{N}\right)_{min} = \frac{K}{\kappa^2} = \frac{10^{(15/10)}}{1} = 31.62 > K = 31.62 \kappa^2 = 31.62 ((RTRR)2 MAX)^2 \quad (3.7)$$

Estimation of Target Location (range measurement)

Range is extracted from the two-way time delay between a transmitted and received pulse. To estimate the location of a target in bistatic radars, receivers measure the time interval, τ_{total} between transmitted pulses and received echo waves, scattering from a target. Hence, the range sum, $R_R + R_T$, can be calculated using the following equation.

The common way to measure range with radar is to measure the time delay between transmits to the receiver. Since the RF energy travels at the speed of light, the time required for the transmit pulse to travel to a target at a range of R_T is

$$\tau_{RT} = \frac{R_T}{c} = (0.333 * 10^{-8})R_T \quad (3.8)$$

The time required for the pulse to return from the target back to the radar R_R is

$$\tau_{RR} = \frac{R_R}{c} = (0.33 * 10^{-8})R_R \quad (3.9)$$

Thus, the 6.66 micro second total round-trip delays between transmission and reception for 2km maximum detection calculated using equation 3.10

$$\tau_{total} = \frac{R_T}{c} + \frac{R_R}{c} = \frac{R_R + R_T}{c} = 6.66 \mu \text{ second} \quad (3.10)$$

Since we can measure τ_{total} in radar, we can compute range by solving (10) for $R_R + R_T$

$$\text{We can then write } R_R + R_T = C * (\tau_{total}), C = 3 * 10^8 \quad (3.11)$$

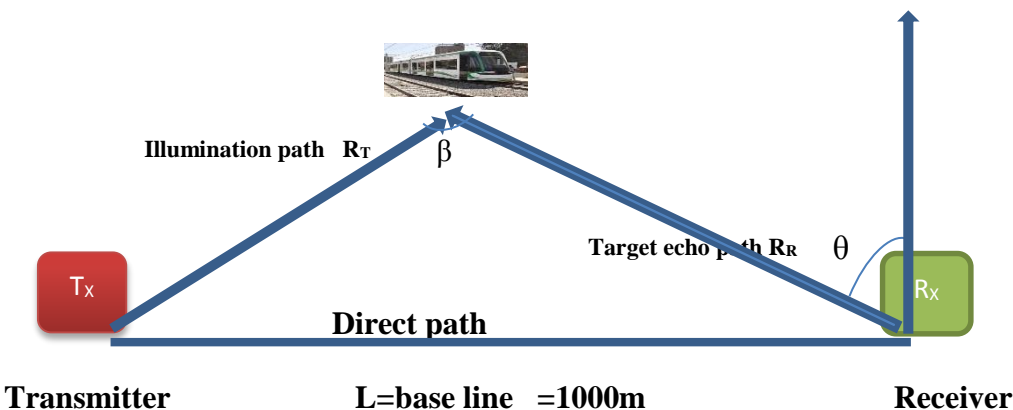


Figure 3.6 Shows Geometry Bistatic Radar

$$R_R + R_T = 3 * 10^8 * \tau_{total} = 2000\text{m}$$

$$\text{Where } R_R = \frac{((R_R + R_T)^2 - L^2)}{2(R_R + R_T + L \sin(\theta))} = \frac{((R_R + R_T)^2 - 1000000)}{2(R_R + R_T + 1000 \sin(\theta))}$$

$$\text{And } R_T = \frac{((R_R + R_T)^2 - 1000000)}{2(R_R + R_T + 1000 \sin(\theta))} \quad (41)$$

The receiver range depends on the bistatic θ . For most ground detections bistatic radar is between 150 to 180 is called forward scattering [36] [37].

Radar Resolution

The target resolution of radar is its ability to distinguish between targets that are very close in either range or bearing. Weapons-control radar, which requires great precision, should be able to distinguish between targets that are only yards apart. Search radar is usually less precise and only distinguishes between targets that are hundreds of yards or even miles apart.

Range Resolution

Range resolution, denoted as ΔR , is radar metric that describes its ability to detect targets in close proximity to each other as distinct objects. Radar systems are normally designed to operate between a minimum range R_{min} , and maximum range R_{max} . The distance between R_{min} and R_{max} is divided into M range bins (gates), each of width ΔR [17]

$$M = \frac{R_{max} - R_{min}}{\Delta R} \quad (3.12)$$

Targets separated by at least ΔR

Selection of the transmitting frequency

The selection transmitting powder based on Police radar guns operate on three frequency bands: X-band, K-band, and Ka-band. Most new police radar guns operate on the super-wide K-band. It is still quite common. Based on this the carrier frequency 24.35 GHZ selected for this thesis work base on k-band the antenna [39]. The gain is between 14 to 19 Db. The beam width of the horn antenna is between 32 to 15 degree from lower to higher frequency [38].

Range Resolution can be determine using equation 3.13

$$\Delta R = \frac{c}{2B} = 3 * \frac{10^8}{2 * 10^6 * 250} = 0.6m \quad \text{Where B is the band width [32]} \quad (3.13)$$

Targets separated by at least ΔR will be completely resolved in range. In this thesis a range resolution of 0.6 meters is considered adequate.

$B = 250\text{MHZ}$ selected for this work due to the following reason

- High data rate for communication systems,

- High resistance to jamming since wide bandwidth is available,
- Very high range resolution for tracking and target detection,
- Increased recognition capability of slowly moving target due to the high Doppler frequency

Low sensitivity to environmental characteristics Atmospheric absorption and attenuation due to inclement weather condition such as fog, dust or smoke are much lower compared to optical and IR frequencies[18] .

$$\text{Radar wave length, } \lambda = \frac{c}{f} = 3 * \frac{10^8}{24.35 * 10^9} = 0.0123\text{m} \quad (3.14)$$

The ranging sensor is Frequency Modulated Continuous Wave (FMCW) radar operating within a frequency range of 24.35 to 24.7 GHz. It has a power output of 1 watts; a range under ideal conditions up to 2000 meters is effective, and a range resolution of 0.6 meters [39].

3.6.5 Bistatic Doppler Shift

The change in the received frequency relative to the transmitted frequency is called the Doppler frequency, denoted by f_B .

Bistatic Doppler shift is a specific example of the Doppler Effect that is observed by a radar or sonar system with a separated transmitter and receiver. The Doppler shift is due to the component of motion of the object in the direction of the transmitter, plus the component of motion of the object in the direction of the receiver. Equivalently, it can be considered as proportional to the rate of change of bistatic range. In Bistatic radar with wavelength λ , where the distance between transmitter and target is R_T and distance between receiver and target is R_R , the received bistatic Doppler frequency shift is calculated as:

$$\begin{aligned} f_B &= \frac{1}{\lambda (d/dt(R_T + R_R))} \\ &= 8.13 (d/dt(R_T + R_R)) \end{aligned} \quad (3.15)$$

The Doppler shift, f_B , is the time rate of change of the total path length of the scattered signal, normalized by the wavelength.

The received echo signal is also frequency shifted with respect to reference signal due to the Doppler Effect. The Doppler frequency shift is related to the bistatic velocity V_B using the following formula [37]

$$f_d = V_B \frac{f_c}{c} = \frac{24.35 \text{ Ghz}}{3 \times 10^8} = 81.16 V_B \quad (3.16)$$

Where f_c is carrier frequency, f_d Doppler frequency offset c is speed of light, V_B is bistatic velocity

$$\text{Bistatic velocity} \quad V_B = \frac{dRR}{dt} \quad (3.17)$$

Minimum Detectable Signal (MDS)

The minimum detectable signal is defined as the useful echo power at the reception antenna, which gives on the screen a visible error. The minimum visible signal at the receiver input-jack leads to the maximum range of the radar; all other nominal variables are considered as constant. A reduction of the minimal received power of the receiver gets an increase of the maximum range. The maximum range R_{\max} is the distance beyond which the target cannot be detected due to insufficient received power P_r . For every receiver there is a certain receiving power as of which the receiver can work at all. This smallest workable received power is frequently often called MDS – Minimum Visible Signal or Minimum Detectable Signal in radar technology [17].

In most cases optimal performance of a radar system can be obtained using the technique of threshold detection. In this method, the magnitude of each complex sample of the radar echo signal, possibly after signal conditioning and interference suppression is compared to a pre-computed threshold. If the signal amplitude is below the threshold, it is assumed to be due to interference signals only. If it is above the threshold, it is assumed that the stronger signal is due to the presence of a target echo in addition to the interference, and a detection or “hit” is declared. In essence, the detector makes a decision as to whether the energy in each received signal sample is too large to likely have resulted from interference alone. If so, it is

assumed a target echo contributed to that sample. The minimum detectable RCS for the passive radar is calculated by the following formula

$$\text{RCS}_{\text{min}} = (4\pi)^3 * (RR)^2 * (RT)^2 * \frac{P_{\text{min}}}{P_T} * G_T * G_R * (\lambda)^2 \quad (3.18)$$

3.6.6 Radar Cross Section (RCS)

The amount of the radiated energy is proportional to the target size, orientation, physical shape and material which are all lumped together in one target-specific parameter called Radar Cross Section (RCS) denoted by σ_b [38]. The RCS is a measure of the effectiveness of the target as a radar reflector [47].

External and Internal Losses

This is the sum of all loss factors of the radar. This is a value that is calculated to compensate for attenuation by precipitation, atmospheric gases, and receiver detection limitations. The attenuation by precipitation is a function of precipitation intensity and wavelength. For atmospheric gases, it is a function of elevation angle, range, and wavelength. Since all of this is taken in account for e.g. 3 Decibels loss, all signals are weakened by half the value. Some of these losses are unavoidable. Some of these can be influenced by radar technicians. In this design the losses due to internal factors, rain and atmosphere are going to be included for the design purpose. As the radar signal is propagated through the atmosphere, its amplitude and intensity are reduced through the atmospheric attenuation process [18]

Probability of detection and false alarm

A false alarm is “an erroneous radar target detection decision caused by noise or other interfering signals exceeding the detection threshold”. In general, it is an indication of the presence of a radar target when there is no valid target. The False Alarm Rate (FAR) is calculated using the False alarms are generated when thermal noise exceeds a pre-set threshold level, by the presence of false signals (either internal to the radar receiver or from sources external to the radar), or by equipment malfunction.

A false alarm may be manifested as a temporary error on a cathode ray tube (CRT) display, a digital signal processor output, an audio signal, or by all of these means. If the detection

threshold is set too high, there will be very few false alarms, but the signal-to-noise ratio required will inhibit detection of valid targets. If the threshold is set too low, the large number of false alarms will mask detection of valid targets. On this thesis pfa (probability of false alarm) is taken to be 10^{-8} . For 15db signal to noise ratio 0.99 probability of detection

Parl developed an excellent algorithm to numerically compute the probability of detection of radar using the MATLAB Function “marcumsg.m” [37]. The formula is summarized by Parl as follows:

$$[a,b]= \left\{ \begin{array}{l} \alpha n / (2\beta n) \exp ((a-b)^2/2) \quad a < b \\ 1 - (\alpha n / (2\beta n) \exp ((a-b)^2/2) \quad a \geq b \end{array} \right. \quad (3.19)$$

$$1 - (\alpha n / (2\beta n) \exp ((a-b)^2/2) \quad a \geq b$$

Same as Chapman & Hall/CRC here we are going to use Parl’s MATLAB Function to compute the probability of detection of the radar system and the syntax is as follows:

$$Pd = \text{marcumsg}(\alpha, \beta)$$

According to parl, signal to noise ratio more 15db has 0.99 probability of detection. For this thesis work 15db take as value of signal to noise ratio.

Component of the bistatic radar

a) Transmitter

The transmitter generates powerful electromagnetic energy at precise intervals. The required power is obtained by using a high-power microwave oscillator, such as a magnetron, or a microwave amplifier, such as a klystron, that is supplied by a low-power RF source [28]. The main components in transmitters are the up-converting mixer or frequency multiplier, filters and the power amplifier. The IF signals is converted into the RF frequency signal by mixers or frequency multipliers. The undesired harmonics and images are attenuated using band pass filters. Finally the power amplifier provides amplification for the transmit signal before it excites the antenna. Couplers are commonly used to provide a sample of the transmit signal or the LO for the receiver down convertor.

a) Receiver

The receiver accepts the weak echo signals from the antenna system, amplifies them, detects the envelope, amplifies, and then routes them to the indicator. One of the primary functions of the

radar receiver is to convert the frequency of the received echo signal to a lower frequency that is easier to amplify. This is because radar frequencies are very high and difficult to amplify. This lower frequency is called the Intermediate Frequency (IF). The type of receiver that uses this frequency conversion technique is the super heterodyne receiver. Super heterodyne receivers used in radar systems must have good stability and extreme sensitivity. Stability is ensured by careful design and the overall sensitivity is greatly increased by the use of many IF stages [32].

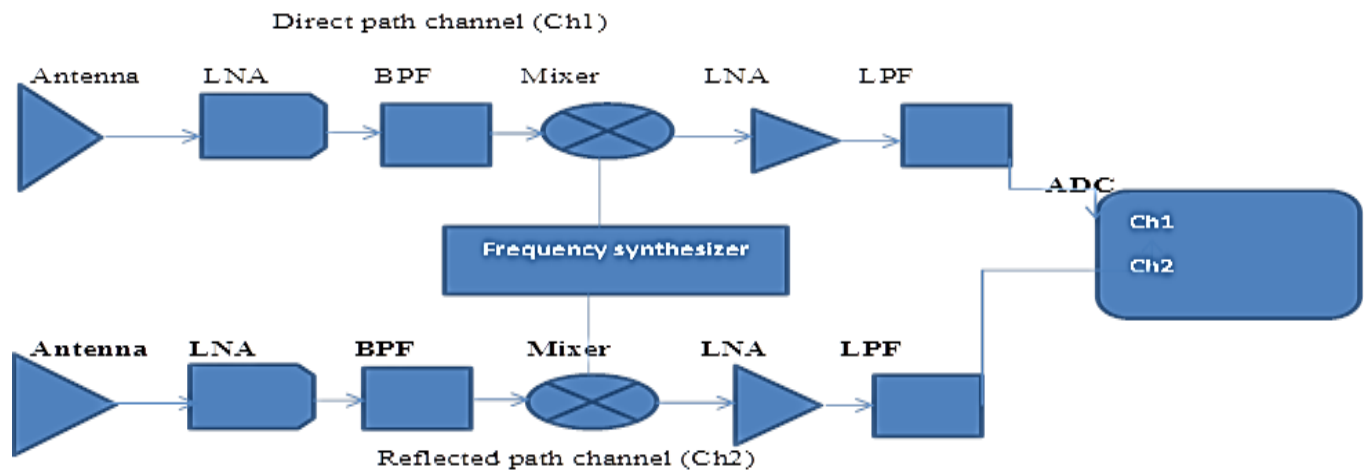


Figure 3.7 Shows Direct Path and Reflected Path Channel [39]

The proposed system consists of two parallel co-located channels; Ch1 and Ch2, as illustrated in the receiver hardware system architecture in Figure 3.6. Ch1 is dedicated to receive the direct path reference signal from the transmitter, while Ch2 is dedicated to receive the echo signal reflected from the targets. The two channels have the same structure, where each channel is started by horn antenna used to receive the transmuted signal carried at the 24.35 GHz carrier [39]. The antenna of Ch1 is directed towards the transmitter direction, while the antenna of Ch2 faces the area where the target should be.

The antenna is followed by a low noise amplifier (LNA); the LNA is used to amplify the received RF signal. Then the desired transmuted downlink signal frequency band is selected by the band pass filter (BPF). Subsequently, the desired signal is down converted to the baseband by heterodyning it with the local oscillator signal using a frequency mixer. An amplifier is used to amplify the baseband signals to provide sufficient gains for the transmitted signal before filtering out the undesired frequencies using the LPF.

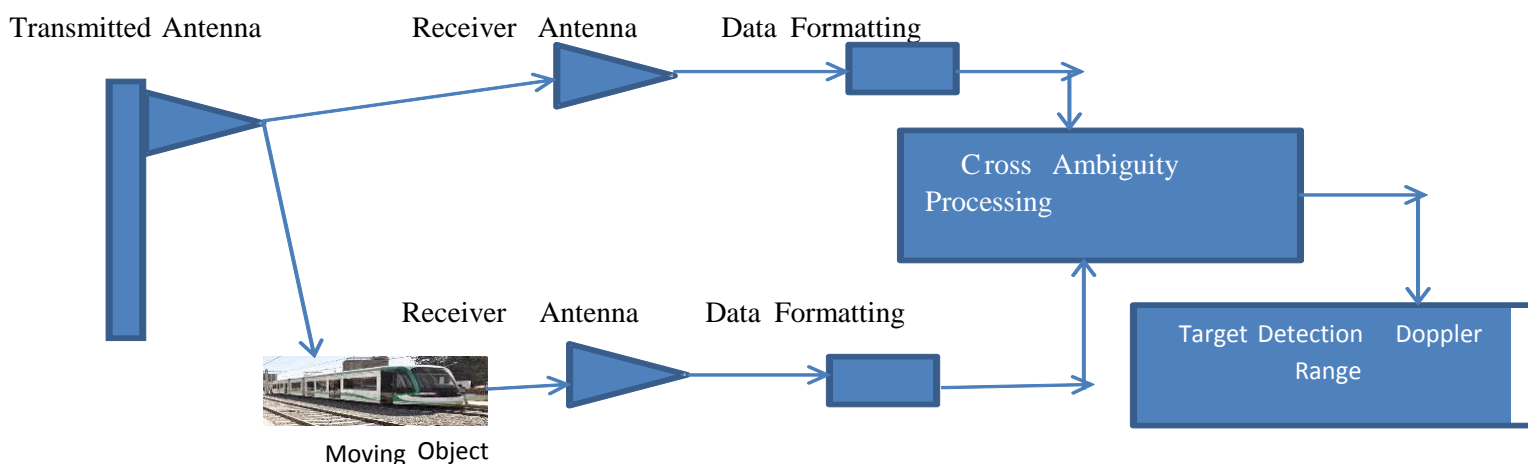


Figure 3.8 Passive Radar Signal Processing Scheme for Target Detection

The two transmitted signals received from Ch1 and Ch2 are unequal by two parameters, which are the time delay and Doppler shift. In fact, these two parameters will decide the range and velocity of the detected moving target. Therefore, the cross ambiguity function (CAF) is applied [28] [21], which is the matched filter response to the joint time-delay and Doppler-shift version of the transmitted signal it is matched to.

b) Base band

Almost all modern radars use digital signal processors to perform processing operations such as correlation, Doppler filtering, image rejection, detection processing and tracking. To provide signal for digital processing, A/D converters are placed at the end of the receiver signal path. Data processors are used to convert data produced by the signal processor into a form that is readily interpretable by radar operators. Table 3.1 shows radar parameter of the thesis.

Radar Parameter	Values(s)	Units
Type	FMCW	
Frequency	24.35	GHZ
Power	1	Watts(W)
SNR	15db	db.
Target RCS	0.1,1,10.0	Meters2(m2)
Transmitter Antenna Gain	19	db.
Receiver Antenna Gain	19	db.
Transmitter loss	1	db.
Receiver loss	1	db.
Environmental loss	1	db.
Bandwidth	250	MHz
Transmitter pattern propagation factor	1	
Receiver transmitter pattern factor	1	

PFA	10-8	-
Range Resolution	0.6	Meter
Wave length	0.0123	Meter
Maximum Range	2000m	Meter
Temperature	290k	Kelvin

Table 3.1 show radar parameter

3.7 Arrival Time Prediction Using Artificial Neural Network

ANNs developed by different researchers in predicting travel time differ in their input-output combinations. In addition, they use explanatory variables such as flow, speed, weather, distance, etc., as inputs.

The purpose of this chapter is, therefore, to explicitly consider arrival time of the train via bistatic radar technology to predict train travel time at grade crossing. Additionally traffic signal phase length forecasting at Adey Ababa intersection. Regardless of which predation method and prediction algorithm is used, the forecast will be subject to some error. Therefore, the forecast train arrival time should be updated as new speed data are obtained in order to reduce the prediction error.

The updated prediction time will be used within the transition preemption methodology. In this thesis, a new train arrival prediction algorithm is developed using time series speed data from bistatic radar.

The ability to forecast train arrival time at highway-railroad grade crossings is essential for the accurate preemption of traffic signals at an IHRGC. However, because of the limitation of detection technologies and estimation algorithms, a wide range in warning times exists. If the train is accelerating or decelerating, the preemption will begin later or earlier than the preemption warning time.

The preemption warning time depends on several characteristics of the site including the distance between the intersection and the crossing, traffic signal timing, longest vehicle allowed on the roadway, pedestrian volume, and other factors.

Generally the preemption warning time is longer than the minimum warning time.

In this thesis, artificial neural network (ANN) models are applied to handle the nonlinear relationship between the train speed profile and arrival time [43].

3.7.1 Network Architecture

Many different ANNs have been proposed in the past few decades for forecasting purposes. The ANN architecture is typically composed of a set of nodes and connections arranged in layers. In this study, three layers were used: input layer, hidden layer, and output layer. The first layer is an input layer when external information is received. The last layer is an output layer where the problem solution is obtained. Usually, one or two hidden layers are used in between the first and last layers to predict reasonably well. The actual processing in the network occurs in the nodes of the hidden layer and the output layer [33] [43].

The input layer is where the data vector is fed into the network. It then feeds into the hidden layer, which, in turn, feeds into the output layer. The connections are typically formed by connecting each of the nodes in a given layer to all of the neural in the next layers. The hidden layer generates the weight of these connections and the bias parameter during the training process. It is the hidden nodes in the hidden layer that allow the neural network to detect the feature to capture the pattern in the data, to perform nonlinear mapping between input and output variables. The basic model of a single artificial neuron consists of a weighted seasonal and an activation (or transfer) functions.

