ASSESSMENT OF DYNAMIC LANE GROUPING FOR ISOLATED SIGNALIZED INTERSECTION AND APPLICATION OF MACHINE LEARNING MODELS

BY

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(قُلْ إِنَّ صَلاَتِي وَنُسُكِي وَمَحْيَايَ وَمَمَاتِي لِلّهِ رَبِّ الْعَالَمِينَ)

DEDICATION

To

My Beloved Parents, Wife, Brothers, Sisters

And

My Small Angels Sajida &Sara

ACKNOWLEDGMENTS

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LIST OF ABBREVIATIONS

ATM	:	Active traffic management
ADM	:	Active demand management
ITS	:	Intelligent transportation system
DLG	:	Dynamic lane grouping
DLM	:	Dynamic lane Management
FLG	:	Fixed lane grouping strategy
LOS	:	Level of Service
VMS	:	Variable message signs
FFNN	:	Feed-Forward Neural Network
ANN	:	Artificial Neural Network
LG	:	Lane group
LGC	:	Lane groups combination
LGC_o	:	Optimum Lane groups combination
α	:	Initial percentage of the left turning movement (%)
β	:	Initial percentage of the through movement(%)
i	**:**	Approach No starts form West bound

k : Entering lane No, k=1,2,…, (starts from median side to shoulder lane)

j : Movement at the intersection, (left-turning, through and right turning movements).

N_T : The total no of intersecting approaches

V_T : total intersection volume (veh/h)

V_i : Approach volume (veh/h)

$(V_L)_i$: Left turning movement of approach i (veh/h)

$(V_{Th})_i$: Through movement of approach i (veh/h)

$(V_R)_i$: Right turning movement of approach i (veh/h)

HCM : Highway Capacity Manual

$S_{i,k}$: Saturation flow rate of lane k in approach i

$\bar{S}_{i,k}$: Saturation flow rate for straight movement

$r_{i,k,j}$: Turning radius for movement j .

$f_{i,k,j}$: Flow factor, is defined as the proportion of movement j at lane k of approach i from total traffic at lane k.

$\boldsymbol{D}$: Control delay per vehicle (sec)

$\boldsymbol{d_{k1}}$ **:** Uniform delay (sec) assuming uniform arrivals for lane k (sec)

$\boldsymbol{PF}$: Progression adjustment factor

$\boldsymbol{d_{k2}}$ **:** Incremental Delay (sec) average delay per vehicle due to random arrivals for lane *k*

$\boldsymbol{d_{k3}}$ **:** Initial Delay, Average delay per vehicle due to initial queue at the beginning of analysis time period for lane *k* (sec)

$\boldsymbol{C}$ **:** cycle length (sec)

$\boldsymbol{g_i}$ **:** effective green of the related phase (sec)

$\boldsymbol{x_{i,k}}$ **:** total lane volume to capacity ratio (v/c) for lane *k*

$\boldsymbol{T}$ **:** duration of analysis period (h)

$\boldsymbol{k_f}$ **:** incremental delay factor

$\boldsymbol{I}$ **:** upstream filtering/metering adjustment factor

$\boldsymbol{c_{i,k}}$ **:** lane capacity (veh/h)

D_a : average intersection delay

AI : Artificial Neural Network

USEPA : US environmental Protection Agency

ABSTRACT

Full Name : [Hekmatullah Habibi]

Thesis Title : **[Assessment of Dynamic Lane Grouping for Isolated Signalized Intersection and Application of Machine Learning Models]**

Major Field : [Civil Engineering]

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The aim of this study is to investigate the usefulness of dynamic lane grouping (DLG) for a 4-leg typical isolated signalized intersection with movement-based signal phasing scheme. A computational algorithm is developed to calculate the relative performance measure of the intersection (average intersection delay) and determine the optimum cycle length. Based on the intersection delay for all possible lane groups, the one with minimum intersection delay is identified to be the optimum lane group. For assessing the usefulness of dynamic lane grouping for isolated signalized intersection, the developed computational algorithm is applied for a wide range of hypothetical volumes for dynamic lane grouping and fixed lane grouping (FLG), respectively. After a statistical analysis of the results for the two types of lane assignments, the usefulness of DLG was assessed. A comparative study was also performed on two phasing schemes: approach-based and movement-based. Artificial Neural Network (ANN) models were developed for the prediction of the proper phasing scheme and optimum lane group combinations (LGC), respectively. These prediction tools enable us to predict the appropriate phasing scheme as long as the optimum LGC for any volume combinations at similar intersection.

ملخص الرسالة

الاسم الكامل: حكمت الله حبيبى

عنوان الرسالة: تقييم الاستخدام الديناميكى للمسارب فى التقاطعات المعز وله، المزوده باشارات ضوئية وتطبيقات نماذج التعلم الالى.

التخصص: الهندسه المدنيه

تاريخ الدرجة العلمية: مايو 2016

تهدف هذه الدراسة إلى بحث فائدة تطبيق ألية المسرب الديناميكي على تقاطع مروري معزول مكون من أربع أفرع. يعمل بنظام الاشارات الضوئية، لتحقيق أهداف هذه الدراسة تم بناء خوارزمية لحساب الفاعليه على التقاطع المروري والمتمثلة في متوسط التأخيرعلى التقاطع للحصول على أفضل دورة زمنيه للإشارة الضوئية, يعتبر التأخير على التقاطع المروري هو العامل الرئيس لاختيار المسرب الامثل من بين عدة مسارب يمكن تطبيقها على هذا النوع من التقاطع.من أجل تقييم أداء الخوارزمية فقد تم تطبيقها باستخدام عدة احجام مرورية افتراضية على مسرب ثابتة ومسارب متغيرة. بناءً على التحليل الاحصائي لنتائج تطبيق الخوارزمية فقد تم التأكد من فوائد تطبيق المسرب الديناميكي وقد تم إظهار ذلك الرسوم البيانية. وبالاعتماد على النتائج السابقة تم تطوير نظام الشبكة العصبية الاصطناعية(ANN)لاختيار المسارب المثلى فى اى تقاطع مشابه.وبناء علي هذا النظام يمكن التنبؤ عن افضل استخدام ديناميكى للمسارب لاى حجم مرورى على تقاطع مشابه.

Chapter 1

INTRODUCTION

1.1 Introduction

Ever-increasing people's demand for travel and use of the existing road facilities with restricted capacities caused various challenging problems in our daily life, including continued increase in traffic congestion that causes high energy consumption and pollutants' release. Many surveys show the high rates of energy consumption and emissions. A survey conducted in USA in 2014 shows that in 471 urban areas, traffic congestion caused 6.9 billion hours annual delay in daily travels and consumption of nearly 3.1 billion gallons of fuel [1, 2]. Based on the U.S. Environmental Protection Agency (USEPA) 2009 report, consumption of fuel by the transportation system caused emissions of 65% nitrous oxide (N_2O), 33% of carbon dioxide (CO_2) and 24% of methane (NH_4). Thus, for any transportation system, mitigation of traffic congestion and reduction of its environmental effects have been vital tasks for sustainability of that system [3].

In urban areas, congestion at peak hours is quite commonly occurring near or around the signalized intersections. One of the major causes of congestion at signalized intersections is tide of traffic or fluctuation of traffic demand on a large scale. As expansion of the existing transportation facilities is quite difficult and a costly task, to maximize the utilization of the currently in use facilities, a number of active traffic management (ATM) and active demand management (ADM) methods and operation strategies within the context of intelligent transportation system (ITS) are developed and applied. Many traffic control policies and applications are introduced in the optimization of traffic signal timing, including cycle length, phase sequence and green times, at an intersection as the controlling strategy to mitigate the congestion problem in urban areas [4]. Traffic signal timing optimization adapts the signal timing with the demand variation. However, these optimization methodologies consider lane use and lane configuration fixed, which restricts the capacity of the intersection to handle traffic demand significant variations [5]. As the methodologies of signal timing optimization alone cannot be responsive to significant variation of demand, it is necessary to adapt the space utilization with the demand variation. This procedure is also called space optimization, which leads to a new ITS and ATM concept named dynamic lane grouping (DLG). Studies show that the DLG strategy is useful for balancing the flow ratio of lanes and mitigate the traffic congestion by reducing the intersection delay.

Traffic demand variability at different times of the day, especially at peak hours, occurs at some urban intersections [6]. This demand variation results in poor lane utilization at pre-timed signalized intersections with static lane configuration as shown in Figure 1.1 [7]. This methodology of lane allocation causes an improper utilization of lanes, which will result in waste of time and space and degrade the intersection performance.

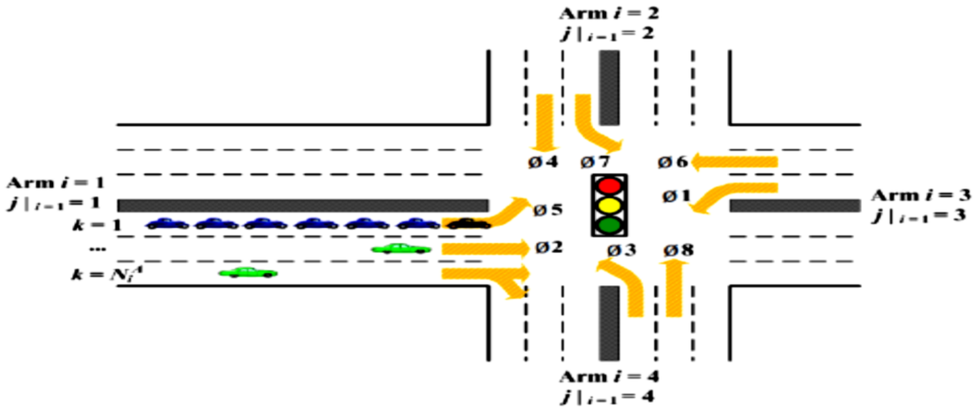

Figure 1.1 Fixed lane assignment poor lane utilization [7]

A more rational and reasonable ITS strategy can provide a better time-space allocation at all roads approaching the intersections by dynamically assigning lanes to each movement according to its demand amount. This process is called dynamic lane assignment strategy or dynamic lane grouping (DLG) as shown in Figure 1.2 [8].

This strategy is supposed to result in a significant improvement in the performance of signalized intersections with all protected movement-based phasing scheme (e.g. significant lower delays) since lane allocation will be changed according to real traffic demands. To increase the efficiency of this strategy, this could be combined with signal timing optimization in order to utilize time-space resources more efficiently.

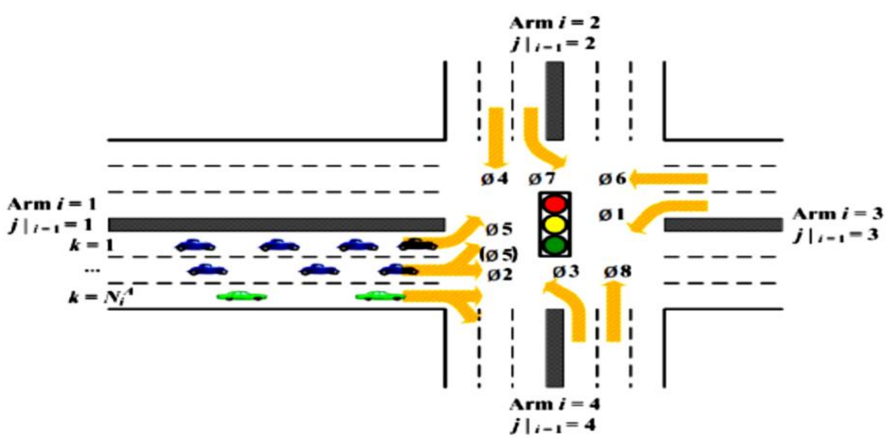

Figure 1.2 Dynamic lane grouping improved lane utilization [8]

Many researches have been conducted to ensure the effectiveness of using the different ATM strategies, including DLG, and how to apply these concepts into real life, i.e. [9-12]. The aim of this study is to investigate the usefulness of dynamic lane grouping for a 4-leg typical isolated signalized intersection with all protected movement-based signal phasing scheme.

1.2 Need of the Research

Operations of signalized intersections considerably affect the performance of the whole road system and further leave impacts on the environment and safety. As a real observation of significant fluctuation in the relative traffic movement demands, at most signalized intersections in Al-Khobar-Dammam metropolitan areas, it is more likely that intersections become blocked and, thus, signals fail to serve vehicles without suffering substantial oversaturation. Dynamic lane grouping is proposed to have a significant positive effect on the performance of the intersection.

The typical signal phasing scheme for all signalized intersections in the Kingdom of Saudi Arabia (KSA) is geographical (approach-based) phasing scheme in which each phase is fully protected and allocated for all movements (left, right and through) of one approach as shown in Figure 1.3.

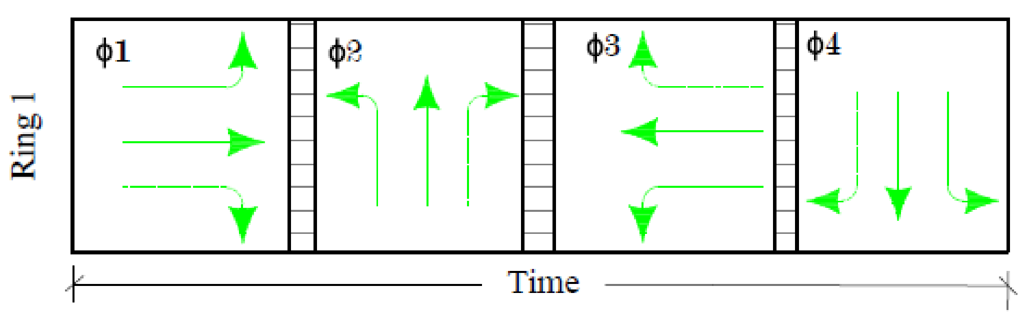

Figure 1.3 Ring barrier diagram for approach (approach-based) phasing scheme

Geographical/approach-based phasing scheme might be hazardous because of the probable improper lane utilization (i.e. vehicles at the right lane make a left turn). Movement-based phasing scheme will generally eliminate such behavior of improper lane utilization. So, a byproduct of the movement-based phasing scheme could be enhancing the safety. All protected movement-based signal phasing scheme is a typical phasing scheme in which the traffic will be served based on movement of vehicles as shown in Figure 1.4.

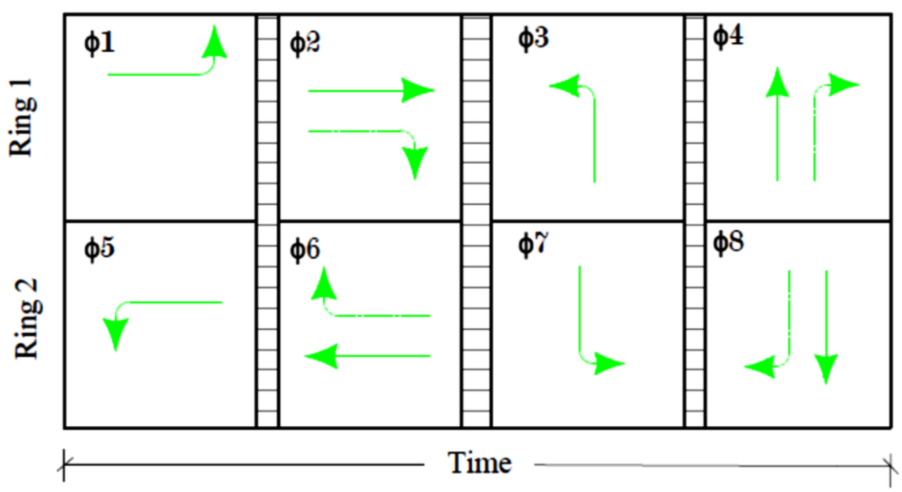

Figure 1.4 diagram for all protected movement-based signal phasing scheme

Therefore, based on these facts, this study will be investigating dynamic lane grouping for a typical isolated signalized intersection with the proposed all protected movement-based signal phasing scheme.

1.3 Objectives of the Study

The main goal of this study is to investigate the effectiveness of applying dynamic lane grouping to a typical 4-leg intersection. The study will be focused on an isolated intersection with fully protected movement-based signal phasing scheme.

Specifically, the following are the objectives of this study but not limited to them:

- Identifying all the possible lane groups which can be encompassed in the movement-based signal phasing scheme.
- Develop a computational algorithm by using Matlab or other programming tools to determine the optimum cycle length and the intersection delay for each possible lane group under any specific intersection volume. This algorithm will also identify the lane group with minimum delay as the optimum lane group for the specific volume under the proposed signal phasing scheme.
- Developing a reasonable number of hypothetical simulated traffic volumes.
- Applying the above-mentioned modeled optimization process for all hypothetical volumes developed to find the optimum cycle length and optimum lane group for each hypothetical volume.
- Using the above results, we intend to come up with a suggested methodology, technique or recommendation in order to identify the possible optimum lane group for any given traffic volume under this specific phasing scheme.

1.4 Organization of the Research

This thesis is organized in five separate chapters; each chapter is devoted to a specific part of this research (Figure 1.5). This chapter (Chapter 1) includes the introduction of the research topic along with explanations about the need, significance and objectives of this study.

The second chapter includes the overall and in-depth review of the related literature about the research topic and related topics. The third chapter contains the information about the study area and the description of the data. The fourth chapter is about the methodology used in this research along with detailed explanations about the new developed model and the Neural Networks. The fifth chapter is devoted to the results and analysis part, which includes the calculations and analysis results and explanations in more detail and the complete process of achieving the different contributions of this research. Chapter six focuses on the general conclusions of this research along with the recommendations about the new proposed strategy of this research. Recommendations for the future work are also added to this chapter.