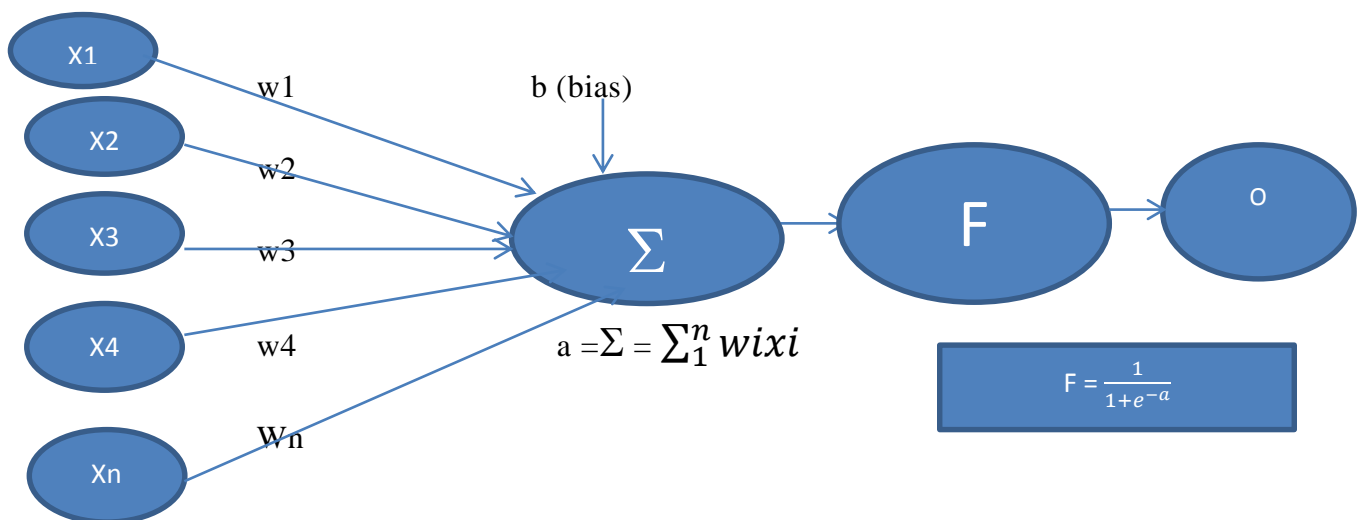


Figure 3.9 Artificial Neural Networks Architecture

Where x_1, x_2, \dots, x_n are inputs, w_1, w_2, \dots, w_n are weights, b is a bias (threshold), F is the activation function and O is the output

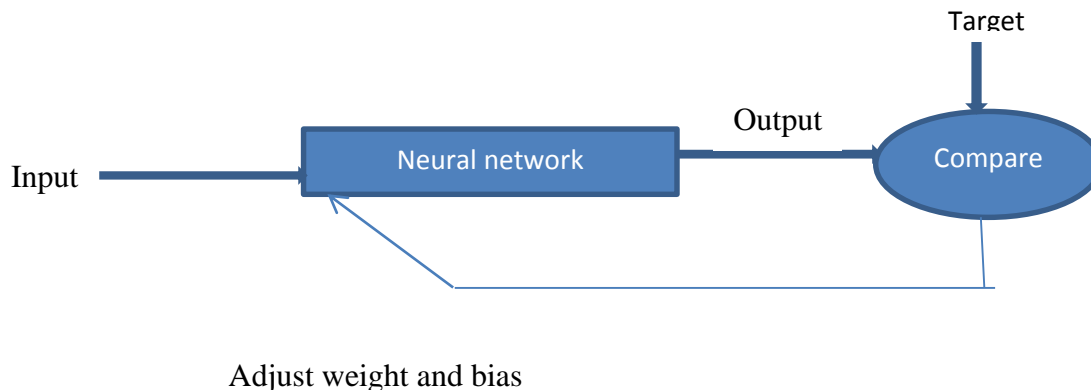


Figure 3.10 Input Output Relationship of ANN

3.7.1.1 Feed forward Networks

A feed forward network consists of an input layer, an output layer and an intermediate layer, called a hidden layer. Note that all neural in a particular layer are fully connected to all neural in the subsequent layer. This is generally called a fully connected multilayer network, and there is no restriction on the number of neural in each layer, and no restriction on the number of hidden layers. Number hidden layer determine during training time. For this thesis work hidden layer form 5, 10, 15, 20, 30, 50 are providing for training purpose.

3.7.1.2 Feedback (Recurrent) Networks

The fundamental feature of a Recurrent Neural Network (RNN) is that the Network contains at least one feed-back connection, so the activations can flow round in a loop. That enables the networks to do temporal processing based on stat space learning process. There are type of Learning in the context of a neural network is the process of adjusting the weights and biases in such a manner that for given inputs, the correct responses, or outputs are achieved.

Neural networks learning can be classified:

a) Supervised learning: The network is presented with training data that represents the range of input possibilities, together with the associated desired outputs. The weights are adjusted until the error between the actual and desired outputs meets some given minimum value. The proposed system use this supervised learning method because it has a capability adjust itself to eliminate the errors during arrival time forecasting.

b) Unsupervised learning: Also called open-loop adaption because the technique does not use feedback information to update the network's parameters. This system cannot correct the error. For thesis work supervised learning implement due to self-adjustment to decrease the error.

The Back-Propagation Algorithm (BPA) is a supervised learning method for training ANNs, and is one of the most common forms of training techniques [43].

3.7.2 Optimization of Neural Network for Error Minimization

It uses a gradient-descent optimization method, also referred to as the delta rule when applied to feed forward networks. Learning in neural networks use gradient descent to search the space of possible weight vector to find the weights that best fit the training this rule is important because it provides the basis for the back propagations algorithm, which can learn networks with many interconnected units. The delta training rule: considering the task of training a threshold perceptron, that is a linear unit, for which the output O is given by:

$$O = F(w_0 + w_1x_1 + \dots + w_nx_n + b) \quad (3.20)$$

Thus, a linear unit corresponds to the first stage of a perceptron, without the threshold. In order to derive a weight learning rule for linear units, let specify a measure for the training error of a weight vector, relative to the training. We are trying to determine the best network parameters (weights and biases) in order to minimize network error the training error can be computed as using equation 3.21.

$$E[w] = 1/2 \sum_{d \in D} (t_d - O_d)^2 \quad (3.21)$$

Where D is set of training, t_d is the target output for the training d and O_d is the output of the linear unit for the training d .

This vector derivative is called the gradient of E with respect to the vector $\langle w_0 \dots w_n \rangle$ written ∇E .

$$\nabla E(w) = [\partial E / \partial w_1, \partial E / \partial w_2 \dots \partial E / \partial w_n] \quad (3.22)$$

$$\Delta (w_i) = -\eta \frac{\partial E}{\partial w_i} \quad (3.23)$$

Here we characterize E as a function of weight vector because the linear unit output O depend. Here is η a positive constant called the learning rate, which determines the step size in the gradient descent search. The negative sign is present because we want to move the weight vector in the direction that decreases E. This training rule can also be written in its component form which makes it clear that steepest descent is achieved by altering each component w_i of weight vector in proportion to $\partial E/\partial w_i$.

The vector of $\partial E/\partial w_i$ derivatives can be obtained by differentiating E. Train the w_i such that they minimize the squared error.

$$\frac{\partial E}{\partial w_i} = \frac{\partial}{\partial w_i} \frac{1}{2} \sum d(td - od)^2 \quad (3.24)$$

$$= \sum d \frac{\partial}{\partial w_i} (td - od)(td - od) \quad (3.25)$$

Then error formula where td and od is the desired and actual network outputs respectively.

The Levenberg-Marquardt algorithm, which is a variation of Newton's method, was used in this thesis. It is designed for minimizing functions those are sums of squares of other nonlinear functions. This algorithm is very well suited to neural network training. A sigmoid function was used as neuron transfer functions in this thesis [33].

Objective function – is an Empirical error (should decay)

Parameters to optimize - are weights and bias

Constraints – are equalities (inequalities) for weights and bias. For this thesis Levenberg-Marquardt method optimization is applied. No need of assign boundary constraint, because the Levenberg-Marquardt algorithms handle without bound constraints. [42]

3.7.2.1 Levenberg-Marquardt Optimization

$$F(x, w) = \frac{1}{1+e^{-a}} = \frac{1}{1+e^{-wx}} \quad (3.26)$$

Where F sigmoid functions

The derivative of the sigmoid activation Function F Become $\frac{\partial F}{\partial x} = F(x, w) (1-F(x, w))$. It has a good property for learning.

$F(x, w) = o$. Where x is the input vector presented to the network, w are the weights of the network, and o is the corresponding output vector approximated or predicted by the network. For this work x is speed profile of the train and volume of vehicles at Adey Ababa intersection.

$$W = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{1n} & \cdots & w_{nn} \end{pmatrix}, \quad x = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{1n} & \cdots & x_{nn} \end{pmatrix} \quad J = \begin{pmatrix} \frac{\partial F(X_{11}, W)}{\partial W_1} & \cdots & \frac{\partial F(X_{1N}, W)}{\partial W_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial F(X_{1N}, W)}{\partial W_1} & \cdots & \frac{\partial F(X_{NN}, W)}{\partial W_n} \end{pmatrix}$$

$$(\mathbf{JtJ} + \lambda \mathbf{I}) \delta = \mathbf{JtE}. \quad (3.27)$$

Where J is the Jacobian matrix for the system, I identity matrix, λ (learning rate) is the Levenberg's damping factor, $\delta(\Delta w)$ is the weight update vector that we want to find and E is the error vector containing the output errors for each input vector used on training the network. The δ tells us by how much we should change our network weights to achieve a (possibly) better solution.

$$\text{From Eq 3.27 we get } \delta(\Delta w) = \mathbf{JtE} (\mathbf{JtJ} + \lambda \mathbf{I})^{-1} \quad (3.28)$$

Once $\delta(\Delta w)$ is determine the weight is updating easily using $w(\text{new}) = w + \delta(\Delta w)$. The error is calculating again based on the new weight value and continues until the mean square reach below thresholds value.

The λ damping factor is adjusted for each iteration, and guides the optimization process. The Jacobian is a matrix of all first-order partial derivatives of a vector-valued function. In the neural network case, it is an N -by- W matrix, where N is the number of entries in our training set and W is the total number of parameters (weights + biases) of our network. It can be created by taking the partial derivatives of each output in respect to each weight. Typically, λ would start as a small value such as 0.1 [43].

The objective function is to minimize mean square error of the function.

min E

Subject to weight and bias

Bias and weight are the constraint for Levenberg-Marquardt optimization of this thesis work.

The back-propagation process continues until all weights have been adjusted. The error must lower than threshold value. If so the forecasting arrival time is optimized. If the threshold value greater than threshold value use a new set of inputs, information is feed forward through the network (using the new weights) and errors at the output layer computed. For this thesis work the threshold value set to 10^{-6} (it is default value in MATLAB) [42].

The process continues until

- (i) The performance index reaches an acceptable low value
- (ii) A maximum iteration count (number of epochs) has been exceeded
- (iii) A training-time period has been exceeded.

3.7.3 ANN Design for Arrival Time Prediction

The back propagation algorithm was used to train the multilayer neural networks. The back propagation algorithm is a generalization of the least mean square algorithm, and both algorithms use mean square error.

The chain rule is employed (as shown above) in the back propagation algorithm in order to compute the derivatives of the squared error with respect to the weights and biases in the hidden layers. However, when the back propagation algorithm converges, there is no guarantee the optimum solution is found.

Consequently, it is best to try several different initial conditions to increase the possibility of finding a total optimum solution. Therefore, all ANNs tested in this thesis were run several times with different initial parameters to find the parameters that gave the best results. [33] [43]. Different architectures, consisting of one, five, ten, twenty, thirty and fifty

hidden neural etc consider and the average absolute error was used as the performance index. The input-output structure of the ANN model used in this thesis is shown in below

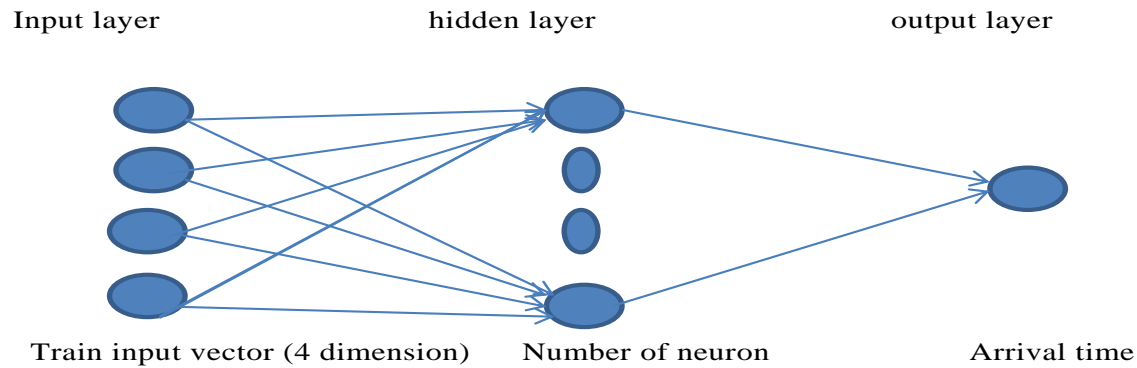


Figure 3.11 Design of Artificial Neural Network

The input vector could be: 1) The position of the train 2) The velocity of the train
3) Acceleration of the train 4) Deceleration of the train

The hidden layer is determining by during training of artificial neuron. The output layer is the arrival time (second) of the train at Adey Ababa grade crossing.

Flow chart of ANN

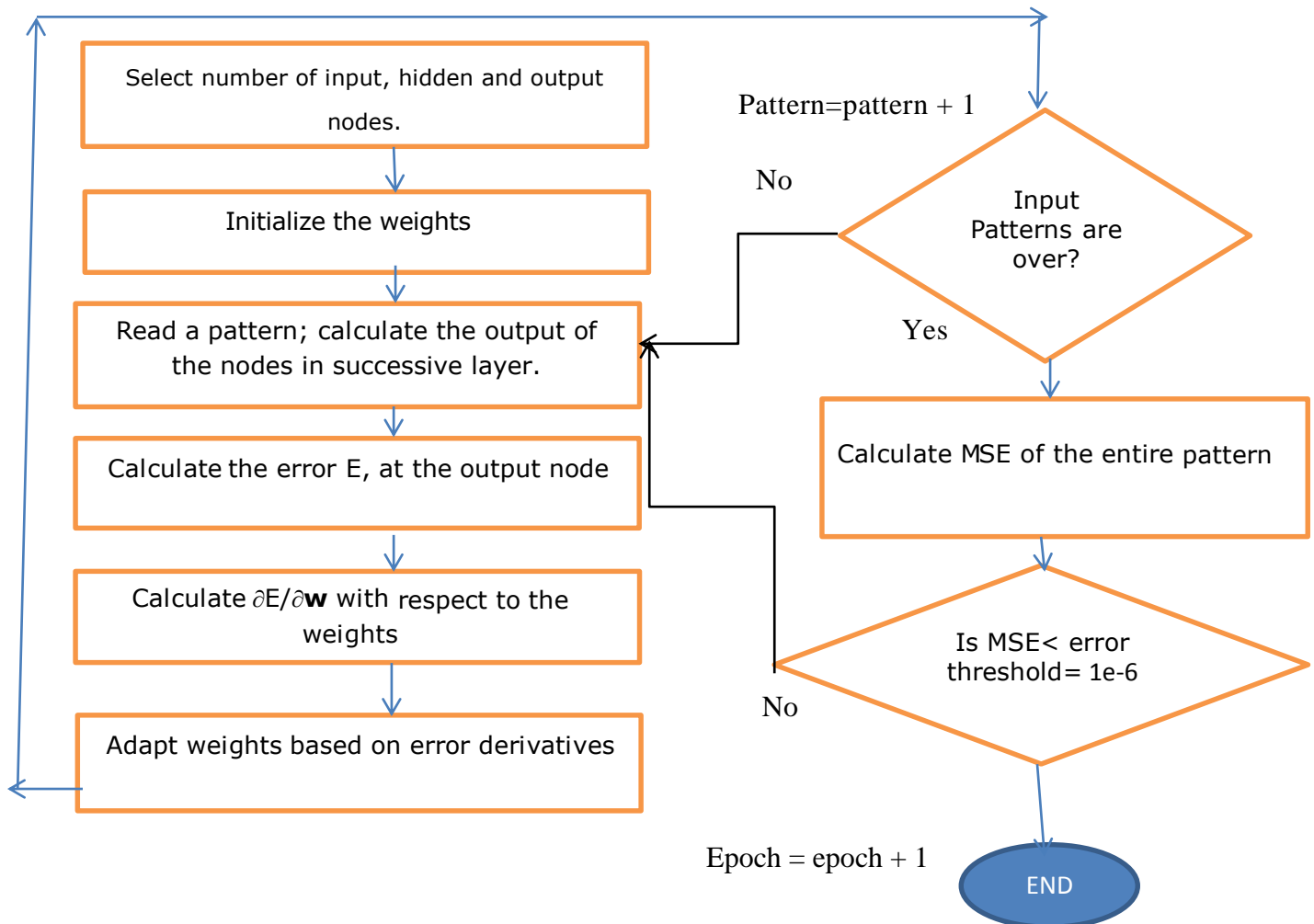


Figure 3.12 flow chart of ANN

The input (position, velocity, acceleration and deceleration of the train) taken from bistatic radar, give to artificial neural network and the above algorithm is implemented using MATLAB function.

3.8 Transitions Preemptions Strategy Algorithm

The TPS (transitions preemptions strategy) is a logic algorithm whose objective is to improve the means by which traffic signal controller units prepare for a railroad preemption event. While maintaining the control requirements and standards explained in the MUTCD (1), TPS attempts to “ready” the signal control for the start of an approaching railroad preemption input, or call, by adjusting phase interval durations and phasing sequence in order to avoid certain shortcoming [46].

Preemption Sequence

All controllers currently in use have the same basic preemption sequencing, in accordance with currently accepted practice [17]. The normal preemption sequence and the required variables for each step are shown in Figure 3-1.

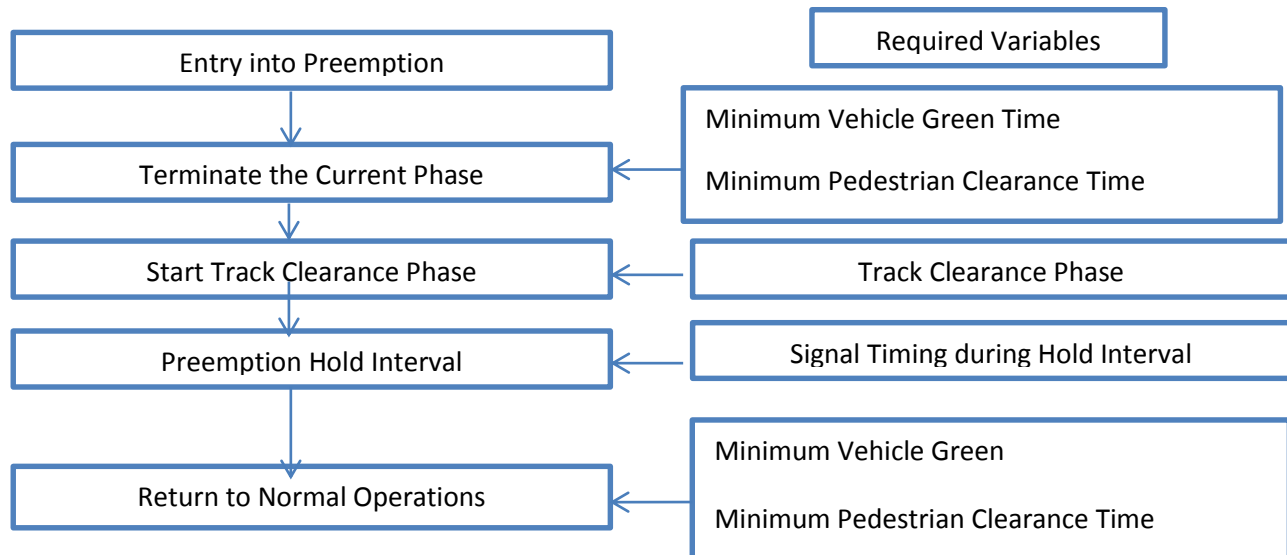


Figure 3.13 Transition Preemption Variables

3.8.1 Preemption Sequence

1. Entry into Preemption

Because time available before the train arrives at the HRGC is relatively short, the signal controller usually initiates the preemption sequence immediately upon detection of an approaching train.

2. Terminating the Current Phase

At certain points in the cycle, the termination can occur immediately at the beginning of preemption and, thus, the track clearance phase is provided directly, that is, in the case that the minimum green time and pedestrian clearance time are already provided at the beginning of preemption. This is called right-of-way transfer time.

3. Timing the Track Clearance Phase.

After the operation phase has been terminated and the clearance interval has been provided, a track

clearance green time must be provided that is long enough to clear vehicles that may be queued over the track. The duration of the track clearance time should be based on the maximum number of queued vehicles that need to be cleared before the train arrives [46].

4. Preemption Hold Interval

The preemption hold interval occurs after the track clearance interval. It occurs when the train is near or in the crossing. Once the preemption hold interval begins, the controller keeps it active until the train has left the detection zone.

5. Return to Normal Operations.

Once the train removed from the crossing, the traffic signal must transition back to its normal mode of operation. Figure 3.13 shows Algorithm for preemption phase sequence

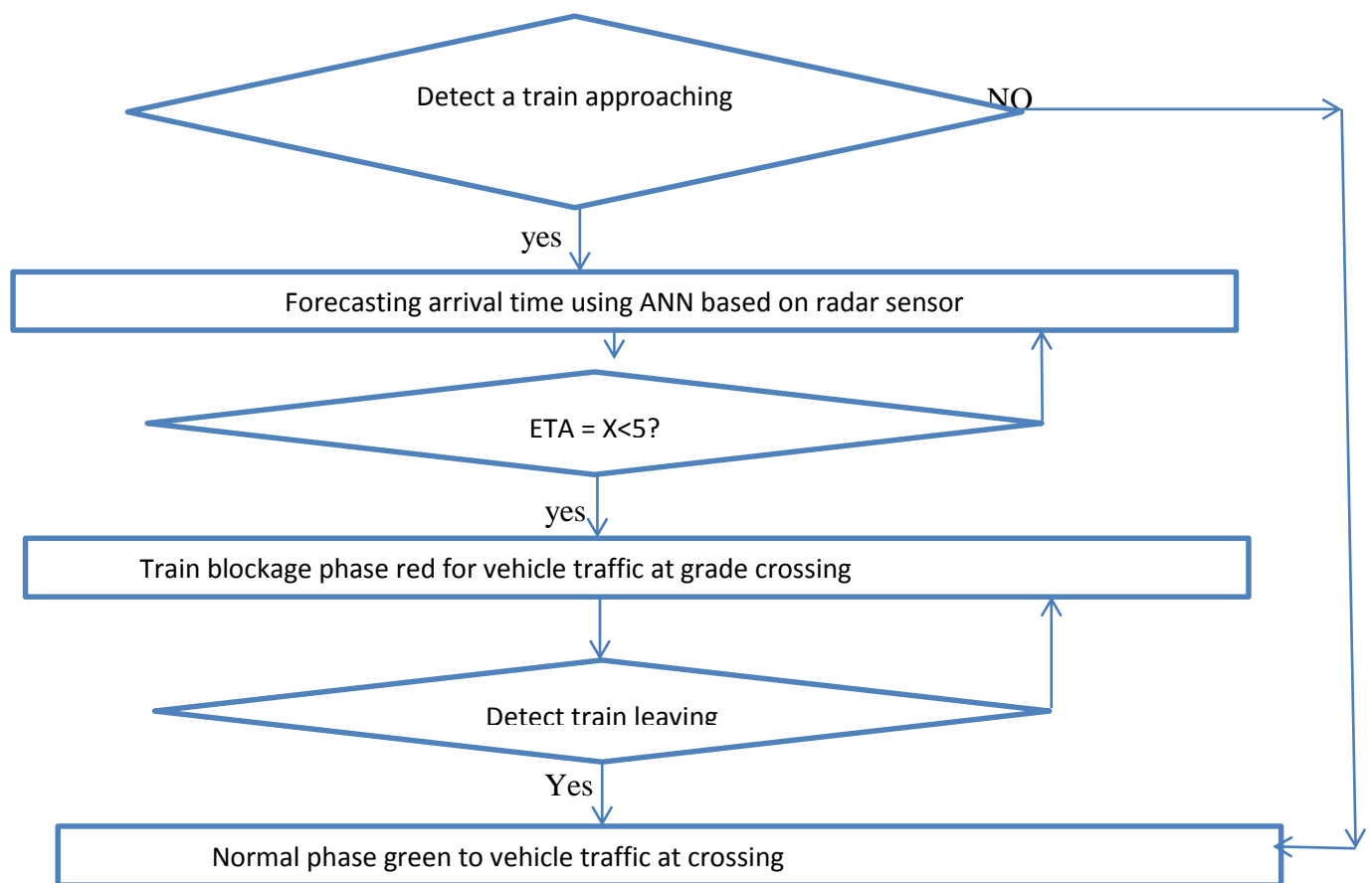


Figure 3.14 Flow Chart of TPS Algorithm

3.8.2. Timing of track clearance

Queue Clearance Time. The length of the track clearance phase should be based on the maximum number of queued vehicles that need to be cleared before the train arrives. Queuing analysis has been applied to estimate the queued vehicles at each particular location [19] [28].