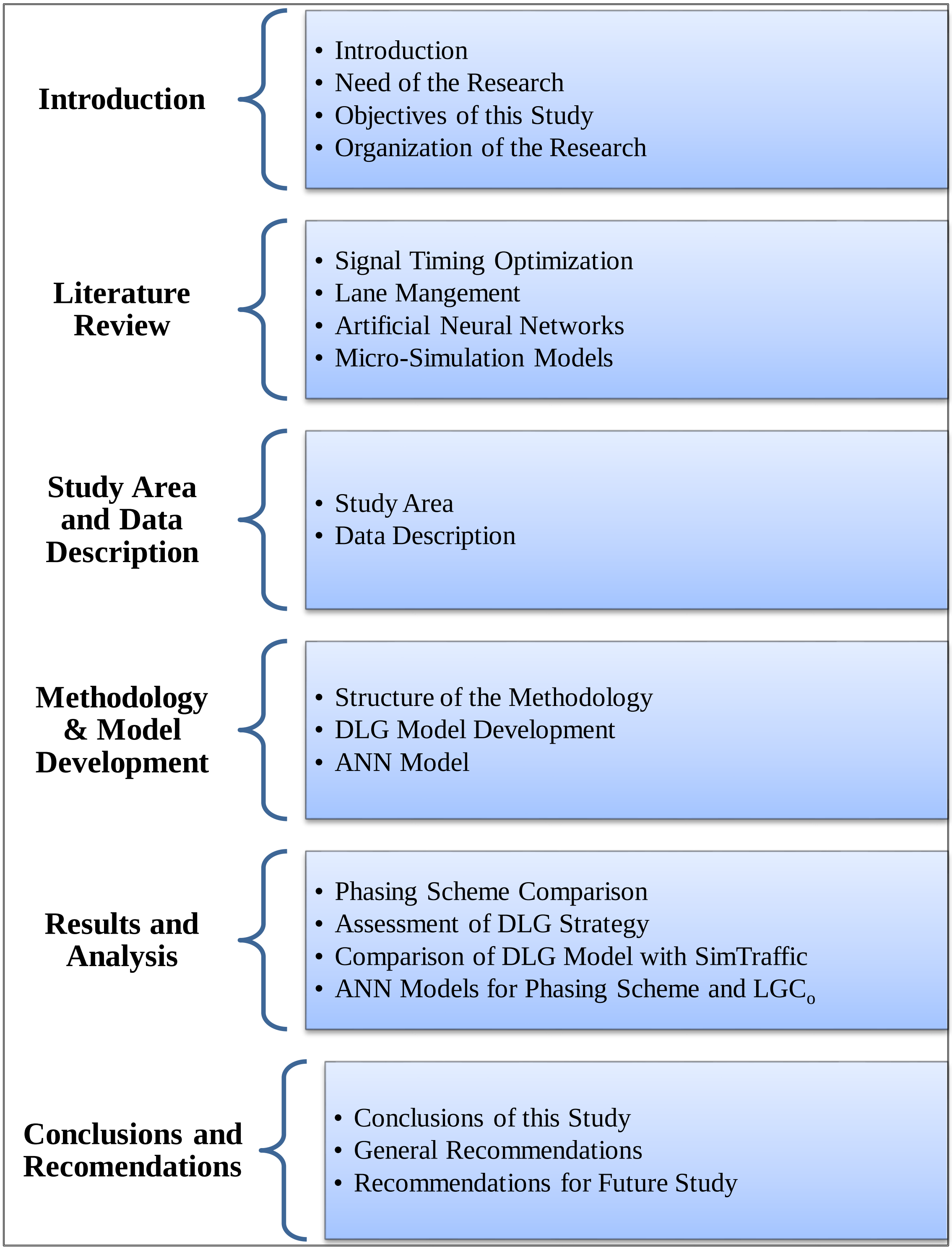

Figure 1.5 Thesis organization flow chart

CHAPTER 2

LITERATURE REVIEW

In urban areas, congestion is the main consequence of the ever-increasing traffic demand. The variability in volumes of turning movements aggravates the enduring problem of congestion. Also, daily peak-hour volume variability has a significant impact on traffic congestion and should be taken into consideration [13].

Temporal and spatial variations in the peak hour volume were investigated by Tarko and Perez-Cartagena [14]. They found that the demand variation during day time is as high as the site-to-site variation [6].

Many studies have been conducted in order to solve this problem of congestion by developing new strategies for enhancing the existing strategies. Different measures of effectiveness (MOEs) were used to evaluate the effectiveness of these strategies. Mostly used MOEs were queue length, total delay and saturation flow ratio at various transportation facilities such as freeways, arterials and isolated intersections [9-12].

2.1 Signal Timing Optimization

Signal timing optimization is an important technique to relieve congestion and improve traffic safety. There are two methods for signal timing: fixed time control and actuated control. Webster model and some other models are used for fixed time control [15]. Fixed time control models are limited to low traffic demand, and for high traffic demand, the efficiency of these models will be less. Nowadays, the sensor or actuated control is the most valuable method for signal timing, which includes all dynamic optimization models of signal timing.

Webster's [15] and other numerous signal optimization methods at intersections focus on how to reduce vehicle delays by checking various phasing patterns assuming a fixed lane configuration. In most cases, based on peak hour demand, traffic lanes will be assigned to specific movements at each approach of the intersection (through, right and left). However, due to the fluctuation in the traffic demand between different movements at the same approach, assuming fixed lane groups, the signal optimization process will result in long signal cycle durations. Long cycle lengths deteriorate the overall mobility levels of signalized intersections and might lead to risky vehicle and pedestrian behaviors [16].

In order to get the best results from the signal phasing optimization of a signalized intersection, the signal phasing and lane use designs should match with each other. For better performance, it is useful to integrate the lane use designs and signal phasing and optimize them simultaneously. Lam et al. [17] developed a mixed integer linear programming model to optimize the lane use and signal phasing simultaneously. For verification of the model, they used TRANSYT-7F with the actual traffic data from Shenzhen city of China. They also found that this optimization method has significant effects on minimizing the overall intersection delay, stop and fuel consumption [5].

Wong et al. [18] developed a lane based optimization method for lane marking design and signal settings at isolated signalized intersections. Capacity maximization and cycle length minimization were considered as the objective functions for the optimization

[19]. Wong et al. [18] developed a method for lane based optimization considering the minimization of intersection delay as the objective function at signalized intersection [20].

Ning [21] introduced a new optimization method, which is basically focused on the analogy of signal timing plan to a construction structure with some exceptions. Sum of delays, fuel consumption and air pollution variables were used interchangeably as the objective functions [22].

A study was performed by Jin et al. [23] in which they proposed a method for signal timing and phase optimization called the particle swarm optimization (PSO). Based on the simulation results, they concluded that this method is a fast and stable method and, in addition, it can reduce the intersection delay effectively [24].

Lane marking patterns perform as exogenous inputs for defining traffic flow grouping for analysis. These patterns restrict the design of signal timing optimization methods. For better results, lane marking patterns and signal timing can be optimized concurrently [25].

Ezzat et al. [26] conducted a study on the optimization of traffic signal timing in oversaturated conditions in Alexandria, Egypt. Traffic signal timings were simulated using ExtendSim simulation software [27]. They used Genetic Algorithm for attaining the optimum signal timings in order to minimize the total time of the vehicle in the system that will directly affect the overall performance of the network [27].

2.2 Dynamic Lane Management

To increase the capacity of road cross-section, the concept of dynamic lane management (DLM), as a congestion relief scheme, has intensively been applied in freeway operation through the opening of hard shoulders to traffic when demand is high. This policy proved to have significant effects on reducing travel time and improving safety [12]. Empirical observations in Hessen, Germany show that in addition to safety improvements after the application of a dynamic lane management strategy, which is basically based on opening dynamically the shoulder to be used by the traffic, especially during congestions (i.e. peak hours), operating speed increases and travel time losses decrease [10]. Dutch experience over 160 km motorway segments, suggests that dynamic management of the hard shoulder operation during peak periods is 2.5 times more cost effective than constructing new infrastructures. Consequently, traffic throughput was found to be increased by 7% to 22% when the concept of opening the shoulder to traffic on peak periods was applied [9]. The UK Highways Agency implemented the strategy of active traffic management (ATM) system as a pilot scheme over the 17 km stretch of the M42 highway (3 lanes + hard shoulder) that allows the operators to open the hard shoulder dynamically to traffic at rush hours of the day [11]. A before-and-after study pointed out significant improvements in peak period travel conditions [11]. Moreover, travel times were reduced by an average of 24% (northbound) and 9% (southbound). The focus of these studies is mainly on links (the road section and road network).

Reversing the lane is another method to increase the capacity of the road and to mitigate the congestion problem without adding extra lanes. In this strategy, the traffic flow is being reversed along a lane and temporarily increases the throughput of the road. Studies show that this lane reversal was conducted statically under specific conditions and specific times of the day [28-30]. Recent studies show that if the reversible lane strategy is applied dynamically in response to variation of the traffic, the efficiency of the strategy is enhanced significantly up to 72% [31].

Many studies were performed to evaluate the effectiveness of some techniques in order to reduce the congestion and increase the capacity of signalized intersection [32-36].

2.3 Dynamic Lane Grouping (DLG)

To improve the operational efficiency of signalized intersections, DLG can be used as a treatment to assign the lanes based on the fluctuating traffic demand. DLG is a technique for decreasing the gap between supply and demand and enhancing the level of service (LOS) of the intersection. One study shows that in 11 intersections in Milwaukee, weekday peak hour volume coefficient of variation was between 6 and 16% [37].

Zhong et al. [38] analyzed the impacts of dynamic lane assignment upon the time allocation at an approach of signal control intersection. An optimization model based on time-space resource combination was proposed. Through numerical analysis, it was concluded that this method produces optimum benefit scheme based on dynamic lane functional partition within a given traffic demand range. This optimum scheme showed significant decrease in traffic delay. However, it is not sure whether these results will be valid if the dynamic lane function optimization method is extended to all approaches of the intersection, which has not been investigated in the literature so far [38].

To deal with the variation of supply versus demand at a signalized intersection, a method of allocating dynamic lane use was discussed by Zho et al. [39]. They developed an integer non-linear model based on approach-group-concept considering the minimization of the total critical flow ratio as the objective function. It was also pointed out that the approach-group-concept can be effective in reducing the number of control variables significantly [40].

Using variable lanes as a control strategy can enhance the intersection capability and minimize delay compared to other control methodologies [41].

The day to day and hour to hour traffic volume variations enhance the need to assign the lane dynamically in different time periods in order to match the supply with fluctuating demand.

In a recent study, Wu et al. [42] analyzed the effects of DLG using the Paramics Simulation Software at a hypothetical isolated signalized intersection assuming predefined demand levels. In the analyzed scenario, they considered only one approach with variable traffic demand and dynamic traffic assignment. It was concluded that the DLG strategy improves the mobility performance in terms of reduction in the number of stops and average vehicle delay. Furthermore, as the demand volume for different turnings changes from the basic demand scheme, the benefits of the strategy increase. Similarly, significant benefits are achieved in fuel consumption and emissions [7]. When traffic demand variation in an intersection significantly increases, changing the lane configuration can act effectively in reducing the delay [43].

The more recent study about DLG was conducted by Su et al. [44] wherein they developed a criteria for identification of those signalized intersections which are likely to benefit from DLG. They came up with a four screening criteria, namely the safe turning geometry criteria, volume change criteria, volume/lane criteria and volume/capacity criteria. The study shows that volume/capacity is the most effective criterion among others. They also conducted a case study in the application of DLG, which shows a 15% reduction in overall intersection delay [45].

Almost all of the previous studies are about applying dynamic lane grouping on one approach of the signalized intersection, as most of the signalized intersections in the Kingdom of Saudi Arabia operate on approach-based phasing scheme (one phase per approach basis) [46]. One recent study was conducted at King Fahd University of Petroleum & Minerals, which investigated the effectiveness of DLG concept for a 4-legged isolated signalized intersection with the current common approach-based phasing scheme (one phase per each approach), in which the DLG strategy was applied to all approaches. This study will focus on the same concept but with different signal phasing schemes in order to ensure the effectiveness of DLG with other phasing schemes.

2.4 Application of DLG

The application of DLG is still rare because of its limitations, but the development of signal control and dynamic display technologies along with the development of infrastructure to vehicle (I2V) communication systems will make the implementation affordable, effective and practical. In all previous dynamic lane management experiences, variable message signs (VMS) or pre-signals can be used as communication tools by road operators to inform the road users about the operational conditions such as speed limit, lane configuration and so on.

2.4.1 Variable Message Signs (VMS)

DLG can be deployed with fiber optic technology and VMS to display the assigned lane to the driver. The other option for driver awareness is sending the control messages to the vehicle and driver through infrastructure to vehicle (I2V) communication channel [47]. Using VMS as a tool for dynamic lane assignment at a signalized intersection will be quite promising.

VMSs are increasingly used in the transportation sector to give dynamic information in order to improve and make the journey more efficient and safe. One of the principal issues with VMS is that, what kind of information should be provided? Several works showed that the effects of traffic information can be varied with information provision strategy [48]. So, the VMS could be used in order to provide instant information and guidance to the drivers. The information given to the VMS for dynamic lane management should be based on the optimized lane group that gives minimum intersection delay for the real-time traffic volumes.

2.4.2 Pre-Signals

Conventionally, pre-signals are used to enhance the public transportation by giving priority of buses at intersections. These signals make gaps between car queues and allows the bus mode to pass the intersection [49-51].

Pre-signals filter the traffic away from the intersection based on the movements of vehicles. Vehicles at pre-signals similar to the main signals are given green times to the left and through movements. After the pre-signal, the lane configuration changes up to the intersection signal [52].

The area between pre-signal and main signal is called "sorting area". Figure 2.1 shows three different configurations of the lanes in the sorting area.

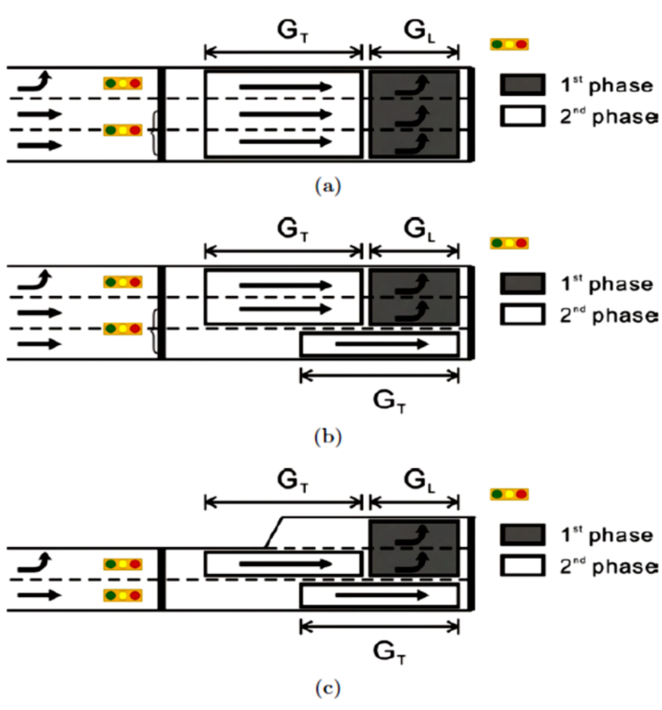

Figure 2.1 Pre-signals and sorting area

Figure 2.1 shows the layout of an intersection approach with three lanes and pre-signals (a) Full sorting with all lanes (b) Partial sorting with two lanes for left turn, and (c) Partial sorting with two lanes for left turn. The gray blocks represent the queue for left turning traffic, and the white blocks represent the through traffic, which shows the location of the queues.

Left-turning traffic is allowed first from the pre-signal followed by through traffic, and after entering the sorting area, drivers use all lanes to queue up until the main signal gives them the green time. The lane configuration of the sorting area mainly depends on but not limited to the geometry and required capacity of the intersection.

2.5 Microscopic Simulation Models

SYNCRO is a macroscopic traffic analysis software, which also has the ability to model road networks, and another model with the same package for microscopic simulation is called SimTraffic. At first, SimTraffic model was developed for signal system timing modeling of arterials, and after upgrading, it has now the ability to simulate urban road networks, freeways, weaving sections, pre-timed and actuated signalized intersections, stop controlled intersection, roundabouts, transit operations, pedestrian activity, etc. [53].

There are numerous similar models developed for modeling traffic operations. Each of these models has its own strength and weak points. A comparative study of TRANSYT-7F and Synchro/SimTraffic, which was conducted for the local conditions of Khobar city, Kingdom of Saudi Arabia, revealed that the SYNCHRO model provides signal timing plan with better performance than the TRANSYT-7F [54].

2.6 Artificial Neural Network (ANN)

During the late 1940s, the concept of Artificial Neural Network (ANN) has been introduced in the context of brain learning machine. In the late 1980s, after the development of advanced training algorithms, ANN became more useful for large data sets [55]. ANNs are capable of estimating nonlinear, stochastic and variable data sets. ANNs are composed of interconnected processing units called nodes, which consist of layers and are all added with weighted connections. For any training data, learning procedure gives a network which can adjust the connecting weights and associated accuracy. If sufficient number of hidden units (neurons) are available, ANNs have the ability to estimate any function with desired accuracy [56].

Numerical-learning-based algorithms are used for designing ANN models. The network has the capacity to adjust the parameters based on the training signals. The weights of the network are adjusted according to the set of input and outputs, and the network is trained to estimate any nonlinear function with a desired accuracy [57].