The length of queue expected during any signal cycle is a function of the approach volume, cycle length, saturation flow rate, and green split. Although the signalized intersection capacity analysis procedures in the U.S. Highway Capacity Manual (HCM) provide for the calculation of maximum discharge rates, they do not include a storage requirement for preventing spillback into an upstream intersection [33].

To initiate a preemption sequence, two major executes must occur:

- 1) The traffic signal controller must receive an electronic signal to start the preemption sequence to clear the tracks.
- 2) The active railroad warning devices, including the flashing lights and gates, must be activate to provide the warning signal and stop vehicles from crossing.

The railroad warning devices should be active for a minimum time of 20 seconds before the train arrives at the crossing under normal conditions based on the requirements. However, if the crossing is wide or crosses multiple track, or if requested by the highway authority, a MWT (minimum warning time) longer than 20 seconds may be provided [30]

The following variables are needed in order to use the TPS logic.

Time to Train Arrival (T): The time the train is predicted to arrive at the crossing. The estimator used to predict arrival time is a function of the track equipment and agency objective. This value is updated every second as the train approaches the crossing based on bistatic radar and artificial neural network action.

Track Clearance Time (TK): The time at which the track clearance phase should be initiated.

Remaining Time Available ($X = T - TK$): Effectively, a “countdown” until the track clearance time. For this thesis work $TK = 41$ second

Extended Time (B_i): Time period added into NP to end a vehicle phase i that have a blocking phase.

That is, when there is a vehicle call for phase i , phase i is provided until $X = NP + B_i$, Instead of $X = NP$.

From the above definitions, two other variables that are used in the TPS logic are calculated.

NP: Minimum time necessary to service the next phase (phase i+1); and

N2P: Minimum time needed to service the next two phases (phase i+1 and phase i+2) when the next phase is the track clearance phase. Once the train detection equipment has indicated that a train will arrive at the crossing within the TPS initiation time, the TPS logic monitors and, if necessary affects controller operation

For this thesis advance preemptions is implemented for the sake of safety .we take the minimum green time of track clearance phase take as a track green time.

Actual advance preemptions time			Railroad warning time				
Lights Gate			Warning lights flashing				
			Delay (3sec)	Gate descending		Gates horizontal	
Track green(11 sec)			Yellow(5sec)		Dwell time		
36	25	23	20	17	12	6	3 0

Figure 3.15 Advance Preemptions

Warning Lights Flashing, Gates Descending, Track Green (11 sec), and Yellow Dwell Warning Lights Gates Preempt. After the traffic signal controller receives the preempt notification, the right of way must be transferred to traffic in the approach to the intersection crossing the tracks. The required wait time prior to the track clearance phase is termed the right-of-way transfer time. Once the right of way is transferred, the track clearance phase is active. The track clearance green should be provided at least equal to the queue clearance time, which is the time it requires a vehicle stopped on Grade crossing. Once the train detection equipment has indicated that train will arrive at the crossing within the TPS initiation time (41 seconds), the TPS logic would begin to monitor and, if necessary, affect controller operation. The TPS logic will discuss in section 3.8.

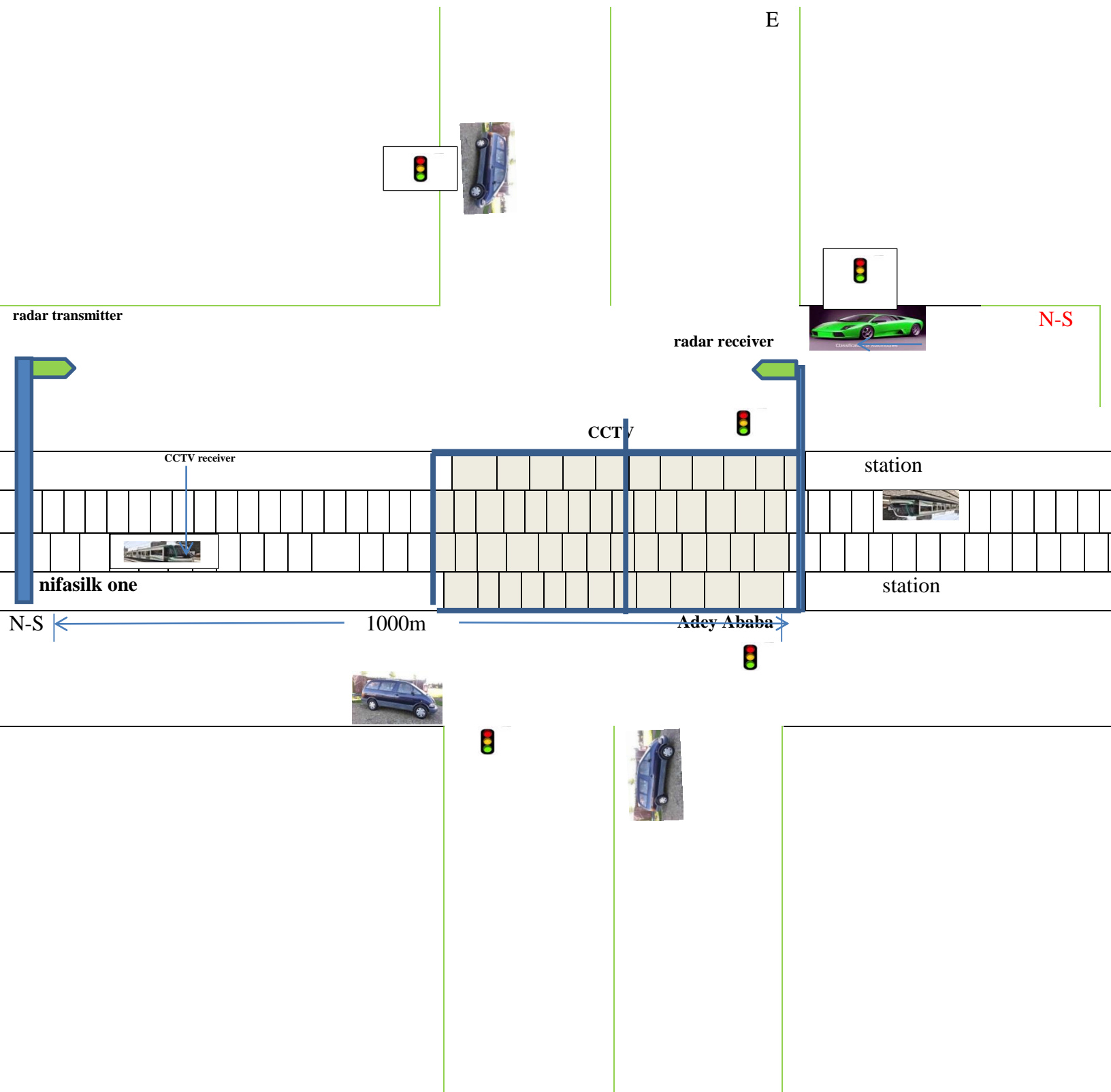


Figure 3.16 Geometry of Adey Ababa Grade Crossing

In the design of train detector position location two cases must be consider.

Case1 If the Grade crossing and station are very near each other like Adey Ababa grade crossing.

Case2 If the Grade crossing is far from the station or the Grade crossing between two stations.

For the case 1 we need only one radar transmitter and receiver. To manage the station side of the Grade crossing, we need to prepare push button at the station.

When the operator (driver) press the push button the traffic controller enters in to preemptions when the train passes exit zone the push button return to normal position. The push button relay is connected to the exit detector for de energizing the relay. The relay is energized by push button but de energized by the exit detector.



Figure 3.17 Show Grade Crossing and Station are Near Each other for Adey Ababa Intersection

For the case 2 we need two transmitter one receiver

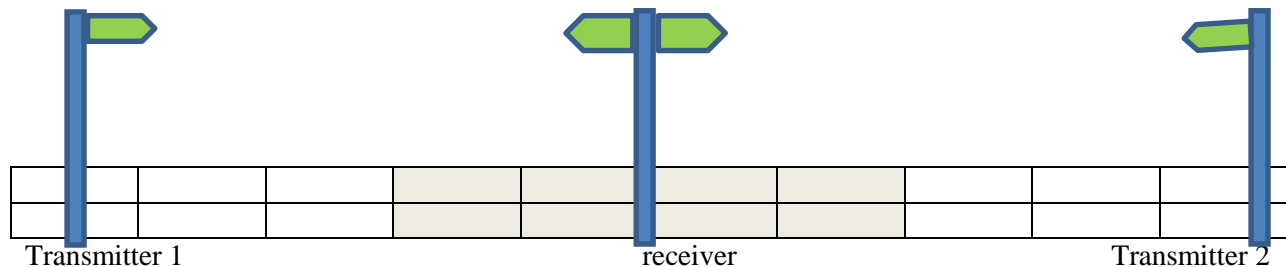


Figure 3. 18 Show Multistatic Radar Setup

All the design prepare for Bistatic radar we can apply directly for this multistatic (two transmitters and two receiver).Both side of the Grade crossing managed by a radar transmitter

3.9 Traffic Signal Design

Traffic signals are one of the most effective and flexible active control of traffic and is widely used in several cities worldwide. The conflicts arising from movements of traffic in different directions are addressed by time sharing principle. This subsection discusses various design principles of traffic signal such as phase design, cycle length design, and green splitting. The concept of saturation flow, capacity, and lost times and other are presented.

3.9.1 Phase design for Adey Ababa Intersection

The reason for of phase design is to separate the conflicting movements in an intersection into various phases, so that movements in a phase should have no conflicts to implement this principle the following design procedure is consider

The signal design procedure involves four major steps. They include: (1) phase design, (2) determination of amber time, (3) determination of cycle length, (4) distributing of green time

The first issue is to decide how many phases are required the Adey Ababa crossing based on geometry and conflict conditions are well understood. It is possible to have two, three, four or even more number of phases. Two phase system is usually adopted if through traffic is significant compared to the turning Movements but the given intersection has a characteristics both through and turning movement. Safety is critical issue for this intersection due to complex geometry and high traffic density, so we decide three phase. This type of phase plan is ideally suited in urban areas where the turning movements are comparable with through movements and when through traffic and turning traffic need to share same lane [45].

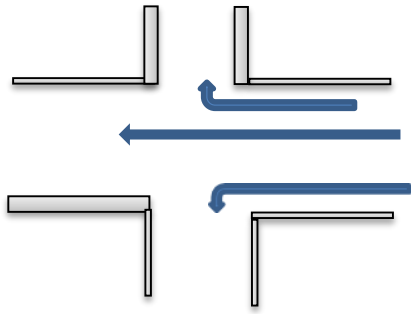


Figure 3.19 From Sarisabo to Kadiso and Saris Adisu Sefre and Left Turn

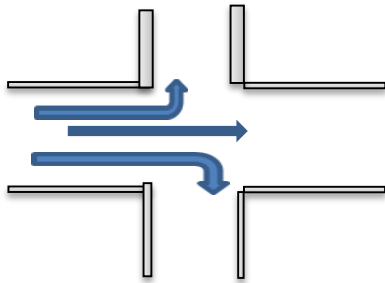


Figure 3.20 From Nifasilk to Saris Abo, Behre Tsiga and Left Turn

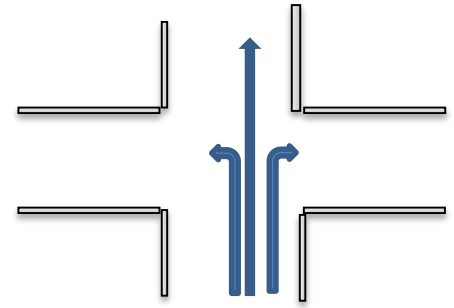


Figure 3.21 From Behre Tsiga to Kadiso, Sarise Adisu Sefre and Sarise abo

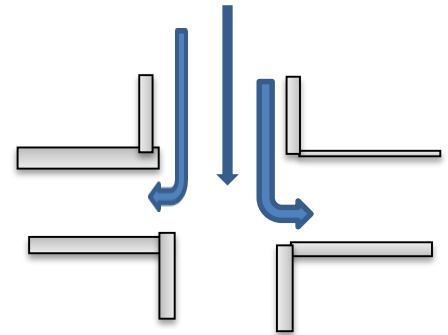


Figure 3.22 From Sarise Adisu Sefre to Behre Tsiga, Kadiso and to Saris Abo

This is the possibility of traffic movement at Adey Ababa grade crossing.

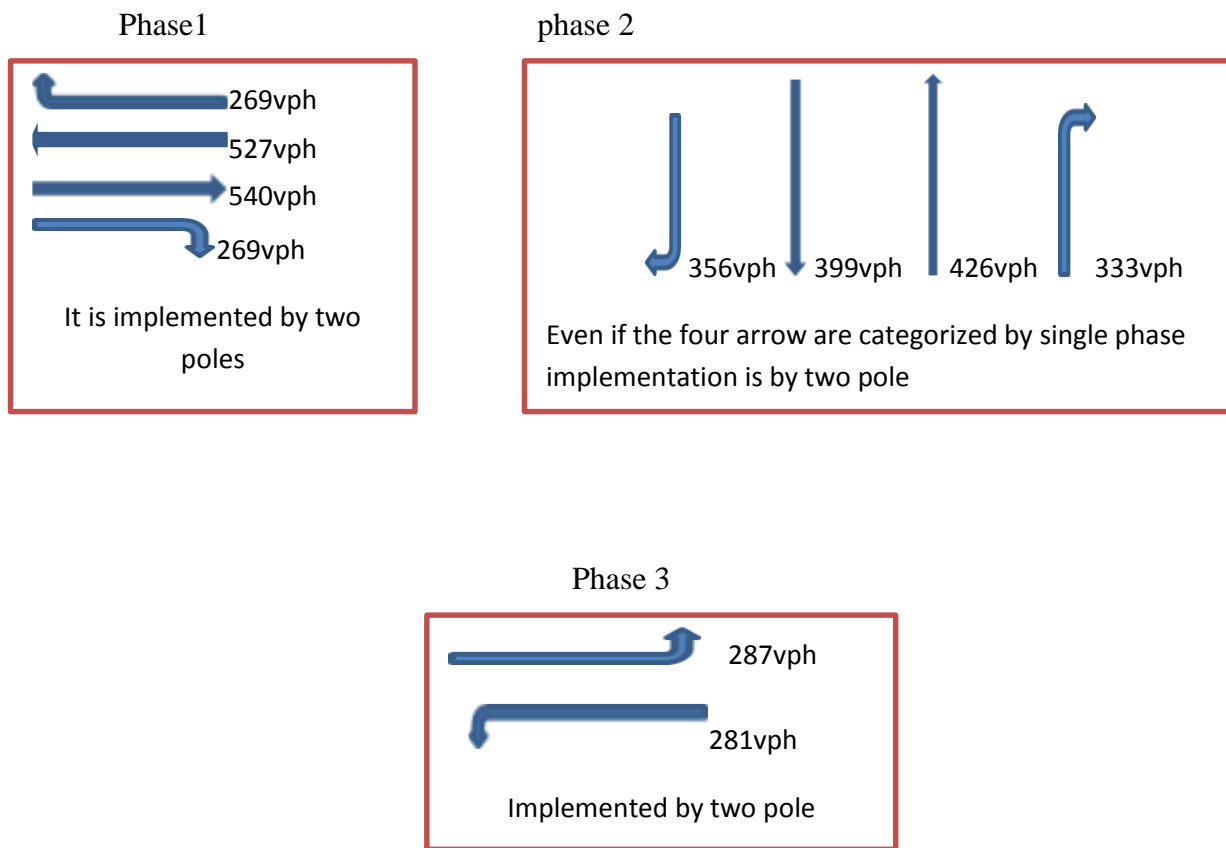


Figure 3.23 Traffic Signal Phase Sequence at Adey Ababa Grade Crossing

To determine the exact signal time of the above phases, we need to know volume of the vehicles for each direction and lanes. Since there is no written data for this specific site, which is Adey Ababa grade crossing. Vehicle occupancy data were collected at four directions around Adey Ababa intersection. This is as shown below

Time	Phase 1					Phase 2					Phase 3		
Time for vehicles arrival at around Adey Ababa grade crossing	Nifase silk to Adey Ababa (TH)	Sarise abo to Adey Ababa (TH)	Nifase silk to Adey Ababa right turn (RT)	Sarise abo to Adey Ababa right turn (RT)	critical volume for phase1	behre Tsiga to Adey Ababa right turn (RT)	behre Tsiga to Adey Ababa (TH)	Saris eadisu sefre to Adey Ababa (TH)	Sarise adisu sefre to Adey Ababa right turn (RT)	critical volume for phase2	Nifase silk to Adey Ababa Left turn (LT)	Sarise abo to Adey Ababa left turn (LT)	critical volume for phase3
7:00-:15 AM	149	161	90	90	149	138	125	111	105	138	75	91	91
7:15-:30 AM	152	156	92	92	152	134	124	110	104	134	71	84	84
7:30-:45 AM	151	169	75	75	151	140	127	113	107	140	77	97	97
7:45-:00 AM	152	172	75	75	152	100	97	83	77	100	37	50	50
8:00-:15 AM	155	182	79	79	155	124	121	107	101	124	61	74	74
8:15-:30 AM	148	128	96	96	148	148	145	131	125	148	85	98	98
8:30-:45 AM	199	120	83	83	199	85	72	58	52	85	74	35	74
8:45-:00 AM	181	161	79	79	181	87	74	60	54	87	76	37	76
9:00-:15 AM	154	167	96	96	154	78	65	51	45	78	67	28	67
9:15-9:30 AM	179	169	50	50	179	96	77	63	57	96	85	46	85
9:30-9:45 AM	205	153	74	74	205	75	62	48	42	75	64	25	64
9:45-10:00 AM	138	115	71	71	138	75	62	48	42	75	64	50	64
10:00-10:15 AM	177	122	78	78	177	75	62	48	42	75	64	51	64
10:15-10:30 AM	195	124	65	65	195	74	62	48	42	74	63	40	63
10:30-10:45 AM	151	132	73	73	151	78	65	51	45	78	67	28	67
10.45-11.00 AM	162	113	58	58	162	98	85	71	65	98	87	48	87
11.00-11.15 AM	150	149	66	66	150	79	66	52	46	79	68	29	68
11.15-11.30 AM	137	111	74	74	137	75	62	48	42	75	64	25	64
11.30-11.45 AM	122	96	56	56	122	79	66	52	46	79	68	29	68
11.45-12.00 AM	83	77	42	42	83	76	63	49	43	76	65	26	65

12.00-12.15 AM	86	121	71	71	86	73	60	46	40	73	62	23	62
12.15-12.30 AM	78	110	56	56	78	54	51	37	31	54	43	40	43
12.30-12.45 AM	78	111	54	54	78	58	45	31	25	58	47	38	47
12.45-1.00 PM	82	98	50	50	82	56	43	29	23	56	45	36	45
1:00-1:15PM	82	98	50	50	82	56	43	29	23	56	45	36	45
1.15-1.30 PM	141	111	61	61	141	75	62	48	42	75	64	25	64
1.30-1.45 PM	127	81	57	57	127	49	36	22	16	49	38	31	38
1.45-2.00 PM	127	89	63	63	127	68	55	41	35	68	57	18	57
2.00-2.15 PM	97	156	79	79	97	124	57	43	37	124	70	74	74
2.15-2.30 PM	73	134	71	71	73	121	54	40	34	124	83	71	83
2.30 -2.45 PM	69	59	69	69	69	121	59	45	39	121	62	71	71
2.45 - 3.00 PM	104	172	70	70	104	76	63	49	43	76	65	26	68
3.00 -3.15 PM	128	168	73	73	128	45	71	57	51	71	60	61	61
3.15 -3.30 PM	95	141	63	63	95	45	54	40	34	54	43	52	52
3.30 -3.45 PM	82	155	59	59	82	78	87	73	67	87	76	79	79
3.45-4.00 PM	101	130	76	76	101	68	97	83	77	97	86	98	98
4.00 -4.15 PM	147	170	45	45	147	79	140	126	120	140	89	93	93
4.15 - 4.30 PM	160	167	43	43	160	103	127	113	107	127	73	76	76
4.30 - 4.45 PM	156	168	76	76	156	154	148	134	128	154	78	93	93
4.45 - 5.00 PM	148	153	52	52	148	142	181	167	161	181	103	107	103
5.00 -5.15 PM	162	171	76	76	162	143	184	211	205	211	114	112	112
5.15 - 5.30 PM	165	136	69	69	165	189	189	211	205	211	109	101	109
5.30 -5.45 PM	156	155	83	83	156	192	196	215	209	215	100	98	100
5.45 -6.00 PM	152	103	74	74	152	201	179	211	205	211	103	96	103
6.00 -6.15 PM	157	130	71	71	157	204	205	207	201	207	106	104	106

as h . This is the headway that can be achieved by a moving platoon of vehicles passing through a green indication. If every vehicle requires h seconds of green time, and if the signal were always green, then s vehicles per hour would pass the intersection [45].

Therefore,

$$S = 3600/h \quad (3.29)$$

- Assume saturation headway is 2.4 seconds (h) = **2.4 second**
Assume all driver has good reaction time .we take $h = 2.4$ second, $s = 3600/2.4 = 1500$
- start-up lost time is 2 seconds per phase
- The clearance lost time is 1 second

Total lost time = start-up lost time + the clearance lost time = 3 second

Where s is the saturation flow rate in vehicles per hour of green time per lane, h is the saturation headway in seconds. As noted earlier, the headway will be more than h particularly for the first few vehicles

2) Effective green time

Effective green time is the actual time available for the vehicles to cross the intersection. It is the sum of actual green time (G_i) plus the yellow minus the applicable lost times. This lost time is the sum of start-up lost time (L_i) and clearance lost time denoted as tL . Thus effective green time can be written as,

$$g_i = G_i + Y_i - tL \quad (3.30).$$

The total start-up lost time is $L = NtL = 3 \times 3 = 9$ second loss

Where $N = 3$ is the number of phases. Assume start-up lost time is the same for all phases. Yellow time is 3 second for the city traffic system.

If C is the cycle length in seconds, then the number of cycles per hour = $3600/C$. The total lost time per hour is the number of cycles per hour times the lost time per cycle and is =

$(3600/C)*L$. Substituting as $L = NtL$, total lost time per hour can be written as $=3600Nt/c$. The total effective green time T_g available for the movement in an hour will be one hour minus the total lost time in an hour [45]. Therefore,

$$T_g = 3600 - 3600Nt/c \quad (3.31)$$

Let the total number of critical lane volume that can be accommodated per hour is given by V_c , then $V_c = T_g/h$. Substituting for T_g from equation 32 and S_i from equation 30 in the expression for the maximum sum of critical lane volumes that can be accommodated within the hour and by rewriting, the expression for C can be obtained as follows:

$$\begin{aligned} V_c &= T_g/h \\ &= 3600/h (1-NtL/c) \end{aligned} \quad (3.32)$$

$$\text{Therefore } C = NtL/1-V_c/s \quad (3.33)$$

3) Determination of cycle length

To determine the cycle length we apply Webster formula. Webster formula gives as the optimal green time of the cycle.

According to Webster formula the effective intersection cycle calculated as follows [46]

$$C = \frac{1.5L + 5}{1 - \sum_1^3 \frac{vci}{s}} \quad (3.34)$$

$L = 3*3 = 9$ for the phase total lost time, $s = 1500$

L , Lost time V_c , critical lane volume s , saturation flow rate

Total critical volume = $V_{c1} + V_{c2} + V_{c3} = 557 + 304 + 409 = 1270 \text{vec}$

$C = (1.5*9 + 5)/1 - (557/1500 + 304/1500 + 409/1500) = 18.5/0.153333 = 120 \text{ second}$

Take $C = 120$ second total cycle time. This is the total time use for the 3 phase of signal intersection

We need to divide this cycle time for the three of the intersection based on the critical volume of the lanes.

For phase 1 critical volume $V_{c1} = 527$, total critical volume $V_{ct} = 1278$, therefore

$$\text{For phase 1 } g_1 = (V_{c1} / V_{ct}) * C = (527/1270) * 120 = \mathbf{52} \text{ second} \quad (3.35)$$

$$\text{For phase 2, } g_2 = (409/1270) * 120 = \mathbf{39} \text{ second}$$

$$\text{For phase 3 } g_3 = (304/1270) * 120 = \mathbf{29} \text{ second}$$

Based on the above calculation the following Table is prepared for vehicles per hour

Time	Critical volume of the vehicles				Cycle time second
	Vc1	Vc2	Vc3	Vct	
1:00-2:00AM	492	400	322	1214	97
2:00-3:00AM	683	403	302	1212	96
3:00-4:00AM	676	324	280	1063	64
4:00-5:00AM	685	325	281	1074	65
5:00-6:00AM	492	309	265	1066	64
6:00-7:00AM	326	251	201	778	56
7:00-8:00PM	492	316	233	1060	63
8:00-9:00PM	374	392	283	1049	62
9:00-10:00PM	425	378	322	1149	79
10:00-11:00PM	436	411	308	1283	128
11:00-12:00PM	420	432	318	1262	117
12:00-1:00PM	557	409	304	1270	120

Table 3.3 Traffic Volumes per Hour at Adey Ababa Intersection

Based on the cycle calculated on the above Table, further calculate the amount of green time for each phase

Phase number	Duration of each phase effective green time in second												
Phase1	39	40	27	28	30	31	29	23	29	56	47	47	52
Phase2	32	32	19	18	19	14	19	21	26	41	40	40	39
Phase3	26	24	17	17	16	11	14	17	22	31	31	29	29

Table 3. 4 Shows Cycle Distributions for Phases

Based on the above phase length Table, the minimum green time and maximum green time for each phase length determine.

For phase 1 minimum green time = 23 second and maximum green time = 56 second

For phase 2 minimum green time = 14 second and maximum green time = 41 second

For phase 3 minimum green time = 11 second and maximum green time = 31 second

This minimum and maximum green time is used for the sake of TPS algorithm implementation. Grade crossing intersection is different from other intersection because the traffic signal timing interrupted suddenly during train blockage. This is the reason why minimum and maximum green time is set. Once the current phase use the minimum green time the TPS algorithm chick, if there is train interruption. If not the phase continue use the time up to maximum green time, otherwise the signal timing is interrupt. The traffic signal boundary are revised below

$$g1_{min} < g1 < g1_{max} = 23 < g1 < 56 \text{ and } g1 > 0$$

$$g2_{min} < g2 < g2_{max} = 14 < g2 < 41 \text{ and } g2 > 0$$

$$g3_{min} < g3 < g3_{max} = 11 < g3 < 31 \text{ and } g3 > 0$$

$$C_{min} < C < C_{max} \text{ where } C_{min} = \text{minimum cycle time and } C_{max} = \text{the maximum cycle time}$$

From Table 3.4 $61 < C < 128$ and $C_{min}, C, C_{max} > 0$

TPS algorithm

$X = T - TK = (T - 41)_{\text{second}}$ the following algorithm work based on this formula.

X = remaining time, T = predicted arrival time And $TK = 36 + 5 = 41$ second.

$g_{1\text{min}} = 23$ second $g_{2\text{min}} = 14$ second and $g_{3\text{min}} = 11$ second

For example from speed profile Table $T = 125$ second, $X = 125 - 41 = 84$ second is remaining time. The current phase is not terminated because it is greater than 5 second. So the algorithm serves other phases of the traffic light. TPS algorithm work based on this concept

The process of preemption is begins once a train has been detected at far from Adey Ababa grade crossing. The predicted arrival times are updated every second by bistatic radar information feed to ANN and ANN can predicted arrival time of the train. Once the predicted train arrival time is less than the advance preemption warning time (36 second), the TPS algorithm is started as listed in the steps described below.

Step 1

The status of the current phase (1, 2, and 3) is checked to determine if both the minimum vehicle green time and minimum pedestrian green/clearance time have been served. If the minimum green time has not been completely served, the current phase remains active. Otherwise, the logic proceeds to step 2.

Step 2

If the remaining time available (X) is equal to or less than the Clearance time interval of the current, the current phase is terminated and the track clearance phase is started. If $X \leq 5$ (clearance time), then, terminate the current phase, start the track clearance phase, otherwise, the logic proceeds to step 3.

Step 3

The current phase is checked. If the current phase is the track clearance phase, then the logic proceeds to step 5B-3.

If current phase = track clearance phase (phase3 for this work.), then, the logic proceeds to step 5B-3 otherwise, the logic proceeds to step 4

Step 4 the next phase is checked.

If the next phase is not the track clearance phase, the logic proceeds to step 5B-1.

If next phase \neq track clearance phase, then, the logic proceeds to step 5B-1 otherwise, the logic proceeds to step 5A-1

Step 5A-1: Next phase is the track clearance phase

The vehicle call status for the current phase is checked. If there is no vehicle call for the current phase ($V_{ci} = 0$), the logic proceeds to step 5A-3.

If $V_{ci} = 0$, then, the logic proceeds to step 5A-3 otherwise, the logic proceeds to step 5A-2

Step 5A-2: Vehicle call for the current phase

If $X \geq N2P$,

If there is no call for both of the next two phases ($V_{cj} = 0$ and $V_{ck} = 0$), the current phase remains. The logic proceeds to step 6.

If there is a call for either of the next two phases ($V_{cj} = 1$ or $V_{ck} = 1$), the current phase is terminated and the next phase is started. The logic proceeds to step 6.

If $X \geq N2P$,

If $V_{cj} = 0$ & $V_{ck} = 0$, then, keep the current phase active and the logic proceeds to step 6

Else if $V_{cj} = 1$ or $V_{ck} = 1$, then, terminate the current phase, start the next phase, and the logic proceeds to step 6

If $N2P \geq X \geq NP$

If there is no call for both of the next two phases ($V_{cj} = 0$ and $V_{ck} = 0$), the current phase remains active. The logic proceeds to step 6.

If there is a call for the next phase and there is no call for the next phase of the track clearance phase ($V_{cj} = 1$ and $V_{ck} = 0$), the current phase is terminated and track clearance phase will start. The logic proceeds to step 6.

If there is a call for the next phase of the track clearance phase ($V_{ck} = 1$) regardless of a call for the next phase, the current phase is terminated and the next phase of the track clearance phase is started. The logic proceeds to step 6.

If $N2P \geq X \geq NP$, If $V_{cj} = 0$ & $V_{ck} = 0$, then, keep the current phase active and the logic proceeds to step 6 else if $V_{cj} = 1$ & $V_{ck} = 0$, then, terminate the current phase, start the track clearance phase, and the logic proceeds to step 6

else if $V_{ck} = 1$, then, terminate the current phase, start the next phase of the track clearance phase, and the logic proceeds to step 6

If $X \leq NP$,

If there is no call for the next phase ($V_{cj} = 0$), the current phase remains active. The logic proceeds to step 6.

If there is a call for the next phase ($V_{cj} = 1$), the current phase is terminated and the next phase is started. Note that because the next phase is the track clearance phase the minimum green time does not need to be guaranteed. The logic proceeds to step 6.

If $X \leq NP$, If $V_{cj} = 0$, then, keep the current phase active and the logic proceeds to step 6

Else if $V_{cj} = 1$, then terminate the current phase, start the next phase, and the logic proceeds to step 6

Step 5A-3:

If $X \geq N2P$,

The current phase is terminated and the next phase will begin timing regardless of a call for the next phase. The logic proceeds to step 6.

If $X \geq N2P$, then, terminate the current phase, start the next phase, and the logic proceeds to step 6

If $N2P \geq X \geq NP$,

If there is no call for the next phase of the track clearance phase ($V_{ck} = 0$) regardless of a call for the next phase, the current phase is terminated and the next phase is started.

The logic proceeds to step 6.

If there is a call for the next phase of the track clearance phase ($V_{ck} = 1$) regardless of a call for the next phase, the current phase is terminated and the next phase of the track clearance phase is started. The logic proceeds to step 6.

If $N2P \geq X \geq NP$,

If $V_{ck} = 0$, then, terminate the current phase, start the next phase, and the logic proceeds to step 6

Else if $V_{ck} = 1$, then, terminate the current phase, start the next phase of the track clearance phase and the logic proceeds to step 6

If $X \leq NP$,

The current phase is terminated and the next phase is started regardless of a call for the next phase. The logic proceeds to step 6.

If $X \leq NP$, then, terminates the current phase, start the next phase, and the logic proceeds go to step 6)

Step 5B-1

Vehicle call for the current phase is checked. If there is still a vehicle call for the current phase ($V_{ci} = 1$), then the logic proceeds to step 5B-2. Otherwise, the logic proceeds to step 5B-3. If $V_{ci} = 1$, then, the logic proceeds to step 5B-2. Otherwise, the logic proceeds to step 5B-3

Step 5B-2

If $NP + B_i < X$ or $X < NP$, the current phase remains active. The logic proceeds to step 6.

If $NP + B_i \geq X \geq NP$, the current phase will be terminated and the next phase will begin timing, the logic proceeds to step 6.

If $(NP + Bi < X)$ or $(X < NP)$, then, keep the current phase active and the logic proceeds to step 6

Else if $(NP + Bi \geq X \geq NP)$, then, terminate the current phase, start the next phase, and the logic proceeds to step 6

Step 5B-3:

If $X < NP$, the current phase remains active. The logic proceeds to step 6.

If $X \geq NP$, the current phase will be terminated and the next phase will begin timing.

The logic proceeds to step 6.

If $X < NP$, then, keep the current phase active and the logic proceeds to step 6

Else if $(X \geq NP)$, then, terminate the current phase, start the next phase, and the logic proceeds to step 6

Step 6:

Decrement T ($T = T - 1$). Return to Step 1 to ensure that the minimum times of the current phase have been satisfied.

The above steps will be performed every time the train's predicted arrival time at the crossing is updated and each time a new signal phase becomes active.

3.9.2 Hardware architecture

Design of the Hardware Component of the System

To achieve this thesis work the following components are required. Figure 3.22 shows us the overall system block diagram of the system. The following are the basic Components of the system.

➤ **Bistatic Radar**

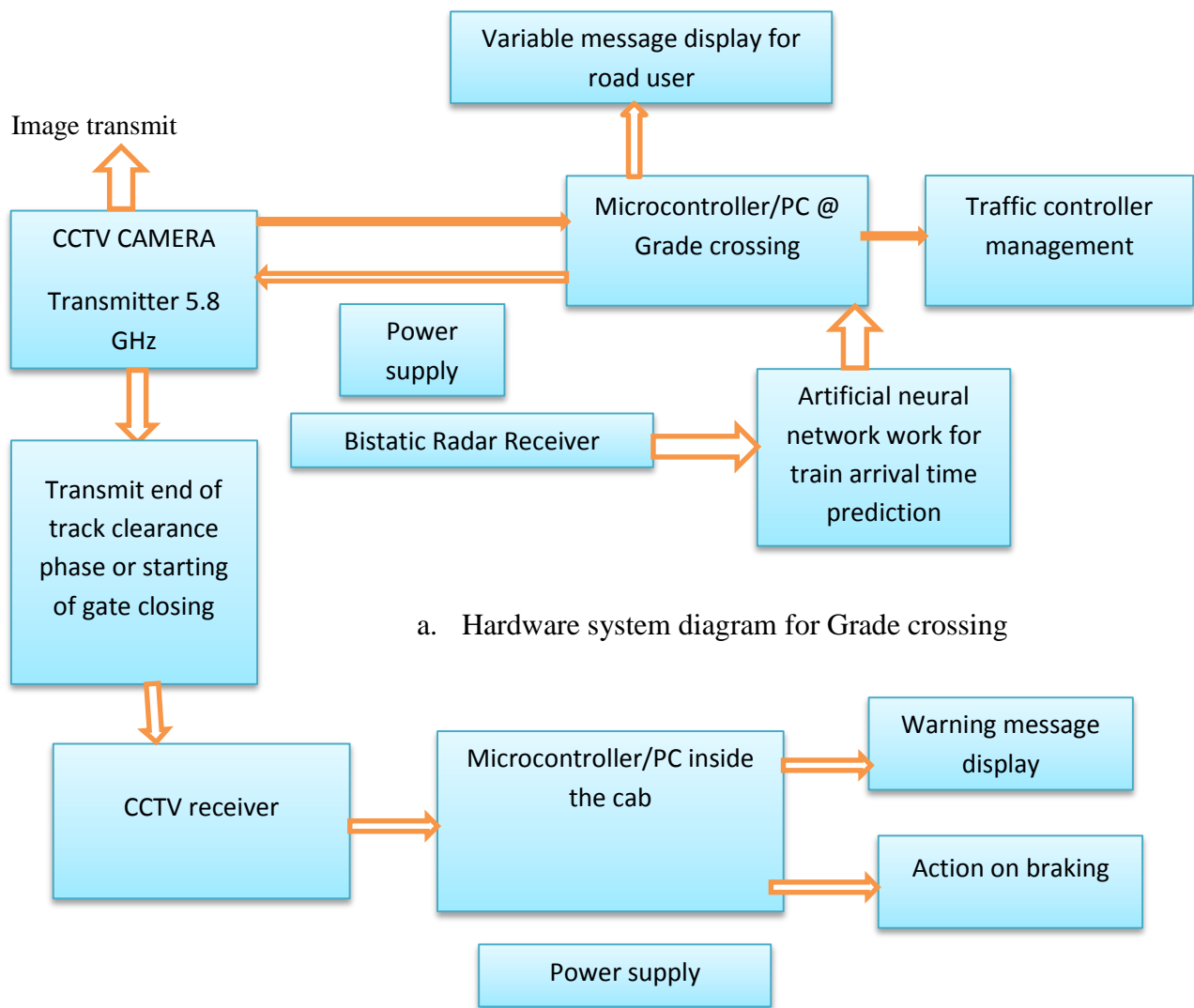
The bistatic radar is the hardware which is used for the detection of the targets coming from nefas silk one. The receiver of bistatic radar is connected to the microcontroller installed at Adey Ababa grade crossing, the raw data from the radar processed by ANN in side microcontroller for arrival time prediction.

➤ **Microcontroller**

This serves as the CPU for the system. It captures a raw data provided by the radar receiver and processed to extract the required location, speed and direction information. It holds all the required information that is to be sent to the train or to flash the appropriate wayside traffic signal to clear the Grade crossing quickly. Which means it is responsible for monitoring any danger of accident between trains and obstacles on the Grade crossing. It actually acts as a bridge between radar receivers, traffic lights and obstacle detections system.

➤ **Traffic Light controller**

Traffic Light controller is the hardware component which helps to show the Red, Yellow or Green signals for the vehicles and pedestrians interring or leaving the Grade crossing. This signals works according to the data sent by the microcontroller based on transition preemption strategy algorithm.



a. Hardware system diagram for Grade crossing

b. Hardware system diagram for onboard monitoring

Figure 3.25 Shows Hardware System Diagram

Chapter Four

4. Results and Discussion

In the previous chapter artificial neural network (ANN) models are design to handle the nonlinear relationship between the train speed profile and arrival time. Train detector technologies, train arrival time prediction algorithms and the transition preemption strategy are design and discussed. In this chapter MATLAB program is applied for simulation.

4.1 Simulation of Artificial Neural Network

4.1.1 Simulation of Artificial Neural Network for Train Arrival Time Prediction

The selected site for this simulation is between station 7 and 8 or Nifasilk one to Adey Ababa. It is 1000m far from Adey Ababa grade crossing.

For this simulation case, the minimum energy and maximum energy train drive taking into account. This is as shown by Table 4.1 below

Distance from Grade crossing(m)	Velocity(m/s)	Acceleration/Deceleration (M/S ²)	Target(second)
800	6.4	0.05	125
	9*	0.101	89
750	7.8	0.02	97
	14*	0.093	54
700	8.4	0.046	84
	17*	0.0714	42
650	8.8	0.04	74
	19*	0.0588	34
600	8.4	-0.2	72
	19*	0	32
550	8.2	-0.05	68
	19*	0	29
500	19	0	29
	19*	0	26
450	7.7	0.04229	55

	19*	0	24
400	7.8	0.0333	52
	16.5*	-0.104	24
350	7.7	-0.01666	46
	15.6*	-0.036	25
300	7.7	0	39
	14.6*	-0.0526	19
250	7.7	0	33
	14*	-0.043	14
200	7.2	-0.1	28
	14*	-0.043	14
150	7.2	0	21
	12*	-0.017	11
100	6.0	-0.3	17
	9*	-0.027	11
50	4.2	-0.3	11
	7*	-0.29	7
15	4	-1	3
0	4	-0.01818	0

*, maximum energy drive

Minimum energy drive

Table 4. 1 Train Speed Profile from Nifasilk on to Adey Ababa [47]

Neural network toolbox provides tools for designing, implementing, visualizing, and simulating neural networks. MATLAB is powerful tool simulate and evaluate ANN. The idea of forecasting using ANN based on the following formula.

$$\mathbf{O} = \mathbf{f}(\sum_1^m \mathbf{w}\mathbf{x} + \mathbf{b}) \quad (4.1)$$

$f(.)$ is an activation function

m is number of inputs applied to neuron

x is set of input variables of neuron

w is the synaptic weight connecting the input to the neuron

O output of the neuron

b is the bias.

- The networks take input and target data for the trainings
- The network is adjusted based on target –output error

The neural network training is start by feeding input and target data to the network:

A) Feeding input Data (x) to the network.

This data contain the position, velocity and acceleration/deceleration of the train. This is feed to the network for simulation.

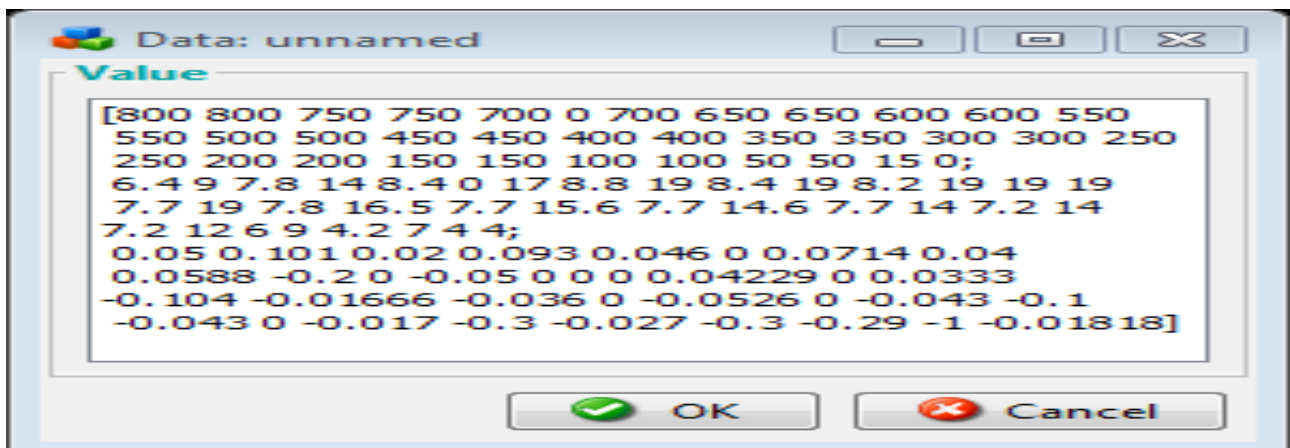


Figure 4. 1 Simulation Results for ANN Input

B) Feeding Target data (t) to the networks.

This is the target data to reach the train grade crossing. By how much second can arrival the train at grade crossing? The maximum arrival time is 125 second at the beginning of detections. This data also feed to the network as a target.

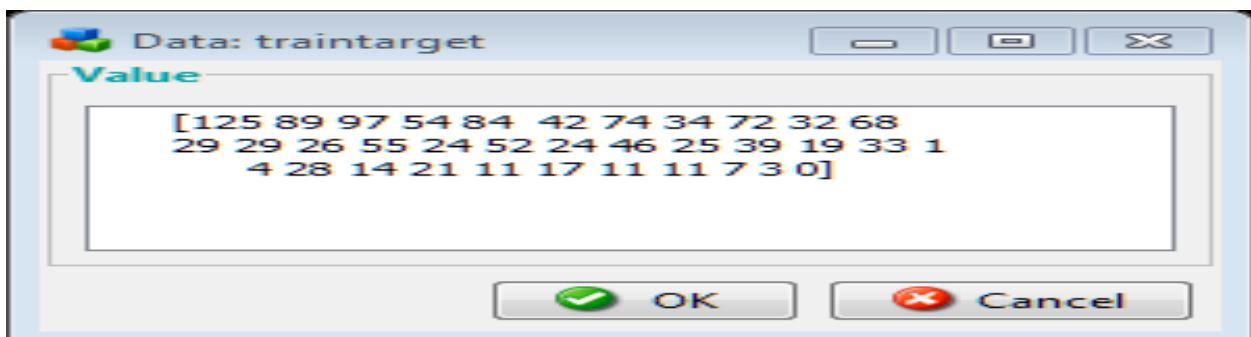


Figure 4.2 Simulation Results for ANN for Train Arrival Target

C) Network created for Ten number of artificial neural network.

Once the neural networks get the input and target data, the next step to determine number of neural, Function type, network type, performance function and type of optimization used. Based on this, figure 4.3 created

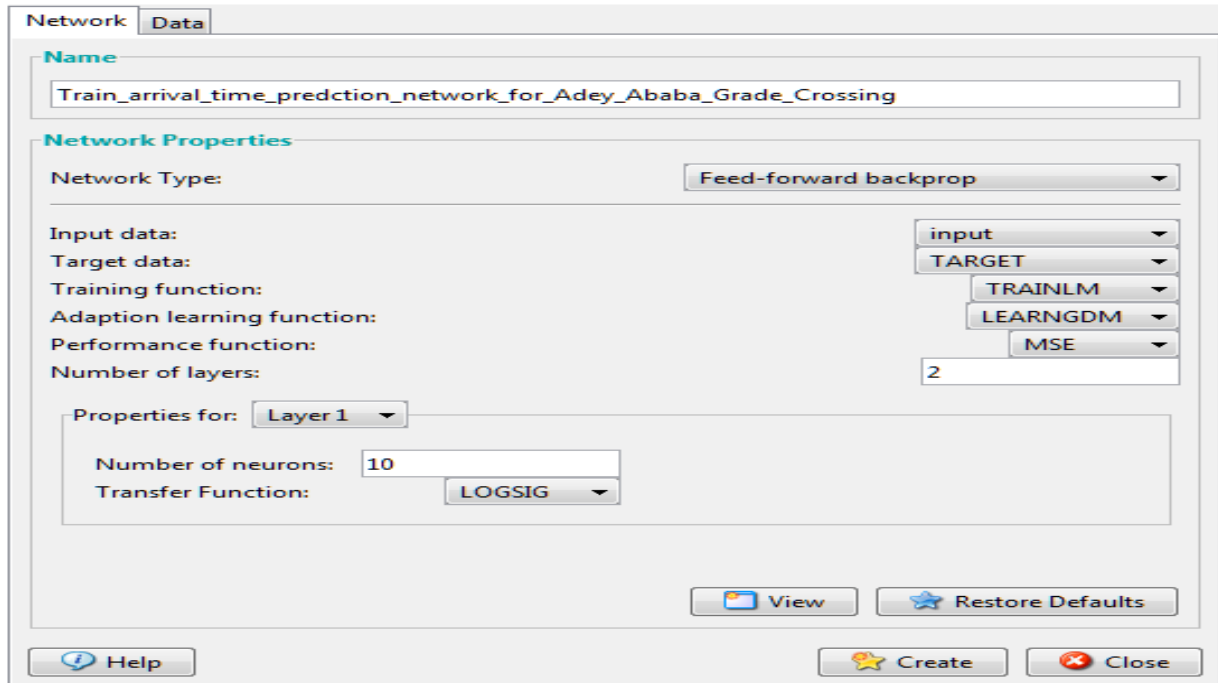


Figure 4.3 Creating Networks for 10 Numbers of Neuron

The following terminology explains the network property for Figure 4.3

Training function trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. Trainlm is often the fastest back propagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. It is network training function that updates weight and bias values according to Levenberg-Marquardt optimization.