ANN with its high estimating capabilities, is considered as one of the universal approximators of the order and organization of the neurons (nodes) in the network referred to as its topology [58]; however, the structure and type of topology depends on the type of problem.

Topology of ANN models depends on the data processing nature; feedforward topology and recurrent architecture are the two types of ANN topologies. In feedforward topology, nodes are arranged hierarchically in all layers of the model from input layer to output layer, including the hidden layer, which provides the main computational power of the ANN model [58]. The learning algorithm associated with this topology is back propagation learning (BPL).

ANN has the ability of self-learning and can approximate any nonlinear function. It is widely used in system dynamic modeling [59]. ANNs are also widely used for traffic flow prediction [60]. ANN models also have the ability of real-time implementation of traffic flow forecasting, so it is important in the application and development of advanced traffic control in ITS. ANN prediction models are found to be more accurate compared to the traditional time-series prediction techniques [61]. These prediction models are mainly focused on freeways [62, 63, 64].

The ANN model was proposed for traffic data prediction by Taylor in 1992 [65]. Recent historical traffic data were used for predicting the traffic flow during the weekday. ANN models are more responsive in a dynamic condition than the historical, data-based models [66]. One of the common ANNs is Feed-Forward Neural Network (FFNN). These networks are organized in layers, starting with the input layer and ending with the output layer. However, the main computational power is provided by the hidden layers located between the input and output layers [58].

Network training, the quantity and quality of the training data, network parameters like numbers of hidden layers, transfer function, number of epoch, number of neurons in hidden layers and the initial weights between the two neurons are influencing the performance of the ANN model. ANN models are effective for short term prediction of traffic flow and need long training time [67].

To select an efficient topology for ANN model, the researchers generally have to rely on time consuming and questionably efficient rules-of-thumb in developing the optimum architecture of the neural network (NN) [68]. Topology of an ANN model is shown in Figure 2.2.

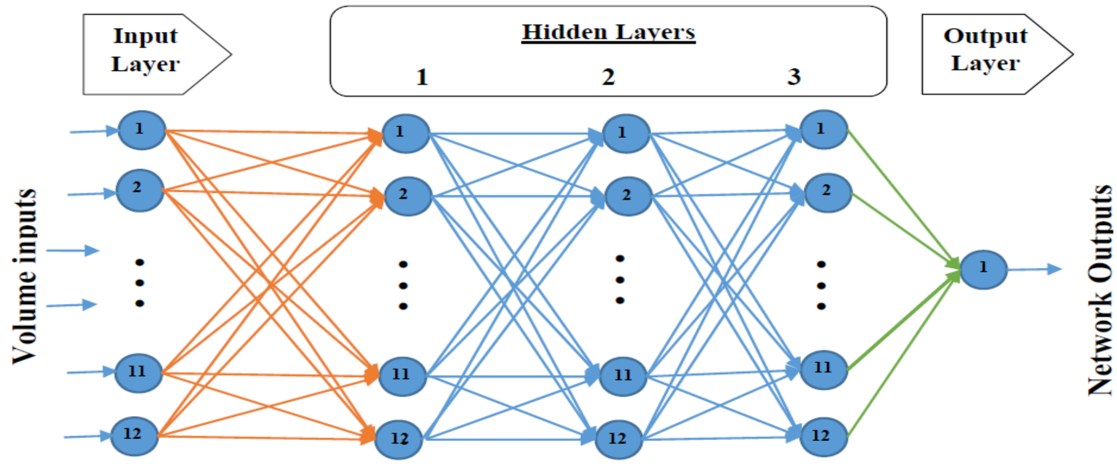

Figure 2.2 Topology of an ANN model

CHAPTER 3

Study Area and Data Description

This Chapter discusses the location where the study was conducted and the reasons why this location was selected. In addition, description of the data collected from the field is also discussed.

3.1 Study Area

This study was performed on a typical signalized intersection located in Dhahran city, Saudi Arabia. This intersection is located near Dhahran mall and connects Prince Faisal bin Fahd and Abu Obadiah Ibn Jarrah roads (Figure 3.1).

Figure 3.1 Intersection location map

The reason for selecting this intersection is the high fluctuation of traffic demand that this intersection experiences. Based on the traffic data, the fluctuation of traffic during the day and between different movements is high enough, causing the intersection to create heavy congestion during peak hours. This intersection is located in a metropolitan area, which can be a good representative of other similar intersections suffering from high congestion.

One other reason behind the selection of this intersection is the previous study, which was conducted at the same intersection. The study was conducted to assess the effectiveness of the DLG strategy for signalized intersection with approach-based phasing scheme. In this study, the effectiveness of DLG is investigated for a signalized intersection with movement-based phasing scheme in order to enable us to compare the effectiveness of the two phasing schemes in addition to assessing the effectiveness of DLG in movement-based phasing scheme.

3.2 Data Description

Intersection traffic demand data were used for this study. The traffic demand data for this study are composed of two real peak hours, morning and evening, and three hypothetical traffic demands (Table 3.1).

Table 3.1 Intersection traffic demands

1	**2**	**3**	**4**	**5**
Morning Peak	Evening Peak	Hypo 1	Hypo 2	Hypo 3
Normal peak	Normal Peak	Variation at all App	Variation on minors	Variation on majors

The hypothetical volumes were selected based on demand variation. The first volume with varying demand is at all approaches, the second hypothetical volume with varying demand is only at major approaches (West & East), and the third hypothetical volume was assumed to have varying demand only at minor approaches (North & South). The remaining two are similar or near to each other as tabulated in Table 3.2. All mentioned assumptions were considered in order to capture all the expected situations occurring in the actual practice in the field.

Intersection total volume was assumed to be fixed and composed of all approaches' demand, but the movement demand volumes were considered to be varied. Different volume distribution combinations were estimated based on randomly selected specific volume ratios for each movement.

Table 3.2 Traffic demands for approaches

Peak hour type	Morning Peak	Evening Peak	Hypo 1	Hypo 2	Hypo 3
	Normal peak	Normal Peak	Variation at all App	Variation on minors	Variation on majors
West Demand	1388	2200	2200	2200	2200
North Demand	630	670	700	1000	700
East Demand	1412	1921	700	1800	700
South Demand	611	525	350	450	650

CHAPTER 4

Methodology and Model Formulations

This Chapter discusses the general methodology of selecting the optimum lane groups. In particular, the principles, assumptions, formulation, constraints and further necessary explanation of the Matlab model for selecting the optimum lane groups at signalized intersections are explained. A short discussion about the significance and usage of artificial neural network (ANN) model for finding the optimum lane groups is also added to this chapter.

For model development purpose, a layout of a real signalized intersection was selected as the subject layout for model formulations. The demand variation is common in all metropolitan areas and this intersection also suffers from congestion caused by the demand variation. This intersection is between Prince Faisal bin Fahd Street with four (4) entering lanes and Abu Obaidah-Ibn-Jarrah Street with three (3) entering lanes, located in Dhahran city, Saudi Arabia as shown in Figure 4.1. It consists of four lanes at West-East (WA-EA) approaches and three lanes at North-South (NA-SA) approaches. Originally, this intersection was controlled by a pre-timed signal with a 4-phase approach-based phasing scheme. Due to some concerns and defects with this type of phasing scheme as discussed in the first chapter, movement-based phasing scheme is proposed in this research for this signalized intersection (Figure 4.2). Each approach is represented by *i*, which starts from the West approach and moves clockwise to the North, East and South, respectively.

The number of lanes on each approach is represented by k, which starts from the most left lane (next to the median) and ends with the most right lane to the shoulder side.

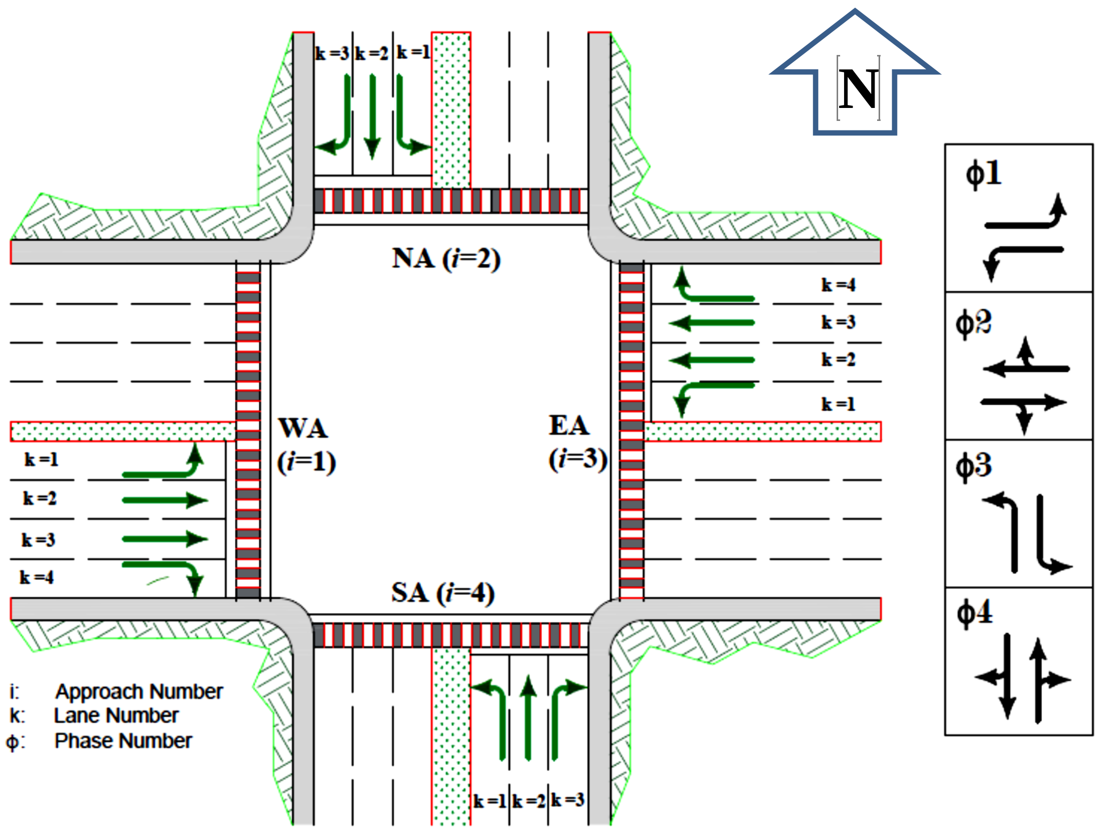

Figure 4.1 Intersection layout and phasing scheme

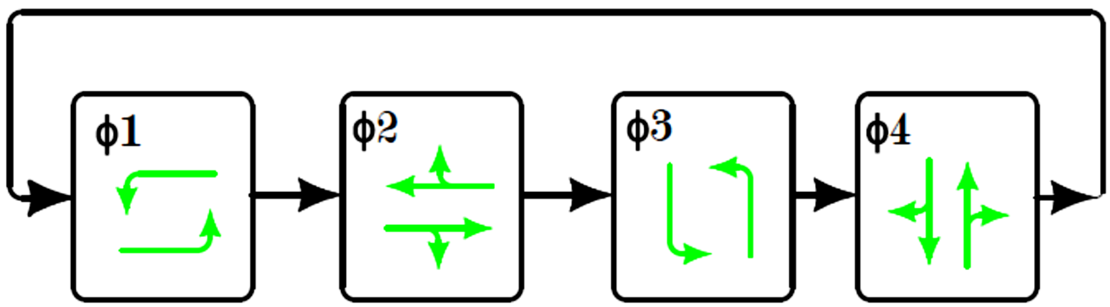

Figure 4.2 Signal phasing sequence

4.1 Structure of the Research Methodology

The methodology of achieving the research objectives includes but not limited to the following steps (Figure 4.3):

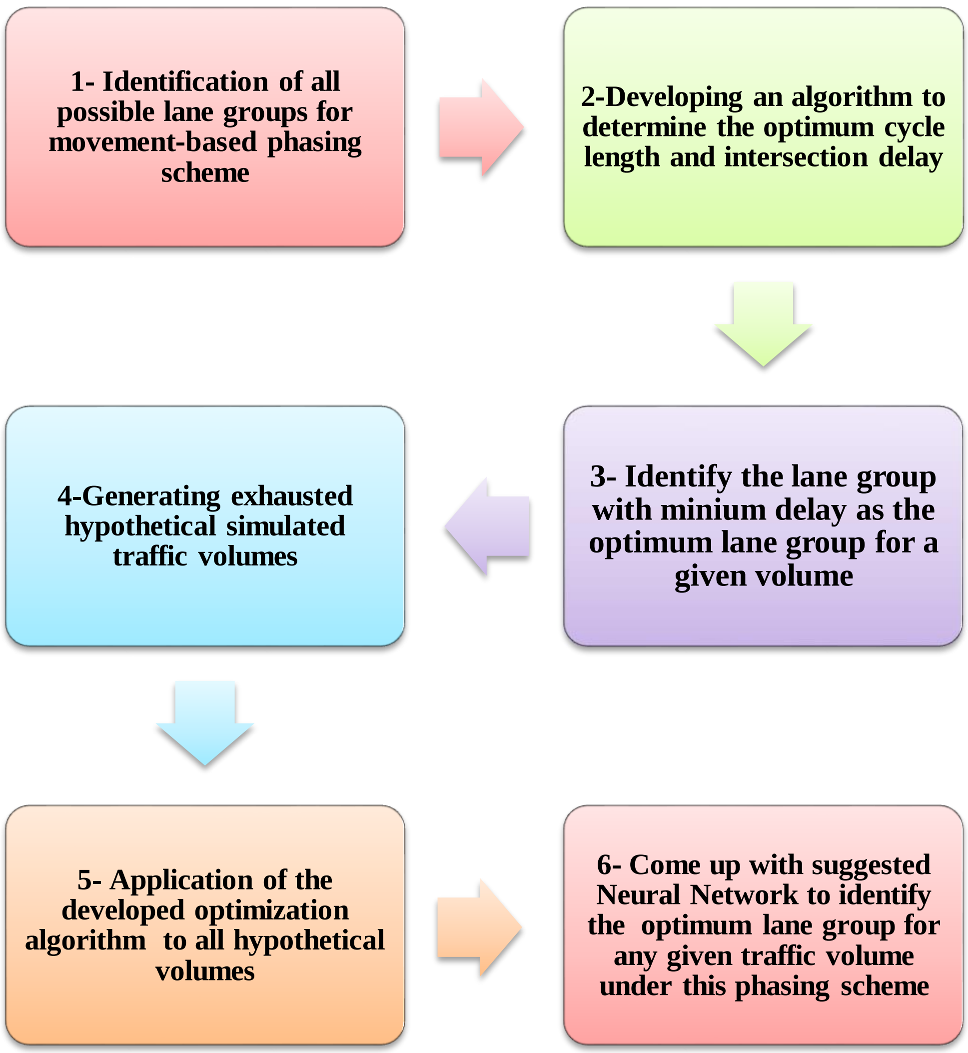

Figure 4.3 Proposed methodology flow chart

a. Identification of all possible lane group combinations, which will encompass the movement-based signal phasing scheme for all the approaches of the intersection.

b. Develop a computational algorithm by using MATLAB or other programming tools to determine the optimum cycle length and calculate the intersection delay for each possible lane group. Also, this algorithm will identify the lane group with minimum delay as the optimum lane group for a specific volume under the proposed signal phasing scheme.

c. The selection of optimal cycle length according to Webster method [15] depends on minimum average delay of the intersection (D_a). For calculating the average delay of the intersection (D_a), HCM2010 has been used.

d. Generating exhausted hypothetical simulated traffic volumes.

e. Application of the developed optimization algorithm to all the hypothetical traffic volumes.

f. Developing a neural network as an application technique to be used for identifying the possible optimum lane group for any given traffic volume of a similar isolated signalized intersection with the specific movement-based phasing scheme.

4.2 Model Development

The model for the dynamic lane grouping was developed using the MATLAB environment. The model development process is discussed in detail as follows:

4.3 Model Assumptions

For the model development, few assumptions are adopted as follows:

1. The intersection is an isolated signalized intersection and there is no any signal coordination with upstream or downstream signals.

2. No U-turning movements.

3. The cycle length is not fixed and the optimum cycle length is calculated for each volume combination case based on minimum intersection delay.

4. Intersection is controlled by 4 protected phases with movement-based phasing scheme.

5. No shared lane with left turning movement.

6. The performance measure used in this study is average intersection delay.

7. The lane selection strategy in the case of lane sharing for two movements is considered based on equalization of saturation ratios (volume/saturation rate) of the adjacent lanes.

The objective function of the model is minimizing the average intersection delay.

4.4 The Model Flow Chart

The flow chart (Figure 4.4) explains the overall structure of the calculation algorithm used in the model. Calculation algorithm is organized in three dependent loops. The calculation algorithm starts with the total approach volumes as the initial inputs along with the basic intersection geometric layout. The calculation process begins with the distribution of the approach volumes into each movement (left, through and right) and then selecting one of the lane group combinations (one lane group for each approach). The next step starts with first and core loop, which is an optimization of signal timing. In signal timing optimization, the optimum cycle length is selected between the minimum and maximum cycle lengths based on minimum intersection delay. The minimum cycle length is assumed to be 60 sec based on HCM2010 recommendations, while the maximum cycle length is assumed to be less than 250 sec as per the local traffic practice in the Eastern Province of the KSA.