Adaption leaning functions learned is the gradient descent with momentum weight and bias learning function

Transfer functions logsig is a transfer function, Transfer functions calculate a layer's output from its net input.

D) The design of artificial neural network for Ten number of neural network

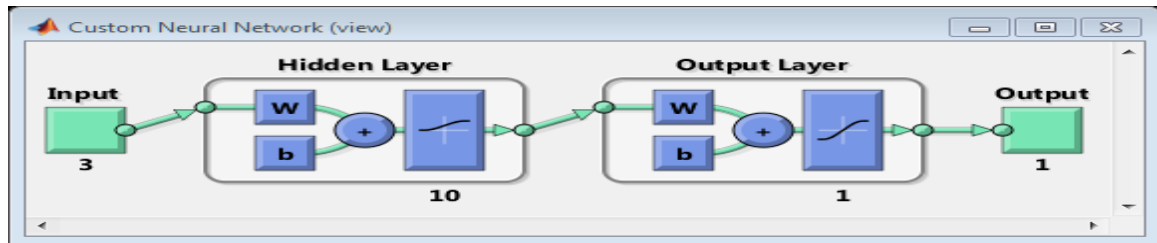


Figure 4.4 Input-Output Structure of Artificial Neural Network Model

- The three inputs are position, acceleration/deceleration and velocity of the train.
- Has one output that is arrival time of the train

To start the training the network initially assigns weight and bias value. This is shown below.

E) Initial weights value before training start for layer one

Since we have three input data and ten number of neural. We expect $3 \times 10 = 30$ weight value. This weight value assign for the ten neural networks for training purpose. This weight value is adjusted depend on target-output relationship. The data is shown below.

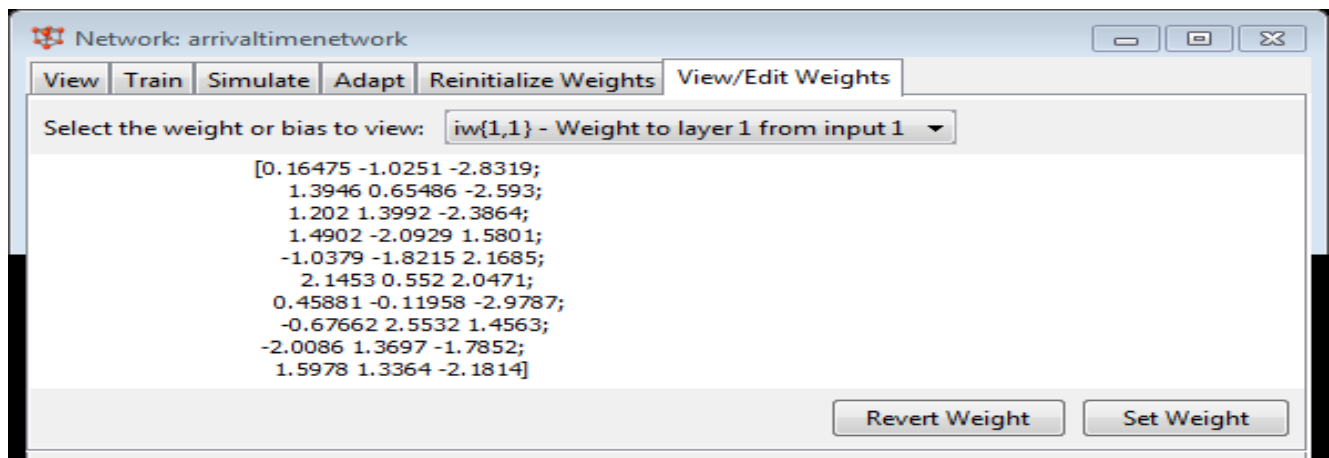


Figure 4.5 Simulation Result of Initial Weights Value for Ten Number Neural

F) Initial weights value before training start for second layer. Layer two is hidden layer, which is the number of neuron set. We expect 1×10 weight value from the simulation. This is shown below

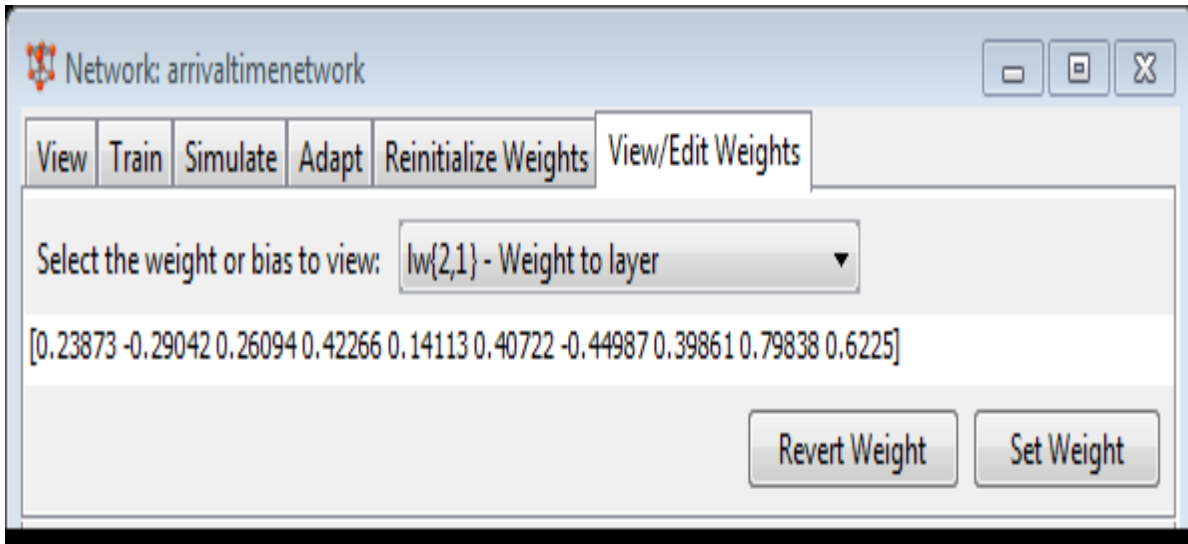


Figure 4.6 Initial Weight Value before Training Start for Layer One

G) Initial value of bias(b) for the first layer

This property defines the bias vectors for each layer with a bias. It is always an $N1 \times 1$ cell array, where $N1$ is the number of network layers. Since we have ten network value, we expect $1 \times 10 = 10$ bias value from the simulation result.

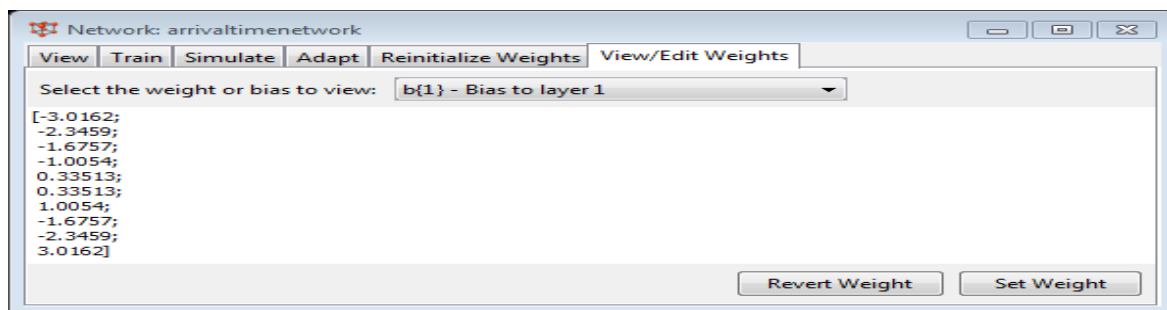


Figure 4.7 Initial Bias Values before Training Start for Layer Two

H) Initial Bias (b) value for second layer

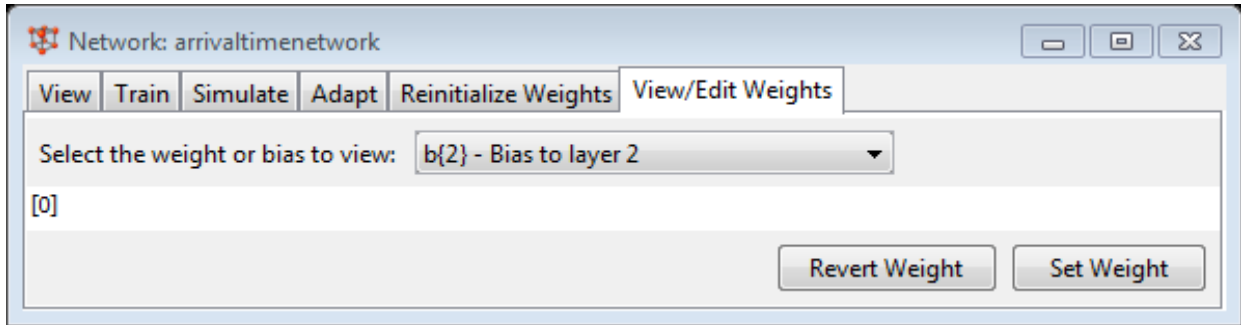


Figure 4.8 Simulation Result of Bias for Layer Two

I) after fifty successful training iteration of a network the initial weight update as shown below for layer one

As we see the weight value of the network is changed, the amount of the changed value for this layer based on target- output relationship. This is shown in the figure 4.9

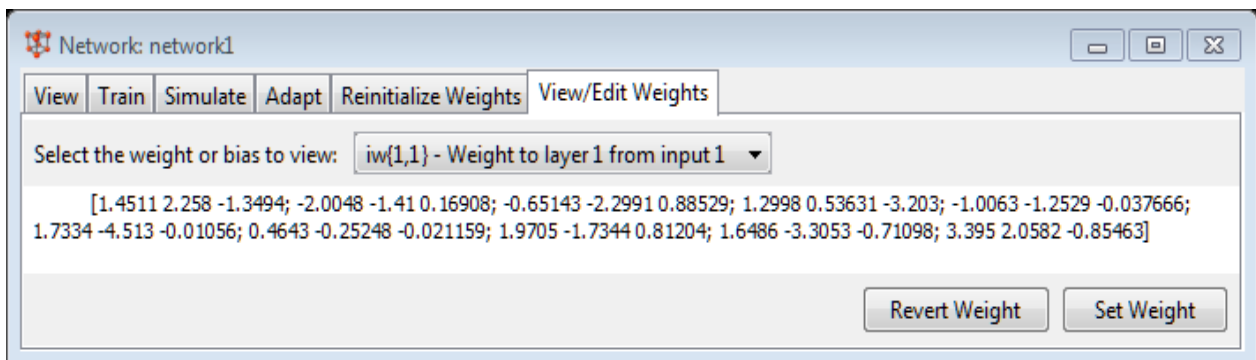


Figure 4.9 Simulation Result of Weight Value after a Network is Trained for Layer One

J) The new weights value for layer two

This value also updated based on target-output relationship.

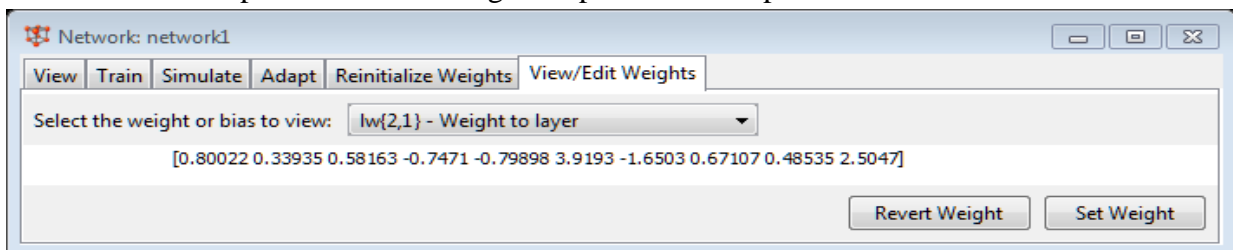


Figure 4.10 Simulation Result of Weight Value after a Network is Trained for Layer Two

K) Updated bias value for layer one

This is the updated bias value after training

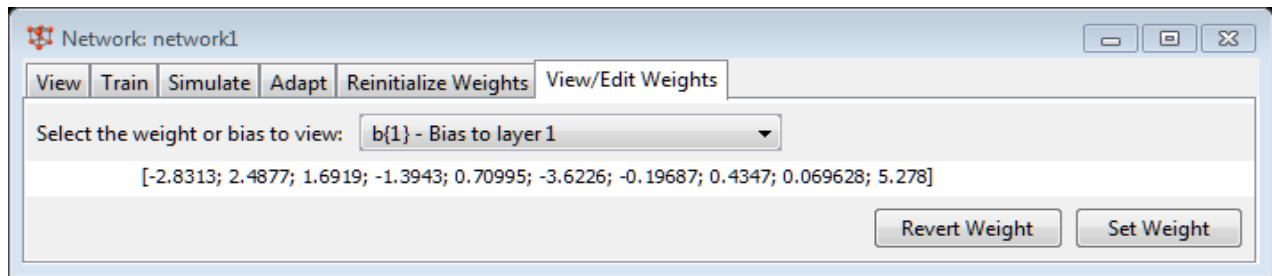


Figure 4.11 Simulation Result of Bias Value after a Network is Trained for Layer One

L) Updated bias value for layer two

After training the updating bias value is shown in the figure 4.14

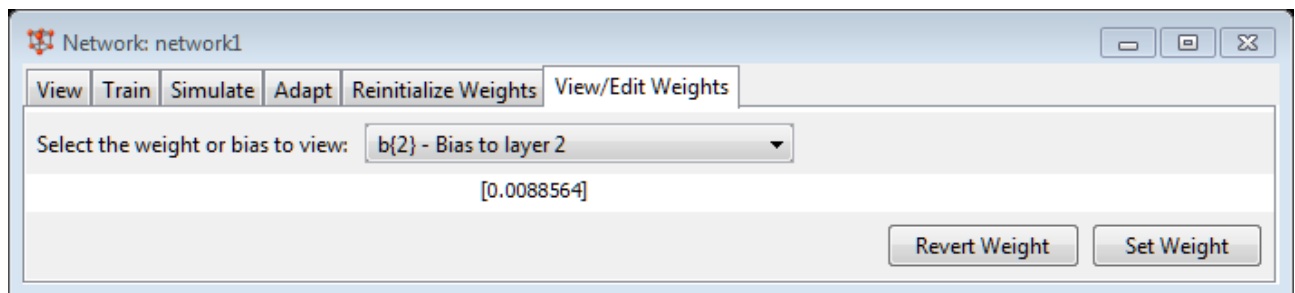


Figure 4.12 Simulation Result of Bias Value after a Network is Trained for Layer Two

M) Performance of the network after fifty training iteration

Once the above parameter is completes (from A to L). The network is trained up to the Mse reach below threshold value. Mean square error (MSE) is a network performance function. It measures the network's performance according to the mean of squared errors. The error is calculated based on output-target relationship. MSE value of this network is 0.52546. It is greater than threshold value. Therefore we need another network structure and training.

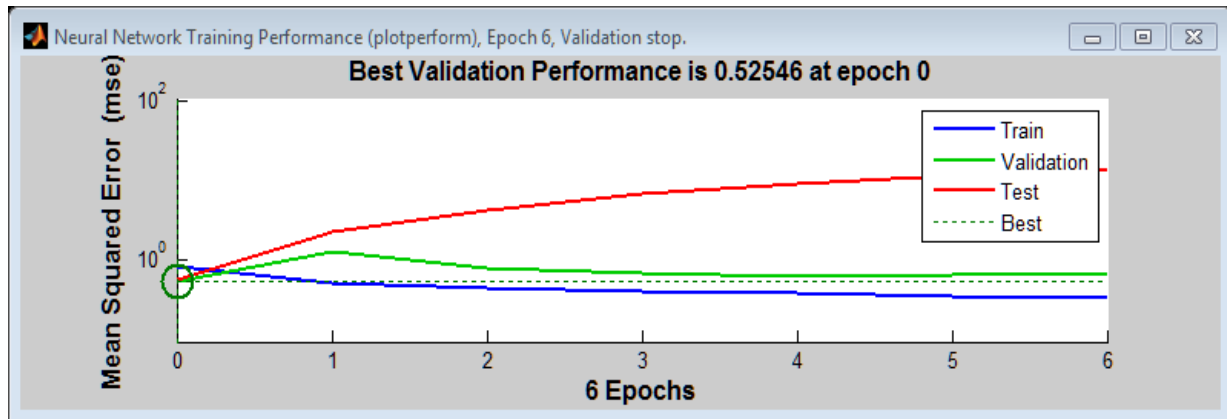


Figure 4.13 Simulation Results for Performances Validation

The flowing terminologies explain Figure4.13.

- Training. These are presented to the network during training, and the network is adjusted according to its error.
- Validation. These are used to measure network generalization, and to halt training when generalization stops improving.
- Testing. These have no effect on training and so provide an independent measure of network performance during and after training. But Test vectors are used as a further check that the network is generalizing well.

N) Simulation result for target-output graph of the network

Figure 4.14 show that the target -output relationship. As the training increase, target output relationship must near each other. From the simulation result output = 0.99target + 0.002.the output value is almost the same as the target value, we can say arrival time prediction is successful.

Analysis

Sample analysis from speed profile Table 4.1

800m(position)	6.4m/s =23.04km/hr.	0.05(acceleration)	125second(target)
800m	9* m/s = 32km/hr.	0.101	89second(target)

.Output =125*0.99+0.002=123.75 at minimum energy

125-123.75= **1.25** error value, this means the train arrives 1.25 second early. So we need further network trainings to get more perfect result.

Using maximum energy derive Output = 89*0.99+0.002= 88.11

89-88.11= 0.89, this shows 0.89 second early arrivals of the train. We can say this is good result for maximum drive.

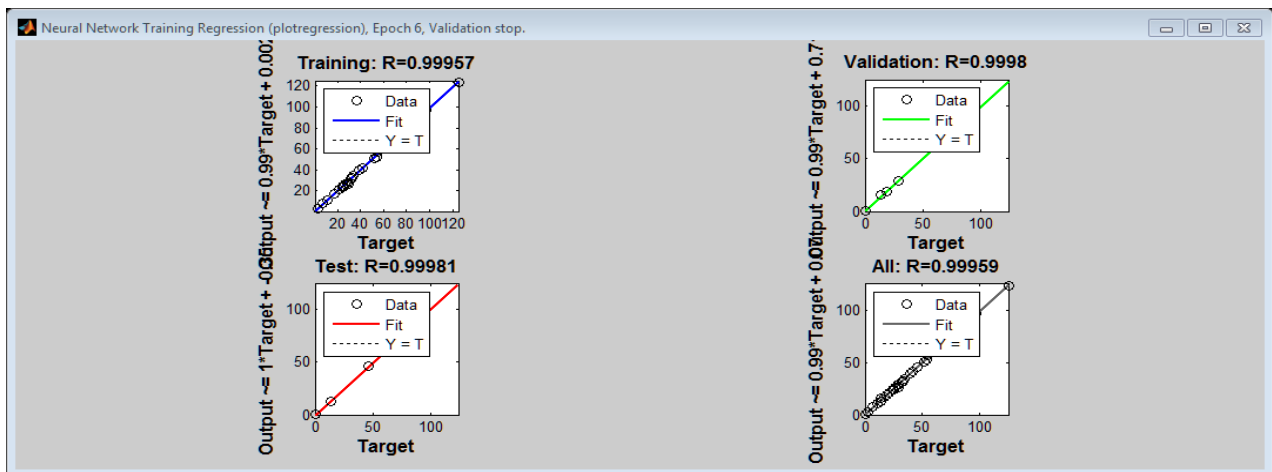


Figure 4.14 Simulation Results for Output-Target Relationship of the Network

Even if the mse error is small but it is above thresholds. To reach the threshold value let us increase number of neuron from 10 to 20

O) Change neural from 10 to 20.

One of the methods to increase the performance validation is increasing the number of neural network.

In this network $3 * 20 = 60$ weight value for first layer and 20 weight value for the second layer

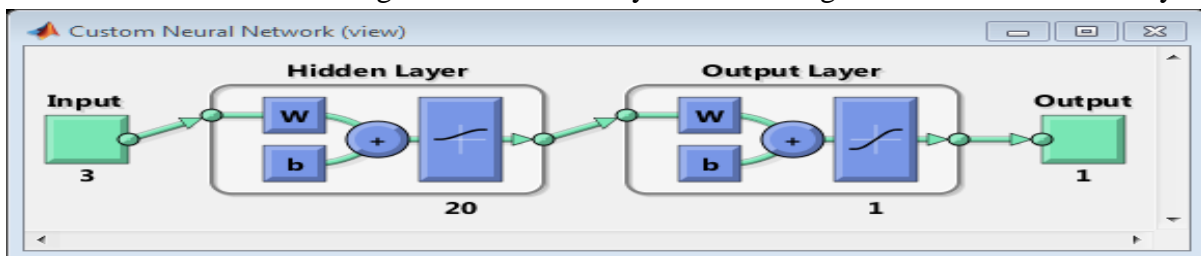


Figure 4.15 Input-Output Structure of Artificial Neural Network Model for Twenty Networks

P) Simulation result for twenty neural networks.