After defining the optimum cycle length and the corresponding intersection delay, we move on to the second loop, which is again selecting another lane group combination (LGC), and then we repeat the same signal timing optimization process for it. This process is continued until we find the optimum cycle length and associated intersection delay for all possible lane group combinations (LGC), and then we define the lane group combination with minimum intersection delay as the optimum LGC for that specific volume distribution. The third loop is to select another volume distribution and then the process of lane group optimization and signal timing optimization is repeated for each volume distribution. Due to the large number of all volume distribution possible cases, applying the model to all of them was a time consuming task. In order to solve this problem and get a representative data set, randomization algorithm was used to use randomly selected volume distribution cases for the model application purpose. Finally, the optimum lane group combination and optimum cycle length are taken as the outputs of the model.

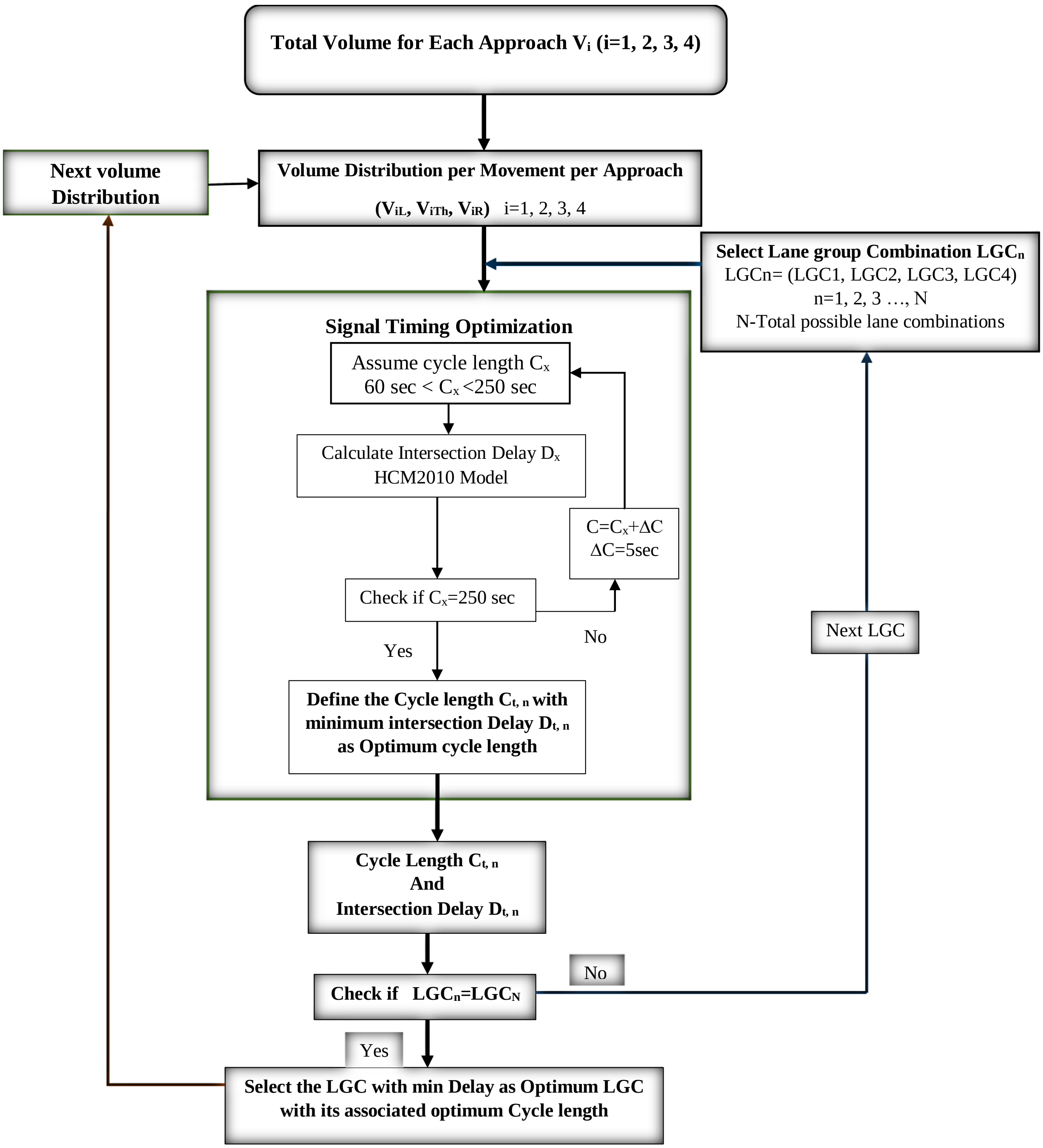

Figure 4.4 DLG Matlab model flow chart

4.5 Model Formulation

The model is developed in such a way that it is applicable to any isolated signalized intersections with any number of lanes and approaches. The total number of intersecting approaches is represented by N_T and the number of entering lanes is represented by K_i for each approach i. The number of exit lanes are assumed to be equal to the number of entering lanes.

To identify the permitted movements "j" at lane "k" for approach "i", a binary equation is defined as follows:

$$\alpha_{i,k,j} = \begin{bmatrix} 0 & forbidden\ (movement\ j\ of\ approach\ i\ at\ lane\ k) \\ 1 & otherwise \end{bmatrix} \tag{4.1}$$

Where:

***i*:** approach number (starts from West bound).

k: entering lane number, k=1,2,…, (starts from median side to shoulder lane).

j: movement at the intersection , j=1,2,3 represents left-turning movement, through movement and right turning movement, respectively.

As the model formulation is composed of some independent but related computations, it makes the model formulation complex. For simplicity of explanation, each part is discussed separately.

4.5.1 Volume distribution

For this model, the total intersection demand and all total approach demands are assumed to be fixed with varying distribution among different movements at each approach.

As the dynamic lane grouping objective is a high demand variation, the variation of demand in this model is formulated by changing the volume percentage for each traffic movement volume at each approach. The following mathematical formulation is used for this purpose:

Total intersection volume: $V_T = V_1 + V_2 + V_3 + \ldots + V_i$

Volume of each approach: $V_i = (V_L)_i + (V_{Th})i + (V_R)i$

Left turning movement at approach i: $(V_L)_i = \alpha V_i$ to $0.72V_i$

Through movement at approach i: $(V_{Th})_i = \beta V_i$ to $(0.8 - (V_L)_i)$

Right turning movement at approach i: $(V_R)_i = V_T - (V_L)_i - (V_{Th})_i$

Where:

V_T : total intersection volume (veh/h).

V_i : Approach volume (veh/h).

$(V_L)_i$: Left turning movement of approach i (veh/h).

$(V_{Th})_i$: Through movement of approach i (veh/h).

$(V_R)_i$: Right turning movement of approach i (veh/h).

α : initial percentage of the left turning movement (%).

β: initial percentage of the through movement (%).

For this model of dynamic lane grouping, the volume distribution for left turning and through movements at each approach is formulated to change with an increment of

10% of the total approach volume. As in this case, we get a huge number of possible volume combinations for the whole intersection, which is a time consuming task to calculate all the possible cases. To solve this problem, we considered a randomization technique through which we can consider any desired randomly selected volume combinations for the study purpose.

4.5.2 Signal timing optimization

The first step for the signal timing optimization and cycle length selection is to estimate the saturation flow ratio for each entering lane of the intersection. The saturation flow rate is estimated for each volume distribution. Saturation flow for through movement is 1900 veh/hr as per HCM recommendations. In order to estimate saturation flow rates for the turning movement, Equation (4.2) developed by Kimber et al. [69] is used.

$$S_{i,k} = \frac{\bar{S}_{i,k}}{1 + 1.5 \sum_{j=1}^{j=3} (\frac{f_{i,k,j}}{r_{i,k,j}})} \tag{4.2}$$

Where:

$S_{i,k}$: Saturation flow rate of lane *k* in approach *i*.

$\bar{S}_{i,k}$: Saturation flow rate for straight movement (assumed to be 1900 veh/hr).

$r_{i,k,j}$ Turning radius for movement *j* (= ∞ for straight-ahead movement).

$f_{i,k,j}$: Flow factor, is defined as the proportion of movement *j* at lane *k* of approach *i* from total traffic at lane *k* as shown in Equation (4.3).

$$f_{i,k,j} = \frac{\boldsymbol{V}_{i,k,j}}{\sum_{j=1}^{j=3} \boldsymbol{V}_{i,k,j}} \tag{4.3}$$

where $V_{i,k,j}$ is the traffic demand of movement *j* via lane *k* at approach *i*.

The flow factor $f_{i,k,j}$ for non-shared lanes (not shared between two or more movements), flow factor $f_{i,k,j}$ equals 0 or 1. And for the shared lanes, the flow factor is defined based on equalizing the saturation flow ratio for the shared lane with adjacent non-shared lane [70].