After fifty training iteration of the network and get 0.0058619 performance value. Even if still this is a better value, so we need further network model and trainings to achieve the threshold value

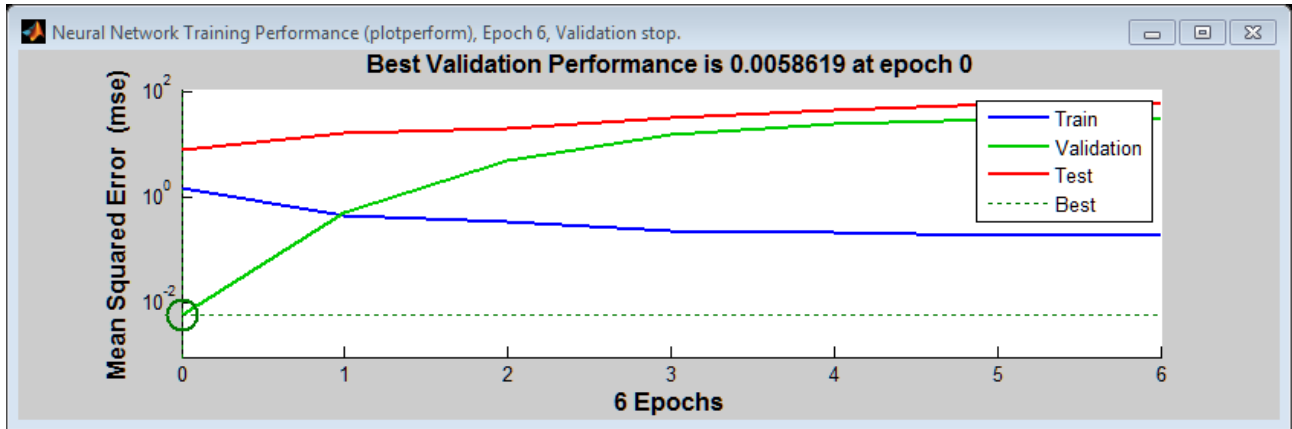


Figure 4.16 Simulation Results for ANN Performance after training

Q) Simulation result for target-output relationship for twenty neural network

Regression R values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. From the figure R = 0.999 is very close to one.

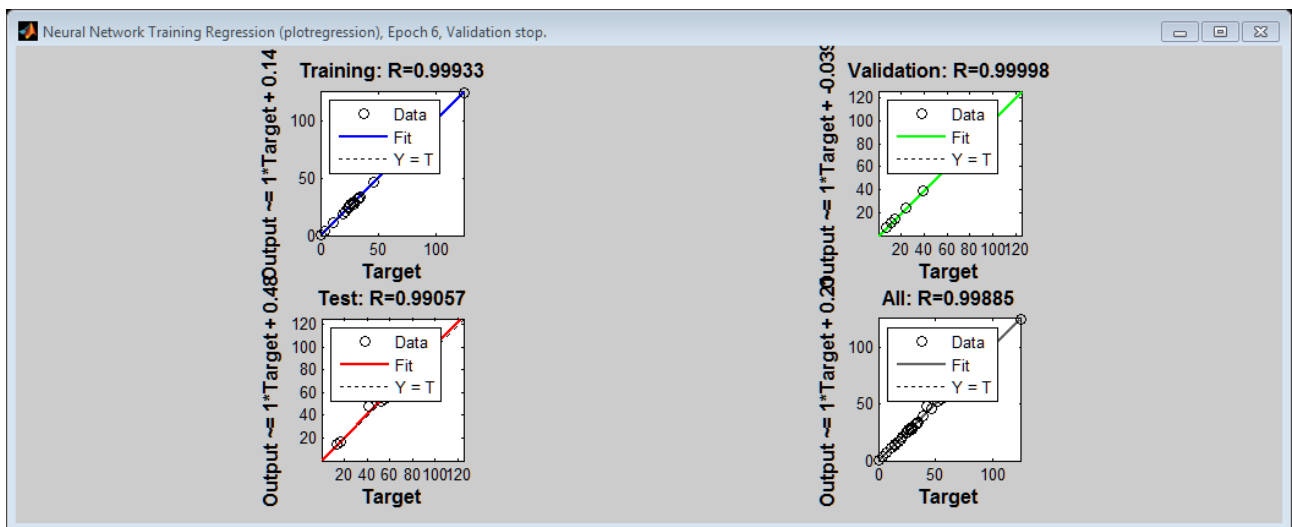


Figure 4.17 Simulation Results for Output-Target Relationship of the Network for Twenty Neural

As the training number of neural increase, target output relationship near each other. From the simulation result output = 1*target + 0.14. The output value is almost the same as the target value, but it is improver from ten number of neural.

Analysis

Output = target + 0.14 = 125+0.14= 125.14.This shows that the train arrive 0.14second delay for minimum energy.

Output=89+0.14=89.14.The train delay 0.14second, still the result is improved compered to ten neural network. To improve the result we need one more network design and training.

R) Change neuron from 20 to 30

To increase the performance validation, we need to increase number neuron from 20 to 30, in this network $3*30=90$ weight value at first layer and 30 weight values for the second layer

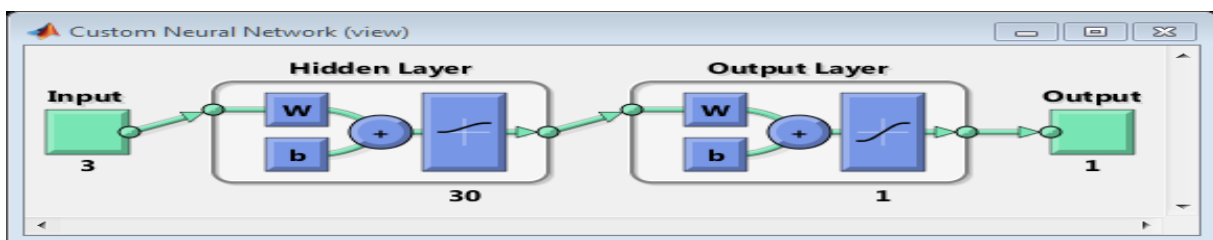
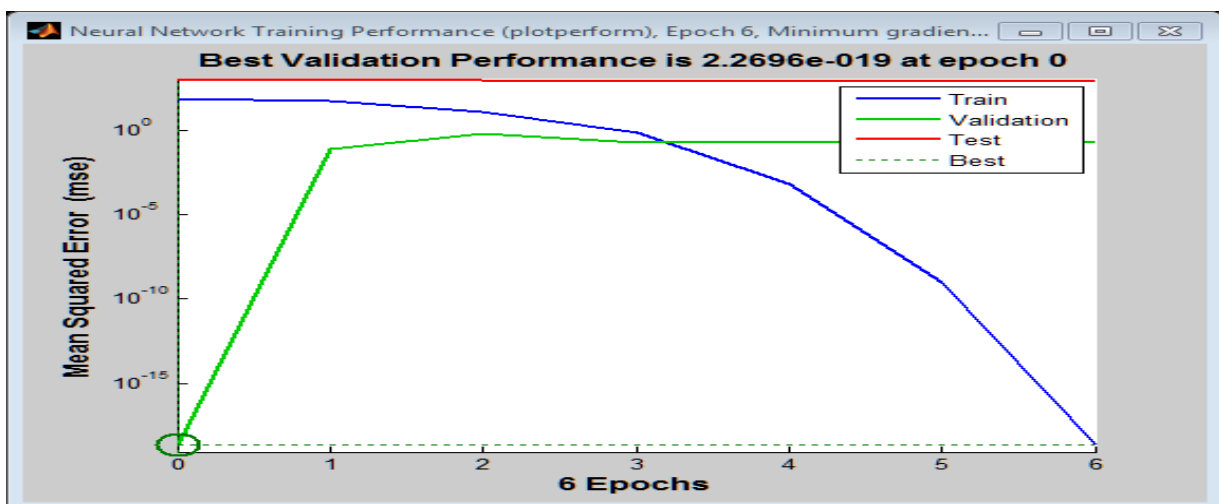


Figure 4.18 Input-Output Structure of Artificial Neural Network Model for Thirty Networks

S) Simulation result Performance of network for thirty neural networks

From The figure 4.19 one can understand that the performance validation is improved, 2.2696×10^{-19} is less than the threshold value, therefore no need of additional network structure and training. The train arrival time prediction training network stop here, because if we continue further training over fitting may face. From this result we can conclude that for the given input and target value, 30 number of neuron is appropriate and successful.



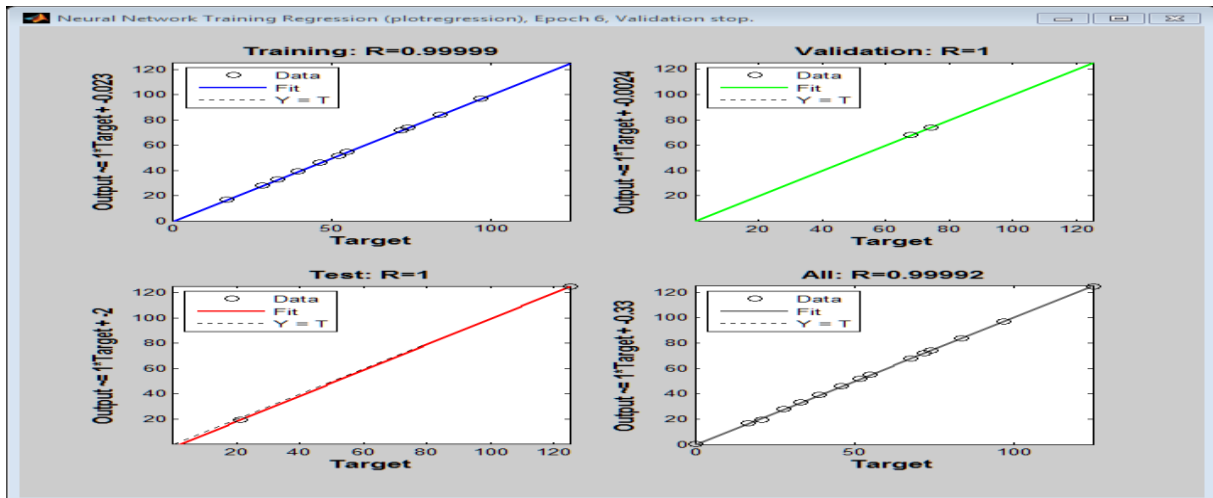


Figure 4. 19 shows Performance and output-target relation for 30 Networks

From the above Figure Output = target – 0.023

Using the previous data, output = 125(target) – 0.023 = 124.977. This shows that the network is highly optimized.

In section 4.1.1 we design and train ANN for train arrival time. In the next section (4.12) design and train a network for traffic signal phase length prediction.

4.1.2 Simulation of Artificial Neural Network for Traffic Signal Phase Length Prediction

Previously we design and trained train arrival time network. In this section artificial neural network is design and train for Traffic signal phase length forecasting for Adey Ababa intersection. The vehicles volumes are collected in 15 minute interval. This is shown in Table 3.3. This data is feed for artificial neural network as an input. The calculated traffic signal phases shown in Table 3.5 are taken as target.

A) Feeding Input data into the network

48 input data is feed into the network. The input is the critical volume of the car that is collected at Adey Ababa intersection in fifteen minute interval. This data feed to the network as input.

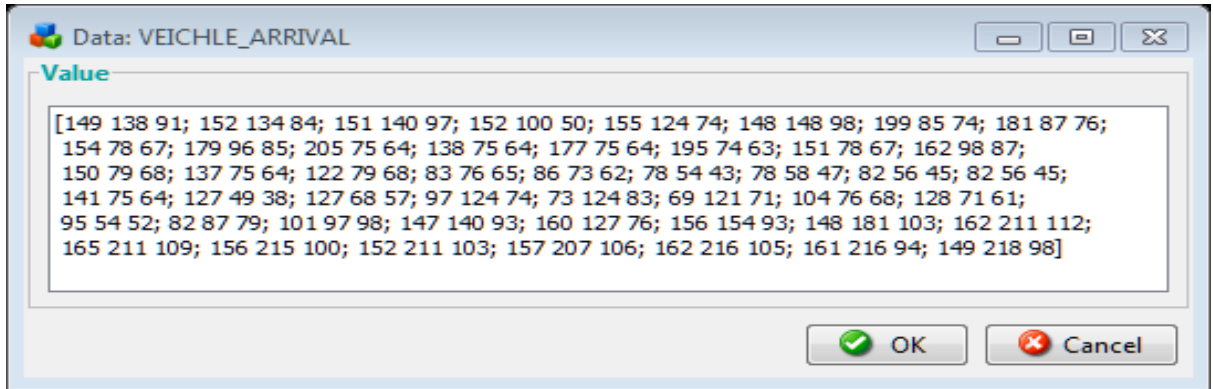


Figure 4.20 Inputs for Volume of Vehicles

B) Feeding Target data into the network

We have three traffic signal phase length target value for adaeey Ababa grade crossing.

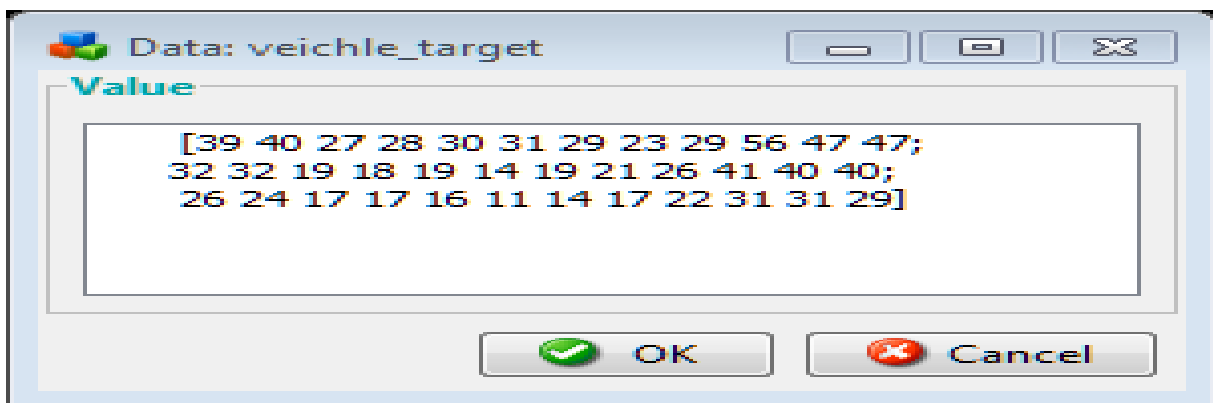


Figure 4.21 Target Value for Traffic Signal Phase Length Predicted Network

C) Network is created for ten numbers of neural

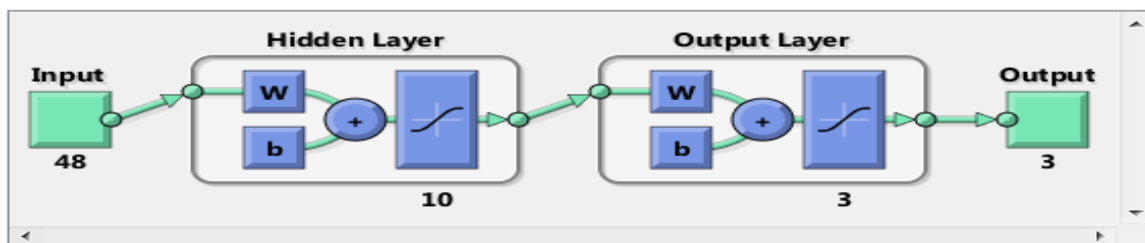


Figure 4.22 Input-Output Structure of Artificial Neural Network Model

D) Initial Weight value for layer one.

Totally we have $10 \times 48 = 480$ weight value for 48 inputs and 10 number of neural .the following result shows the value of each weight of the neural for the first layer without any trainings.

[-0.2554 -0.18205 -0.23081 -0.30645 0.14622 -0.1292 0.023021 -0.15987 -0.22094 0.1863
0.1223 -0.33733 0.1611 -0.21793 -0.29001 0.10104 0.085379 0.053994 0.020844 0.017491
0.24015 0.23185 0.28973 0.15027 0.18371 0.21937 0.1872 0.30881 0.32933 0.1508 -0.21425
0.081875 0.28539 -0.28896 -0.34884 -0.18382 -0.027524 0.09466 -0.27631 0.25338 -0.21765
0.32004 0.28073 -0.25281 -0.28779 0.01635 0.027405;

-0.20141 0.23936 -0.30341 -0.053464 0.12186 0.091217 0.18178 -0.21705 -0.41883 0.063861
-0.057508 0.14395 -0.10593 -0.13297 0.096248 -0.23404 0.084186 0.26082 0.27707 0.39687
0.071135 0.14851 0.043809 0.31192 0.41581 -0.12048 0.049389 -0.017226 -0.32275 -0.40583
-0.25604 -0.10361 0.16967 -0.030657 0.19067 0.28664 0.11699 0.10412 -0.077703 -0.3834
0.21363 -0.0020345 0.069288 0.08897 -0.14846 -0.14669 0.41287;

-0.2852 -0.29398 0.068255 -0.22512 0.036107 0.28314 -0.22136 -0.17729 -0.12672 0.17095
0.13419 0.23273 0.056312 0.29881 -0.33755 0.23265 -0.22598 -0.066372 0.24763 0.14523
0.30931 -0.20183 -0.32239 -0.11825 -0.21634 -0.29457 -0.21823 -0.18513 -0.30961 0.20771 -
0.11952 0.26035 -0.084586 -0.33868 -0.1007 0.24656 0.28806 -0.11876 0.26511 0.13227 -
0.10612 0.17611 0.057116 -0.16947 0.18609 0.22905 0.17617;

-0.048581 -0.073018 0.27597 -0.32608 -0.19397 0.2815 -0.11248 -0.23797 0.13736 0.10014 -
0.16736 0.32444 -0.26415 -0.075231 0.05041 0.32415 -0.28188 0.33609 0.19888 -0.12946 -
0.30205 -0.12516 -0.30699 0.1033 0.19345 0.062611 -0.0014114 -0.071362 -0.13463 -
0.24599 0.26171 0.19601 0.16167 0.28558 0.19297 0.31901 -0.23287 0.20847 0.03312
0.32959 -0.055994 0.1668 0.24422 -0.121 -0.18295 0.21351 0.3306;

-0.17028 -0.34841 0.30826 0.31899 0.19109 0.06426 -0.21909 0.32021 0.087876 -0.26434 -
0.34394 -0.31084 -0.31034 -0.15911 0.20327 0.24301 -0.1717 -0.28765 -0.1278 -0.14631
0.059382 -0.25691 0.21402 0.33313 -0.21342 0.28778 0.01252 0.14388 0.056261 -0.015102 -
0.020274 -0.024587 0.31859 0.10014 -0.04444 -0.0077876 0.15128 0.35042 -0.091904 -
0.15205 -0.24154 0.23231 -0.32633 -0.068901 0.16863 0.039989 -0.18607;

-0.15893 -0.21929 -0.21889 -0.054486 -0.21351 -0.13144 -0.1398 0.34202 0.033807
0.0034526 0.025344 -0.038999 0.37665 -0.27324 -0.20775 0.0047099 0.2815 -0.14057 -
0.03752 0.27505 -0.1687 0.13461 -0.038174 -0.33289 0.38653 -0.24041 0.38801 0.045973
0.024309 -0.1909 -0.07539 0.24649 0.033611 -0.39142 -0.049808 -0.21957 0.06103 0.3776 -
0.22897 -0.28751 0.25044 -0.26967 0.30258 -0.073503 0.15137 -0.18609 0.022421;

-0.061438 -0.40775 -0.014168 0.37738 -0.10558 0.28867 -0.078609 0.26059 -0.049845 -
0.12488 -0.18037 0.06743 -0.17593 -0.084127 -0.0425 -0.1808 0.3361 0.0093283 0.20623
0.33657 0.26796 0.058044 -0.095952 0.071149 0.24714 -0.055298 0.29014 0.20983 0.32804 -

0.10703 -0.26227 0.32578 0.032792 -0.38397 -0.36858 -0.22386 -0.054537 -0.30494 -
0.048286 0.15149 0.10214 -0.034906 -0.075442 -0.093053 0.26497 0.14764 -0.36676;

-0.27942 -0.22808 -0.090982 0.19256 0.28686 -0.042268 0.035637 0.1675 -0.15598 -0.29928
0.32744 0.13695 0.069691 -0.091927 0.050894 0.18097 0.14649 -0.32242 -0.28628 0.1022 -
0.22675 -0.24232 0.21254 -0.063189 -0.055602 0.18283 0.33931 0.36358 0.029755 0.1187
0.34409 -0.051924 -0.13861 -0.21392 -0.33048 0.026994 0.28195 -0.19648 0.33475 0.30045
0.17505 0.086661 -0.3402 0.080571 0.24067 -0.19544 0.18849;

-0.0034595 -0.25072 0.016677 -0.34549 0.24992 0.28357 -0.31646 -0.22735 0.0011635 -
0.24696 0.28503 0.15388 0.32411 -0.25869 -0.30758 -0.18449 0.15792 0.15827 -0.27368 -
0.17155 -0.040303 -0.24709 -0.095173 -0.13385 0.1605 -0.32316 0.12549 0.3243 -0.047701 -
0.2317 -0.0649 -0.11618 -0.30069 -0.031582 -0.28675 0.18381 -0.075001 -0.33407 -0.26366
0.077751 0.21397 0.30308 0.17262 -0.2336 -0.14491 -0.030558 0.071517;

0.17712 -0.19901 -0.20176 0.15449 -0.083721 -0.40058 0.045249 -0.11981 0.22443 -0.259 -
0.092087 0.12875 -0.26963 -0.055741 -0.0031845 0.39244 -0.23178 0.04853 -0.19746 -
0.35296 -0.091463 -0.020526 0.027759 -0.20265 -0.0014128 0.38299 -0.082805 0.030091
0.036612 -0.18982 0.2956 0.082932 -0.27289 -0.31984 0.080693 -0.1308 -0.27547 0.092187 -
0.025088 0.34322 -0.37136 0.28754 -0.29619 -0.26765 -0.16358 -0.099052 0.30648]

E) Initial Weight for the second layer

We have $3 \times 10 = 30$ weight value for the network

[0.72375 -0.74062 -0.41609 0.36691 -0.23993 0.67819 0.068779 0.43967 0.47787 0.343;
0.6953 0.066179 -0.282 0.40231 0.53802 0.63596 -0.24821 0.39805 -0.76874 0.45552; -
0.20794 -0.67165 -0.92853 0.099505 0.12081 -0.32976 0.28221 -0.86054 -0.19665 -0.30499]

F) Initial Bias for layer one

For each neuron there is a corresponding bias value.so we have ten bias values

[1.4703; 1.1436; 0.81683; 0.4901; 0.16337; -0.16337; -0.4901; -0.81683; -1.1436; 1.4703]

G) Initial Bias value for layer two

[-1.5626; 0; -1.5626]

H) The weight value after training for the first layer of the network

[-0.32461 -0.27292 -0.28559 -0.26239 0.12116 -0.59661 -0.031514 -0.097226 -0.082576 0.23661
0.16873 -0.35488 0.15227 -0.2558 -0.26596 -0.068319 0.15747 0.026594 -0.12227 -0.3085 0.23585
0.1937 0.31483 0.15001 0.13399 0.18788 0.095366 0.52865 0.51636 -0.025437 -0.12937 0.21815
0.39844 -0.34208 -0.35654 -0.19733 -0.093436 -0.10126 -0.55323 0.9547 0.12662 0.64076 0.74453 -
0.44618 -0.58912 -0.45956 -0.44969;

0.097358 0.58114 -0.076235 0.2849 0.44225 0.4922 0.31392 -0.10349 -0.26789 0.092276 0.081823
0.2967 0.07181 0.031386 0.19999 -0.20226 0.17235 0.36255 0.30886 0.28103 0.1615 0.41564 0.19636
0.4485 0.49746 0.061679 0.14075 -0.017455 -0.50769 -0.44256 -0.14019 0.0039443 0.3707 0.084261
0.0028113 0.067717 0.15873 0.40649 -0.16195 -0.75703 0.097964 0.0027412 -0.015651 0.2145 -
0.14034 0.052561 0.57633;

0.095065 0.10242 0.4038 0.15352 0.42341 0.72689 -0.046958 -0.021849 0.043796 0.29252 0.3167
0.44804 0.29305 0.53337 -0.20094 0.34271 -0.096432 0.059252 0.32951 0.092605 0.44811 0.14847 -
0.076222 0.099068 -0.091783 -0.063779 -0.098019 -0.017503 -0.2779 0.39325 0.076623 0.58182
0.25334 -0.014933 0.12373 0.40854 0.51194 0.26151 0.4305 0.43321 0.1689 0.59542 0.40339 0.12746
0.42037 0.50737 0.42233;

-0.17056 -0.19046 0.18712 -0.42027 -0.33198 -0.11323 -0.18625 -0.22386 0.10885 0.20396 -0.16268
0.44013 -0.17596 -0.058895 0.016984 0.23506 -0.26184 0.24556 0.072842 -0.36902 -0.53707 -
0.14829 -0.24981 0.24441 0.12418 0.18833 -0.13089 0.24395 0.23971 -0.23291 0.06318 0.43723
0.20102 0.25367 0.57159 0.82759 0.035176 0.013187 0.23999 0.76958 -0.082171 0.010385 0.051901 -
0.43779 -0.30094 -0.12185 -0.027981;

-0.40268 -0.72537 0.33435 -0.10493 -0.047643 -0.19866 -0.4566 0.084805 -0.34152 -0.17653 -
0.60083 -0.59257 -0.60677 -0.34756 -0.064738 0.34719 -0.3805 -0.59545 -0.18569 0.077201 -0.14537
-0.53388 0.039173 0.11022 -0.38674 -0.086261 -0.24487 0.11428 0.2695 0.14756 -0.099066 -0.31058
0.062476 0.33681 0.055761 0.10782 0.17334 0.30994 0.14999 0.014399 0.02569 0.36322 -0.026418
0.19034 0.43553 0.26875 0.11652;

0.033862 -0.062181 0.016154 0.044161 -0.1147 0.0025837 -0.17629 0.37221 0.076225 0.053504
0.025725 0.010089 0.38321 -0.29682 -0.18057 -0.016397 0.33778 -0.12864 -0.030906 0.32146 -
0.15686 0.1905 0.029896 -0.23387 0.39495 -0.21383 0.37814 0.12733 0.088263 -0.19519 -0.056911
0.32452 0.18451 -0.32275 0.32041 -0.089968 0.15305 0.52058 -0.22235 -0.26203 0.20119 -0.37199
0.19224 -0.19441 0.039498 -0.34486 -0.14815;

-0.35889 -0.56839 -0.48175 0.31981 -0.25901 0.071966 0.048331 0.3221 0.057637 -0.20762 -
0.084109 0.18824 -0.026572 0.024575 0.037651 -0.1958 0.36439 0.12222 0.23155 0.22921 0.27515
0.12866 -0.080206 0.12314 0.31037 0.13579 0.40581 0.075883 0.17522 -0.32124 -0.36407 0.5436 -
0.026588 -0.53625 -0.45306 0.040564 0.030632 -0.62199 0.13194 0.80246 0.39996 0.3213 0.25212
0.0076123 0.46234 0.12013 -0.41042;

-0.0052113 0.038976 0.17296 0.42613 0.52777 0.17488 0.050968 0.26723 -0.0079149 -0.19494
0.39258 0.22406 0.11529 -0.063225 0.14598 0.19303 0.27588 -0.24666 -0.23407 0.17735 -0.071182 -
0.054943 0.38493 0.097788 0.0093029 0.2291 0.38375 0.58198 0.19378 0.19808 0.5124 -0.070245 -
0.01403 -0.10631 -0.55912 -0.25758 0.27498 0.071686 0.17838 -0.036399 0.098356 0.056105 -
0.38632 0.12736 0.10564 -0.12087 0.25701;

-0.12866 -0.32153 -0.16286 -0.43356 0.14309 0.35144 -0.49366 -0.39592 -0.11368 -0.51754 0.096689
-0.048773 0.10147 -0.50397 -0.44384 -0.38869 0.0069549 0.04959 -0.40277 -0.23213 -0.12886 -
0.39192 -0.29293 -0.31628 0.01447 -0.51357 0.012754 -0.096929 -0.51664 -0.71349 -0.24201 -

0.34572 -0.49825 -0.26644 -0.51309 0.027339 -0.18244 -0.3911 -0.28213 -0.18991 0.081843 0.16917 -0.013367 -0.20384 -0.14253 -0.044988 0.060202;

0.00020444 -0.39815 -0.35429 0.094088 -0.16997 -0.75624 0.09352 -0.11537 0.22286 -0.26338 -0.040003 0.13446 -0.19666 0.032221 -0.030506 0.3606 -0.27196 0.003931 -0.29195 -0.64873 -0.15709 -0.011327 0.026592 -0.24967 -0.036965 0.4266 -0.12775 0.012101 -0.019 -0.24775 0.3315 0.23619 -0.16052 -0.24191 0.18173 -0.14081 -0.383 -0.16505 -0.21667 0.39195 -0.49047 0.18097 -0.38435 -0.51513 -0.34939 -0.35609 0.05239]

I) weight value for the second layer

[2.139 -0.89961 1.3354 0.33704 -0.77245 0.44514 0.086135 0.73529 -0.0045324 0.6128;

1.2747 0.53179 -1.3979 0.26572 0.29169 0.60965 -0.80137 1.3894 -1.7893 0.58843;

1.2623 -0.90044 -0.7267 1.1297 -0.46895 -0.22114 1.2335 -0.16047 -1.5093 0.40547]

J) Bias value after training for first layer

[1.6807; 0.92752; 0.43358; 1.0211; -0.096783; 0.10028; -0.44265; -0.77122; -0.80358; 1.1448]

K) Bias for second layer

[-0.90273; 0.18665; -1.1777]

L) Simulation result of the performance of the network

After fifty training 2.7083 validations is recorded. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. An acceptable result is less threshold (i.e. 10^{-6}).since this is above the threshold value, the training will continue

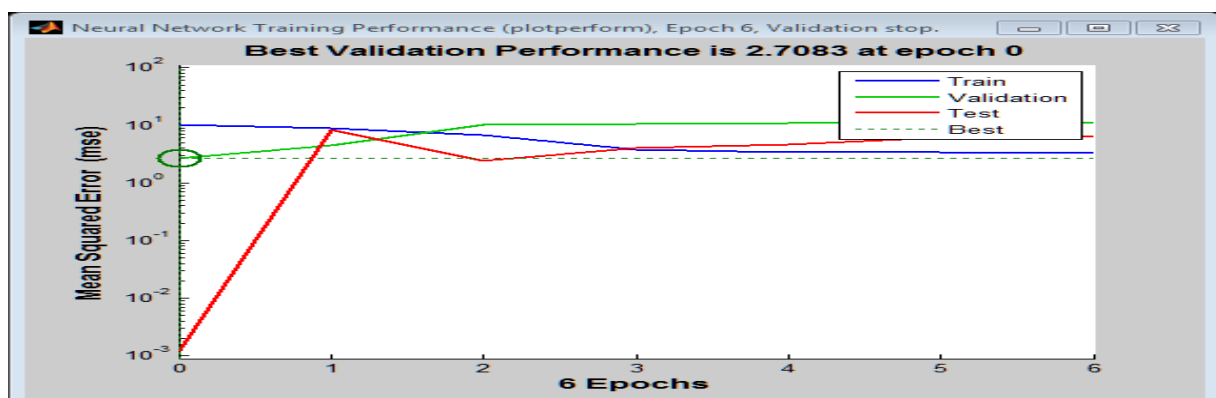


Figure 4.23 Shows Mean Square Error of the Network

M) Artificial neural Network training for fifty numbers of neural

We try to increase the network from 15, 20,30,35,40 and 50 but there is no any converged performance result observed. After so many training the performance of a network, for fifty

numbers neural is 14.02, and cannot be converged quickly. Because to update, $48 \times 50 = 2350$ number of weight value is very difficult. This is the reason why the performance of the network is not improved significantly.

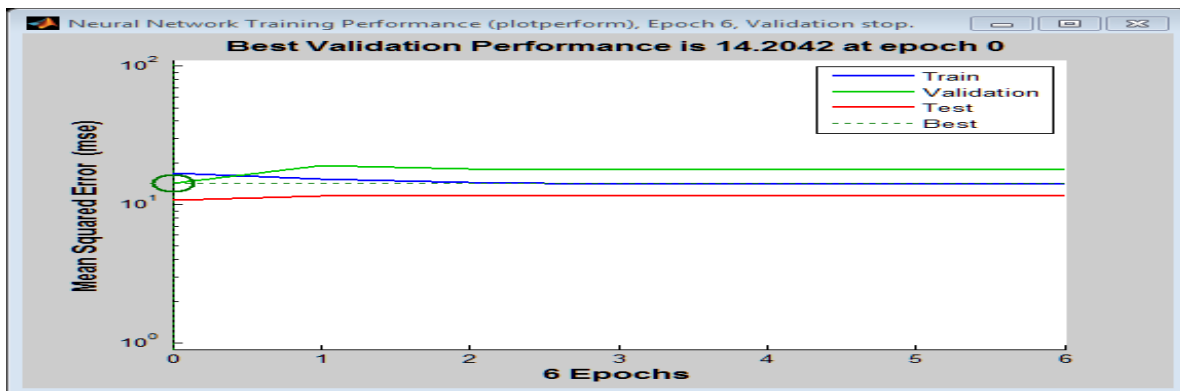


Figure 4.24 Simulation Results of Network Performances

To improve the performance of the network, we decrease the number of neural to ten and give more trainings time. Performance is improved as shown in the figure 4.26 below.

N) Simulation result of the performance a network Using 10 neural

Finally the performance the network is 8.338×10^{-9} after seventy trainings iteration, which below threshold value. From this we can conclude that the network is well train.

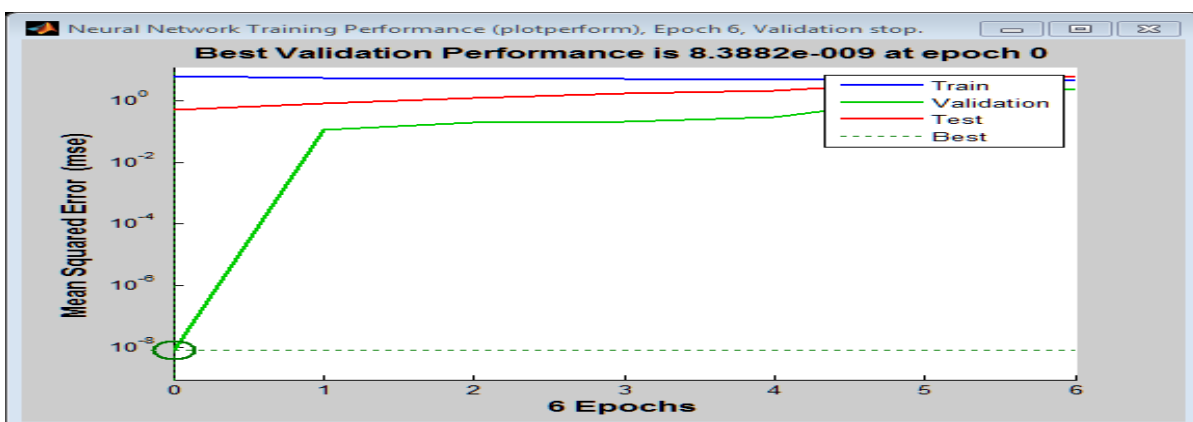


Figure 4.25 Show Performance of Network for Traffic Signal Phase Length Forecasting

From previous two trainings networks we can conclude that:

1) For train arrival time prediction network thirty number of neuron is preferable and effective

2) For Traffic signal phase length forecasting network, ten number of neuron is preferable and effective

4.2 Simulation of Image Processing

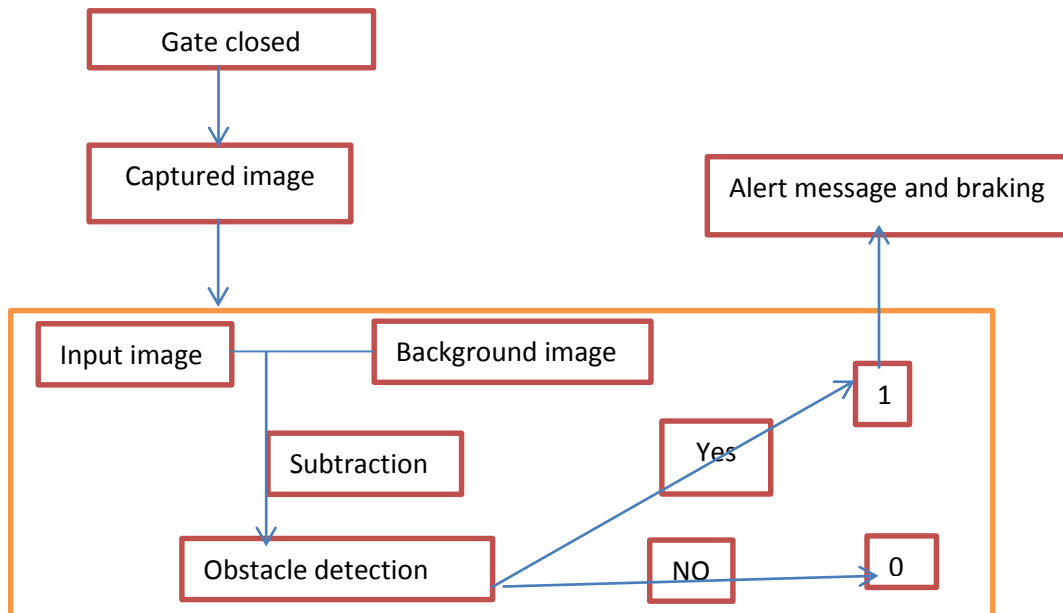


Figure 4.26 Show Flow Chart of Image Processing

a) Creating image without obstacle

`BK (l, m) = imshow ('obstacle.jpg')`. This command used to show the given image from saved directory

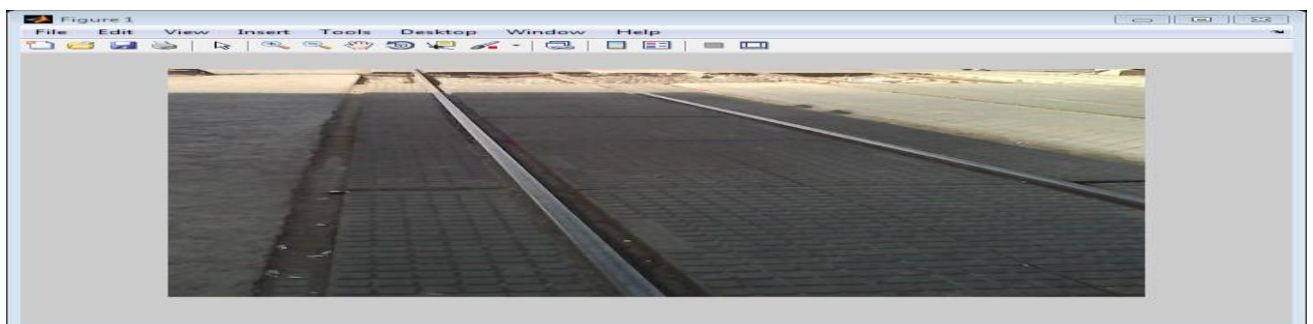


Figure 4.27 Show RGB Image without Obstacle

b) Changing the image in to gray image

`I = gray = rgb2gray (BK);`

The command use to change RGB to gray image. The reason why this process is done is that, to remove background effect of the image like light and shadow effect.

$K = \text{imtool}(I, [0 \ 80])$; the command use to resize the image.

$\text{imshow}(k)$.this command use to show the newly changed gray image. This image consider for this thesis work as a back ground image. And every captured image compared with this image, if there is difference the system considers as obstacle.

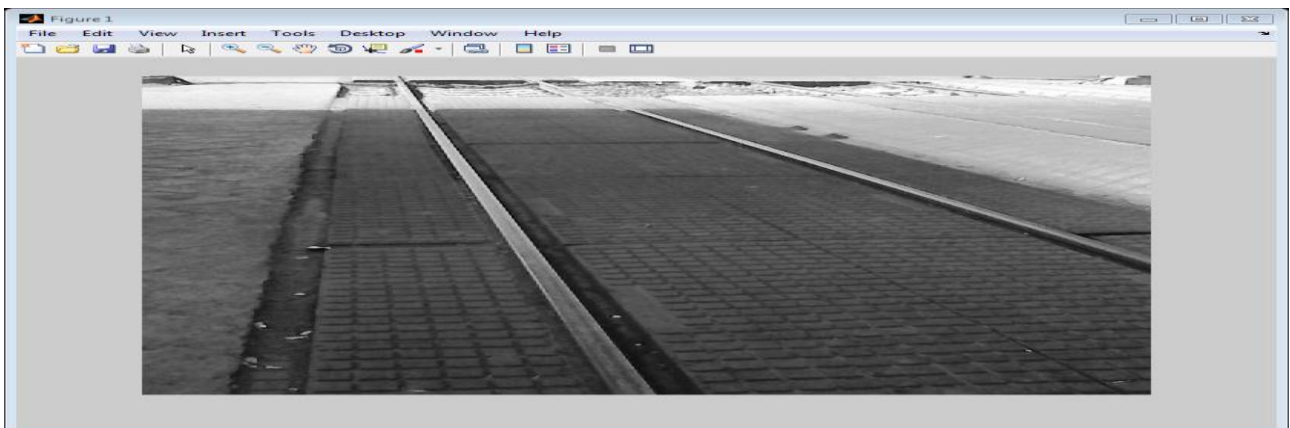


Figure 4.28 Show the Gray Image without Obstacle

- The above image changed to segmented matrix as shown below. The following matrix value is taking as threshold value for image processing algorithm. Because this is not containing any obstacle. The algorithm compares the captured image with this and if the value is different from zero, the system consider as obstacle existence. The imread (gray) command will read an image into a matrix:

$Bk = \text{imread}('k')$; Background Image. The following matrix is assign for BK

0.0094	0.0094	0.0094	0.0660	0.0660	0.0660	0.1226	0.1226	0.1226
0.0189	0.0189	0.0189	0.0755	0.0755	0.0755	0.1321	0.1321	0.1321
0.0283	0.0283	0.0283	0.0849	0.0849	0.0849	0.1415	0.1415	0.1415
0.0377	0.0377	0.0377	0.0943	0.0943	0.0943	0.1509	0.1509	0.1509
0.0472	0.0472	0.0472	0.1038	0.1038	0.1038	0.1604	0.1604	0.1604
0.0566	0.0566	0.0566	0.1132	0.1132	0.1132	0.1698	0.1698	0.1698

0.1792	0.1792	0.1792	0.4151	0.4151	0.4151	0.6509	0.6509	0.6509
0.1887	0.1887	0.1887	0.4245	0.4245	0.4245	0.6604	0.6604	0.6604
0.1981	0.1981	0.1981	0.4340	0.4340	0.4340	0.6698	0.6698	0.6698
0.2075	0.2075	0.2075	0.4434	0.4434	0.4434	0.6792	0.6792	0.6792
0.2170	0.2170	0.2170	0.4528	0.4528	0.4528	0.6887	0.6887	0.6887
0.2264	0.2264	0.2264	0.4623	0.4623	0.4623	0.6981	0.6981	0.6981
0.2358	0.2358	0.2358	0.4717	0.4717	0.4717	0.7075	0.7075	0.7075
0.2453	0.2453	0.2453	0.4811	0.4811	0.4811	0.7170	0.7170	0.7170
0.2547	0.2547	0.2547	0.4906	0.4906	0.4906	0.7264	0.7264	0.7264
0.2642	0.2642	0.2642	0.5000	0.5000	0.5000	0.7358	0.7358	0.7358
0.2736	0.2736	0.2736	0.5094	0.5094	0.5094	0.7453	0.7453	0.7453
0.2830	0.2830	0.2830	0.5189	0.5189	0.5189	0.7547	0.7547	0.7547
0.2925	0.2925	0.2925	0.5283	0.5283	0.5283	0.7642	0.7642	0.7642
0.3019	0.3019	0.3019	0.5377	0.5377	0.5377	0.7736	0.7736	0.7736
0.3113	0.3113	0.3113	0.5472	0.5472	0.5472	0.7830	0.7830	0.7830
0.3208	0.3208	0.3208	0.5566	0.5566	0.5566	0.7925	0.7925	0.7925
0.3302	0.3302	0.3302	0.5660	0.5660	0.5660	0.8019	0.8019	0.8019
0.3396	0.3396	0.3396	0.5755	0.5755	0.5755	0.8113	0.8113	0.8113
0.3491	0.3491	0.3491	0.5849	0.5849	0.5849	0.8208	0.8208	0.8208
0.3585	0.3585	0.3585	0.5943	0.5943	0.5943	0.8302	0.8302	0.8302
0.3679	0.3679	0.3679	0.6038	0.6038	0.6038	0.8396	0.8396	0.8396
0.3774	0.3774	0.3774	0.6132	0.6132	0.6132	0.8491	0.8491	0.8491
0.3868	0.3868	0.3868	0.6226	0.6226	0.6226	0.8585	0.8585	0.8585
0.3962	0.3962	0.3962	0.6321	0.6321	0.6321	0.8679	0.8679	0.8679
0.4057	0.4057	0.4057	0.6415	0.6415	0.6415	0.8774	0.8774	0.8774

0.8868	0.8868	0.8868	0.9151	0.9151	0.9151	0.9434	0.9434	0.9434
0.8962	0.8962	0.8962	0.9245	0.9245	0.9245	0.9528	0.9528	0.9528
0.9057	0.9057	0.9057	0.9340	0.9340	0.9340	0.9623	0.9623	0.9623

c) Image created for the case of with obstacle.

`Bk (l, m) =imshow ('obstacle.jpg')`.this command use to show RGB image with obstacle.

`h = imtool (Bk, [0 80]);`

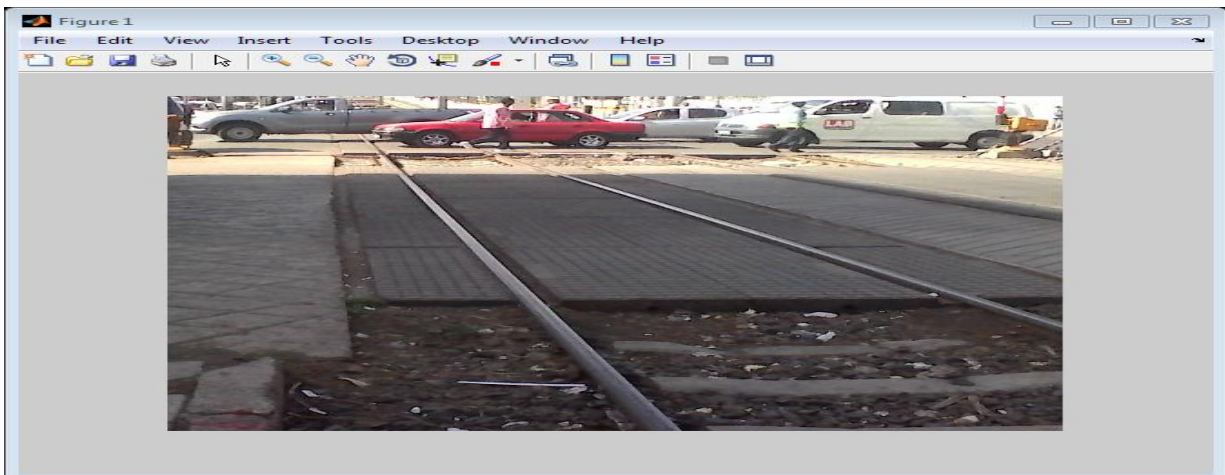


Figure 4.29 Show the RGB with Obstacle

d) Image change to gray image

`Fk = rgb2gray (Bk);`

`Imshow (gray)` no obstacle image change to gray image



Figure 4.30 Show Gray Image without Obstacle

Fk = Current Frame. The following segmented matrix assign for FK

The following matrix is the equivalent of the gray image with obstacle.

0.0097	0.0097	0.0097	0.0777	0.0777	0.0777	0.1456	0.1456	0.1456
0.0194	0.0194	0.0194	0.0874	0.0874	0.0874	0.1553	0.1553	0.1553
0.0291	0.0291	0.0291	0.0971	0.0971	0.0971	0.1650	0.1650	0.1650
0.0388	0.0388	0.0388	0.1068	0.1068	0.1068	0.1748	0.1748	0.1748
0.0485	0.0485	0.0485	0.1165	0.1165	0.1165	0.1845	0.1845	0.1845
0.0583	0.0583	0.0583	0.1262	0.1262	0.1262	0.1942	0.1942	0.1942
0.0680	0.0680	0.0680	0.1359	0.1359	0.1359	0.2039	0.2039	0.2039
0.2136	0.2136	0.2136	0.2718	0.2718	0.2718	0.3301	0.3301	0.3301
0.2233	0.2233	0.2233	0.2816	0.2816	0.2816	0.3398	0.3398	0.3398
0.2330	0.2330	0.2330	0.2913	0.2913	0.2913	0.3495	0.3495	0.3495
0.2427	0.2427	0.2427	0.3010	0.3010	0.3010	0.3592	0.3592	0.3592
0.2524	0.2524	0.2524	0.3107	0.3107	0.3107	0.3689	0.3689	0.3689
0.2621	0.2621	0.2621	0.3204	0.3204	0.3204	0.3786	0.3786	0.3786

0.3883	0.3883	0.3883	0.5728	0.5728	0.5728	0.7573	0.7573	0.7573
0.3981	0.3981	0.3981	0.5825	0.5825	0.5825	0.7670	0.7670	0.7670
0.4078	0.4078	0.4078	0.5922	0.5922	0.5922	0.7767	0.7767	0.7767
0.4175	0.4175	0.4175	0.6019	0.6019	0.6019	0.7864	0.7864	0.7864
0.4272	0.4272	0.4272	0.6117	0.6117	0.6117	0.7961	0.7961	0.7961
0.4369	0.4369	0.4369	0.6214	0.6214	0.6214	0.8058	0.8058	0.8058
0.4466	0.4466	0.4466	0.6311	0.6311	0.6311	0.8155	0.8155	0.8155
0.4563	0.4563	0.4563	0.6408	0.6408	0.6408	0.8252	0.8252	0.8252
0.4660	0.4660	0.4660	0.6505	0.6505	0.6505	0.8350	0.8350	0.8350
0.4757	0.4757	0.4757	0.6602	0.6602	0.6602	0.8447	0.8447	0.8447
0.4854	0.4854	0.4854	0.6699	0.6699	0.6699	0.8544	0.8544	0.8544
0.4951	0.4951	0.4951	0.6796	0.6796	0.6796	0.8641	0.8641	0.8641
0.5049	0.5049	0.5049	0.6893	0.6893	0.6893	0.8738	0.8738	0.8738
0.5146	0.5146	0.5146	0.6990	0.6990	0.6990	0.8835	0.8835	0.8835
0.5243	0.5243	0.5243	0.7087	0.7087	0.7087	0.8932	0.8932	0.8932
0.5340	0.5340	0.5340	0.7184	0.7184	0.7184	0.9029	0.9029	0.9029
0.5437	0.5437	0.5437	0.7282	0.7282	0.7282	0.9126	0.9126	0.9126
0.5534	0.5534	0.5534	0.7379	0.7379	0.7379	0.9223	0.9223	0.9223
0.5631	0.5631	0.5631	0.7476	0.7476	0.7476	0.9320	0.9320	0.9320

Result

From the above process, the two images (image with and without obstacle) are changed to number. Once the image is change to number, manipulation become is an easy task. That is subtraction of two matrixes.

$$T = \text{abs}(BK)$$

$$D_k = 1 \quad \text{if } F_k - B_k > T$$

= 0 Otherwise

F_k: Current Frame

B_k: Background Image

D_k: Difference Image

$D_k = F_k - B_k$, if the subtraction of the image matrix is different from zero this indicate that obstacle is detected. Note that to subtract two matrixes the inner dimension of the matrix must be identical.

$D_k = F_k - B_k$

Obviously the subtraction of the two matrixes is different from zero therefore obstacle is detected.

4.3 Simulation of Radar

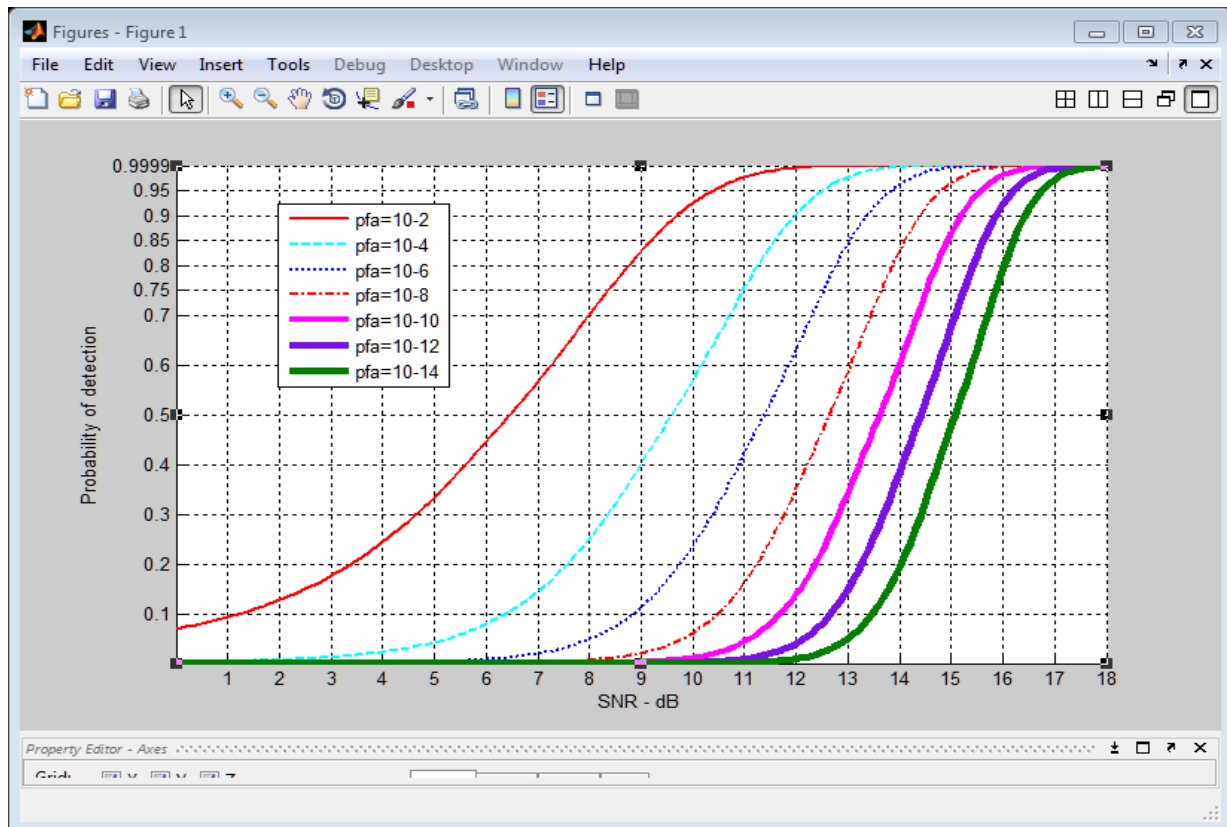


Figure 4.31 PD vs. SNR Simulation Result with Diff PFA

From Parl formula figure 4.31 is generated. This graph show plots of the probability of detection, P_d , versus the SNR, with the probability of false alarm, p_{fa} as a parameter. From the plot, we can conclude that the amount of SNR needed to achieve a fixed amount of probability of detection is greater when the probability of false alarm get smaller.

This graph indicted that as SNR increase, the probability of train detection is less error Therefore during manufacturing or purchasing of radar one has to consider SNR greater than 15db.

Chapter five

Conclusion and Recommendation

5.1. Conclusion

In conclusion, we discussed Bistatic radar for train detection radar modules to detect a target located in a multipath channel. The proposed bistatic radar has several advantages compared to ordinary radar as explained in section 3.6.1. The simulation results show that SNR greater than 15 db gives high degree of probability of detection.

Traffic management at Grade crossing is a new phenomenon for our country. Implementing TPS for Grade crossing traffic management is crucial issue currently. Because traffic complexity become current issue of the city around grade crossing .To solve this problem the proposed system design TPS algorithm. Additionally design dynamic traffic management system, instead of fixed clock traffic management.

From the simulation of image processing, we have developed image segmentation algorithm to implement image processing for obstacle detections on Grade crossing. It is real time image processing technic for accident prevention. Additionally it is promises to be a significant commercial application that will reduce the driver's workload so that driving can become safer and less exhausting.

5.2. Recommendation

Here are list of recommendations to the possible extensions of the works of this thesis research:

- ❖ To implement online optimization it is better use online vehicles detection instead of data collected by survey.
- ❖ It is better to implement GPS (global positioning system) technology instead of radar for the case of train arrival prediction system.
- ❖ ANN training for Traffic signal phase length forecasting around grade crossing needs long time data. We recommend the input data feed to ANN must be updated for every time for traffic fluctuation period of time if online vehicles detection is not practicable.
- ❖ All nearby intersection must be interconnected by traffic signal to make smooth traffic flow around Grade crossing. Green offset signal can be applied to coordinate from one intersection to another intersection. Figure 5.1 shows interconnection of intersections.

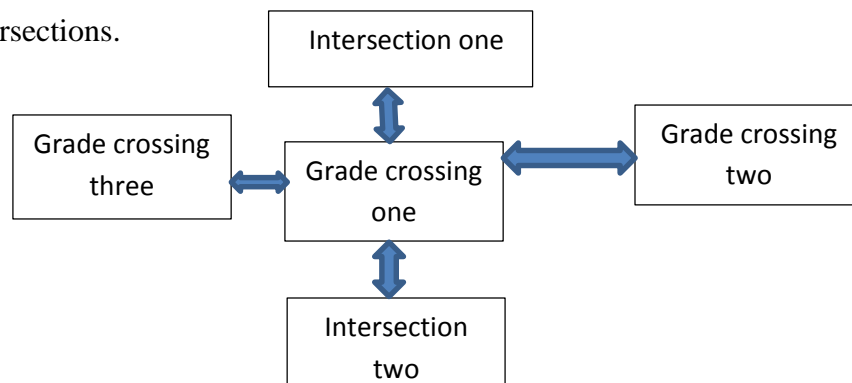


Figure 5.1 Show Grade Crossing and Road Intersection Interconnected Each Other

Manual on Uniform Traffic Control Devices (MUTCD) recommend that intersection within 200m must be interconnected for smooth traffic signal management system.

Reference

- [1] Ministry of Federal Affairs, “Addis Ababa Development and Improvement Project,” A.A, July 2002.
- [2] China railway limited, ‘Ethiopian Railway Corporation, Project Brief Outline’, 2007.
- [3] Jacobson, M., Venglar, S., and J. Webb “Developed Transition Preemption Strategy algorithm” by the Texas Transportation Institute (TTI), 2004.
- [4] Office Report, July. ‘China Railway Group Limited ,Addis Ababa E-W & N-S (Phase I) Light Rail Transit Project, “Preliminary Design" Chapter XIV Signaling System (Volume in One), June 2013.
- [5] Addis Ababa E-W & N-S (Phase I) “Light Rail Transit Project, Preliminary Design, Chapter XIII Communication System”, Vol.1.2007
- [6] Addis Ababa E-W & N-S (Phase I) “Light Rail Transit Project Preliminary Design,” Chapter XIV signaling System, Vol.1, 2012
- [7] Pankaj Jain and Dr. Mohan, “International Journal of Emerging Technology and Advanced Engineering, ” Volume 4, March 2014.
- [8] Li Zhang, ‘Optimizing Traffic Network Signals around Railroad Crossings Model Validations’, Washington, D.C., 2002
- [9] Hanson Cho and Laurence R. Rilett. ‘ Improved Transition Preemption Strategy for Signalized Intersections near At-Grade Railway Grade Crossing’, In Journal of Transportation Engineering, Volume 13), 2007.
- [10] Darcy M. Bullock et al. “Track Clearance Performance Measures for Railroad-Preempted Intersections”, Washington, D.C., 2010
- [11] Kim, “Determining Optimal Sensor Locations in Freeway Using Genetic Algorithm-Based Optimization”. Berlin, 2011
- [12] Jacobson, M., S. Venglar, and J. Webb, ”Advanced Intersection Controller Response to Railroad Preemption - Stage I Report,” Texas Transportation Institute, Texas A&M University, College Station, TX, May 1999.
- [13] Chen, ‘ Traffic Signal Operations near Highway-Rail Grade Crossing,’ In Synthesis of Highway Practice 271. TRB, National Research Council, Washington, D.C, 1999.
- [14] McGee, and R. Patterson, ”Railroad-Highway Grade Crossing Handbook, 2nd Edition. Office of Implementation”, FHWA, U.S. Department of Transportation, September 2012

- [15] Pitter and nana, "A Radar Vehicle Detection System for Four-Quadrant Gate Warning Systems and Blocked Crossing Detection", Office of Research and Development Washington, DC, final Report December 2012.
- [16] Merrill I. Skolnik. "Introduction to Radar Systems 3rd ed". Mc Graw-Hill, 2001.
- [17] Mehrnoosh Vahidpour, "A Millimeter-Wave Radar Micro fabrication Technique and Its Application in Detection of Concealed Objects" The University of Michigan , 2012
- [18] Mehrnoosh Vahidpour, "A Millimeter-Wave Radar Micro fabrication Technique and Its Application in Detection of Concealed Objects" The University of Michigan, 2012
- [19] N. Fakhfakh, L. Khoudour, E.M. El-Koursi, J. Jacot and A. Dufaux, "A Video-Based Object Detection System for Improving Safety at Grade crossings", the Open Transportation Journal, 2011
- [20] Mowatt, M.G., "A Regional Implementation ITE Compendium of Technical Thesiss", Institute of Transportation Engineers, Washington, D.C, 1995
- [21] Incremental Train Control System, Traffic Engineering Council Update. ITE Traffic Engineering Council Committee, Institute of Transportation Engineers, Washington, D.C 1995.
- [22] Chen, M., X. Liu, J. Xia, and S. Chien, "A dynamic bus arrival time prediction model based on APC data," Journal of Computer-Aided Civil and Infrastructure Engineering, U.S.A,2004
- [23] Jeong, R and L. R. Rilett, "Bus arrival time prediction using artificial neural network model", IEEE Intelligent Transportation Systems Conference, Washington, DC, 2004
- [24] Track USDOT, "Vehicle proximity alert system for highway-rail- road grade crossings: Final report, 2001
- [25] Hsu, K. L., Gupta, H. V., and Sorooshian, S."Artificial neural net-work modeling of the rainfall-runoff process", Water Resource. 1995
- [26] Louahdi Khoudour & Mohamed Ghazel & Fouzia Bouko Ur & Marc Heddebaut & El-Miloudi El-Kours, "Towards safer level crossings: existing recommendations, new applicable technologies and a proposed simulation model," European Conference of Transport Research Institutes (ECTRI), 2008.
- [27] Jay Heavisides, John Barker & Michael Woods, "Hot topics in controlling risk at level crossings", Arthur D. Little, UK and 2Rail Safety & Standards Board, UK,2009

- [28] P. Jan, N. Zdenek, D. Radovan, B. Pavel, "Computing of bistatic C," Symposium on Industrial Electronics, 2013.
- [29] Wireless CCTV camera system, New York, April, 2015
<http://www.cctvcamerapros.com/Wireless-Camera-Systems-s/279.htm>
- [30] Meadow, L. Los Angeles, "Metro Blue Line Grade Crossing Safety Program", national Conference on Highway-Rail Safety, St. Louis, MO, July 1993.
- [31] Dougherty, M.S., H.R. Kirby, and R.D. Boyle, "The Use of Neural Networks to Recognize and Predict Traffic Congestion," traffic Engineering and Control, Vol. 34, No. 2, 2007.
- [32] Choi, S.K. "Korea Railway in view of Statistics". Korea Railroad Research Institute. (2008)
- [33] Cho, B.-K., Ryu, S.-H., Hwang, H.-C, "Accident prevention technology at a Grade crossing," Journal of the Korean Institute of Electrical Engineers, 2008.
- [34] Christopher L. and J. Moody. "Passive coherent location radar demonstration", 2002
- [35] Dr. Clayton Stewart, "Operational Considerations for Passive Bistatic Radar", Presented at 1st RADAR Conference & Exhibition for the Kingdom of Saudi Arabia 8 December, 2014
- [36] Nicholas J. Willis, "Bistatic Radar," SciTech Publishing, Inc., 2005.
- [37] John W. Franklin, "passive bistatic radar", 2007
- [38] Horn antenna and standards gain for traffic radar, Washington, D.C. April 5, 2015.
<http://www.atmmicrowave.com/waveguide/horn-antenna-standard-gain-wide-band/>, 2015
- [39] David E. Fields and Joe S. O'Conner, "Integrated Microwave Range and Velocity Sensors for Railroad Crossing Warnings". New York, 2008
- [40] Alene Ritibey, "Design and Analysis of Rail way Level Crossing Accident Prevention for AA-LRT", A.A, 2015
- .
- [41] Hagan, M. T., H. B. Demuth, and M. Beale. "Neural Network Design" PWS, Boston.1996
- [42] MATLAB for artificial neural network optimization, New York, April, 2015
<http://www.mathworks.com/help/optim/ug/lsqnonlin.html>
- [43] Jonathan, "Neural Network learning by the Levenberg-Marquardt Algorithm with Bayesian Regularization (part 1)".Norway, 2011
- [44] M. Jacobson, "Preemption of Traffic Signals at or Near Railroad Grade Crossings with

Active Warning Devices,” traffic Engineering Council Committee TENC-4M-35. Institute of Transportation Engineers, Washington, D.C, February 1997.

[45] William and Elena S Prassas. 'Traffic Engineering'. Prentice- Hall, Upper Saddle River, New Jersey, 1998

[46] Christopher, ‘MnDOT Traffic Signal Timing and Coordination Manual’, 2003.

[47] Abebe Teklu, ‘Addis Ababa City Light Railway Transit Speed Profile for Optimum Train Drive, ‘Case of Line from Menelik Square to Kality Addis Ababa’, August, 2014

Annex

%% a Matlab programing for probability of detection vs. SNR

function PD = marcumsq (a,b) % this function uses Parl's method to compute PD

max_test_value = 1000; % increase to more than 1000 for better results

if (a < b)

alphan0 = 1.0;

dn = a / b;

else

alphan0 = 0;

dn = b / a;

end

alphan_1 = 0;

betan0 = 0.5;

betan_1 = 0;

d1 = dn;

n = 0;

ratio = 2.0 / (a * b);

r1 = 0.0;

betan = 0.0;

alphan = 0.0;

while betan < max_test_value,

n = n + 1;

alphan = dn + ratio * n * alphan0 + alphan;

betan = 1.0 + ratio * n * betan0 + betan;

alphan_1 = alphan0;

alphan0 = alphan;

betan_1 = betan0;

betan0 = betan;

dn = dn * d1;

end

PD = (alphan0 / (2.0 * betan0)) * exp (-(a-b) ^2 / 2.0);

if (a >= b)

PD = 1.0 - PD;

end

return

% this program is used to produce Figure 'Probability of detection VS SNR

clear all

for nfa = 2:2:14 % Marcum false alarm number

b = sqrt (-2.0 * log (10^ (-nfa)));

```
index = 0;
hold on
for snr = 0:.1:18
index = index +1;
a = sqrt(2.0 * 10^(.1*snr));
pro(index) = marcumsq(a,b);
end
x = 0:.1:18;
set(gca,'ytick',[.1 .2 .3 .4 .5 .6 .7 .75 .8 .85 .9 .95 .9999])
set(gca,',[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18])
plot(x, pro, 'k');
end
hold off
xlabel ('SNR - db')
ylabel ('Probability of detection')
grid
```

Matlab Code for Artificial Neural

```
% Choose Input and Output Pre/Post-Processing Functions
x = Input_data %
o = out_data %
trainfcn = 'trainlm'; % Levenberg-Marquardt backpropagation.
% Create a Fitting Network
hiddenLayerSize = [10, 5,20,30];
net = fitnet(hiddenLayerSize,trainFcn);
% For a list of all processing functions type:nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};
% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Choose a Performance Function
% For a list of all performance functions: nnperformance
net.performFcn = 'mse'; % Mean Squared Error
% Choose Plot Functions
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotregression', 'plotfit'};
% Train the Network
```

```

[net,tr] = train(net,x,t);
% Test the Network
    y = net(x);
Performance = perform(net,t,y)
% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{ 1 };
valTargets = t .* tr.valMask{ 1 };
testTargets = t .* tr.testMask{ 1 };
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform (net,testTargets,y)
Image Processing with MATLAB
BK (l, m) =imshow ('noobstacle.jpg') %show image without obstacle from saved directory
I = gray = rgb2gray (a); %Changing the image in to gray image
K = tool (I, [0 80]); % the command use to resize the image.
Imshow (k); %this command use to show the newly changed gray image
Bk =imread ('k'); %image change to matrix
p = (l, m) =imshow ('obstacle.jpg');%to show RGB image with obstacle.
q = rgb2gray (Bk);
h = imtool (p, [0 80]);
Imshow (gray) no obstacle image change to gray image
Fk = imread ('h'); % the following segmented matrix assign for FK
Dk = FK-BK; %subtractions of the matrix
If DK = 0;
    display ('real time image displays')
Else braking action
Function createfigure (cdata1)
%CREATEFIGURE (CDATA1)
% CDATA1: image cdata
% Create figure
figure1 = figure;
% Create axes
axes1 = axes('Visible','off','Parent',figure1,'YDir','reverse',...
    'TickDir','out',...
    'Position',[0.0996350364963504 0.0903225806451613 0.800486618004866
0.861290322580645],...
    'Layer','top',...
    'DataAspectRatio',[1 1 1]);
% Uncomment the following line to preserve the X-limits of the axes
xlim (axes1,[0.5 987.5]);

```

```
% the following line to preserve the Y-limits of the axes
ylim(axes1,[0.5 801.5]);
box(axes1,'on');
hold(axes1,'all');
% Create image
image(cdata1,'Parent',axes1);
function createfigure1(cdata1)
%CREATEFIGURE(CDATA1)
% CDATA1: image cdata
% create figure
figure1 = figure;
colormap('gray');
% Create axes
axes1 = axes('Visible','off','Parent',figure1,'YDir','reverse',...
    'TickDir','out',...
    'Position',[0.0996350364963504 0.0903225806451613 0.800486618004866
0.861290322580645]
    'Layer','top',
    'DataAspectRatio',[1 1 1].
    'CLim',[0 255]);
% the following line to preserve the X-limits of the axes
Xlim(axes1, [0.5 801.5]);
% the following line to preserve the Y-limits of the axes
ylim(axes1,[0.5 801.5]);
box(axes1,'on');
hold(axes1,'all');
```