The saturation flow ratio for lane *k* at approach *i* is defined as:

$$\mathrm{y}_{i,k} = \frac{\sum_{j=1}^{j=3} V_{\ i,k,j}}{\mathrm{S}_{i,k}} \tag{4.4}$$

4.5.3 Lane groups combinations

Generally, the term lane group is used for the lane assignment at each approach, while the combination of all approach lane groups is called lane group combination (LGC). In DLG strategy, the optimum lane group will be selected based on the traffic demand in order to minimize the average intersection delay. For this purpose, all possible lane groups are defined for each approach. For movement-based phasing scheme, we can have 3 lane groups and 6 lane groups for the three-lane approaches and four-lane approaches, respectively (Figure 4.5).

The concern of this research is to predict the lane groups for all four approaches at the same time in which the combination of all approaches should give the minimum intersection delay. This phenomena is called lane group combination. Each lane group combination is composed of four lane groups (one per approach).

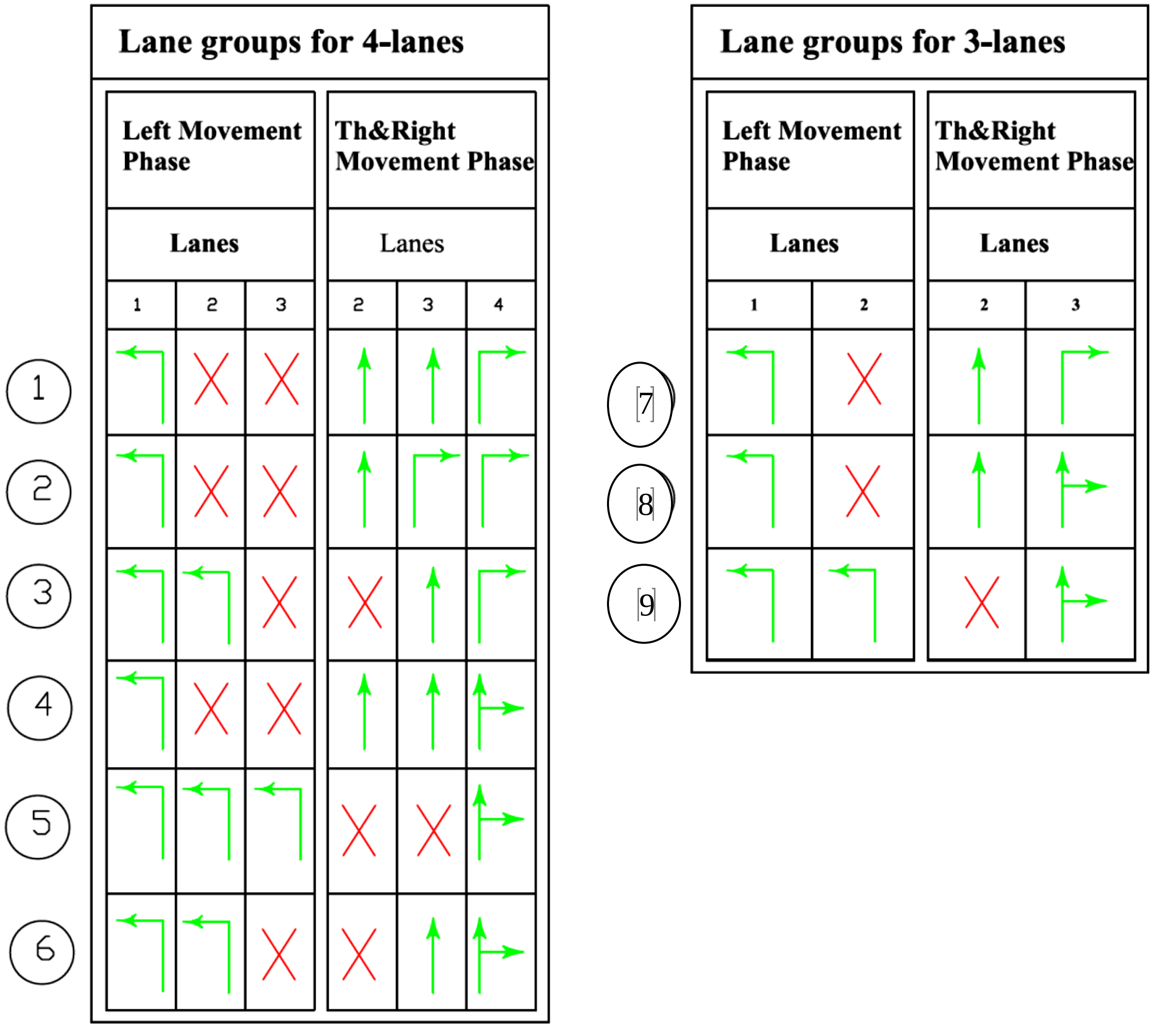

Figure 4.5 Lane groups

4.5.4 Calculation of intersection delay

Intersection delay is the objective function of the model for which the optimum cycle length and optimum lane group combination (LGC) is being selected. The cycle length and LGC with minimum average intersection delay are defined as optimums. To estimate the average intersection delay, various models should be existing. In this study, Highway Capacity Manual (HCM) 2010 model is used to estimate the average intersection delay.

The average control delay for a given lane is defined by Equation (4.5)

$$d_{i,k} = d_{1,i,k}(PF) + d_{2,i,k} + d_{3,i,k} \tag{4.5}$$

Where:

d: Control delay per vehicle (sec).

$\boldsymbol{d_{k1}}$**:** Uniform delay (sec) assuming uniform arrivals for lane *k* (sec).

PF: Progression adjustment factor, as the intersection is assumed isolated; it is assumed to be 1.

$\boldsymbol{d_{k2}}$**:** Incremental delay (sec), average delay per vehicle due to random arrivals for lane *k*.

$\boldsymbol{d_{k3}}$**:** Initial delay, average delay per vehicle due to initial queue at the beginning of analysis time period for lane *k* (sec).

The average uniform delay for lane *k* at approach *i* is estimated using Equation (4.6) [71].

$$d_{1,i,k} = \frac{0.5C(1 - \frac{g_i}{C})^2}{1 - [\min\left(1, x_{i,k}\right).\frac{g_i}{C}]} \tag{4.6}$$

Where:

***C*:** cycle length (sec).

$\boldsymbol{g_i}$**:** effective green of the related phase (sec).

$\boldsymbol{x_{i,k}}$**:** total lane volume to capacity ratio (v/c) for lane *k*, where $c_{i,k}= \mathrm{S}_{i,k}\,(\frac{\mathrm{g_i}}{\mathrm{C}})$ at each phase, the maximum v/c is considered.

For estimating the incremental delay d_2, Equation (4.7) is used [71].

$$d_{2,i,k} = 900T\left((x_{i,k} - 1) + \sqrt{(x_{i,k} - 1)^2 + \frac{8k_f I x_{i,k}}{c_{i,k}T}}\right) \tag{4.7}$$

Where:

T**:** duration of analysis period (h);

k_f**:** incremental delay factor;

I**:** upstream filtering/metering adjustment factor;

$c_{i,k}$**:** lane capacity (veh/h).

Since the model is developed for isolated signalized intersections, the value of the upstream filtering-metering adjustment factor (I) is assumed as 1.0 when the value of the incremental delay factor (k_f) is assumed as 0.5 since the signal operation is not actuated as recommended by HCM 2010 [71].

For simplicity, the initial queue is assumed not to be existing and, therefore, the initial delay d_3 equals zero 0.

The average approach delay is the weighted average of all the control delays for all lanes in that approach. In order to estimate the average delay per approach per lane $d_{i,k}$, Equation (4.8) is used.

$$di = \frac{\sum_{k=1}^{K} d_{i,k} V_{i,k}}{\sum_{k=1}^{K} V_{i,k}} \tag{4.8}$$

Where K_i is the total number of lanes at approach i.

The average intersection delay D_a (sec/veh) is the weighted average of all approach delays calculated in Equation (4.8). Then, the average intersection delay D_a is calculated using Equation (4.9).

$$D_a = \frac{\sum_{i=1}^{I_T}\left(\sum_{k=1}^{K} d_{i,k} V_{i,k}\right)}{\sum_{i=1}^{I_T}\left(\sum_{k=1}^{K} V_{i,k}\right)} \tag{4.9}$$

Where I_T is the total number of approaches at the intersection.

To identify the optimum cycle length, an algorithm that is based on iterative process is developed. A minimum cycle length of 60 sec is adopted following the HCM (2010) recommendation as the minimum acceptable cycle length to serve pedestrians, while no limitation is proposed for the maximum cycle length, which is usually selected by the local jurisdiction. For the purpose of this study, a maximum cycle length of 250 sec is used, which is similar to the adopted maximum cycle length by the local authorities in Dammam-Khobar region in the Kingdom of Saudi Arabia. Using an increment of 5 sec, average intersection delay D_a is estimated for all cycles between 60 sec and 250 sec. The cycle length that results in the minimum D_a for a specific demand combination using a specific lane group combination (LGC) is selected as the optimized cycle length for the demand and the lane group combinations under consideration (Figure 4.6).

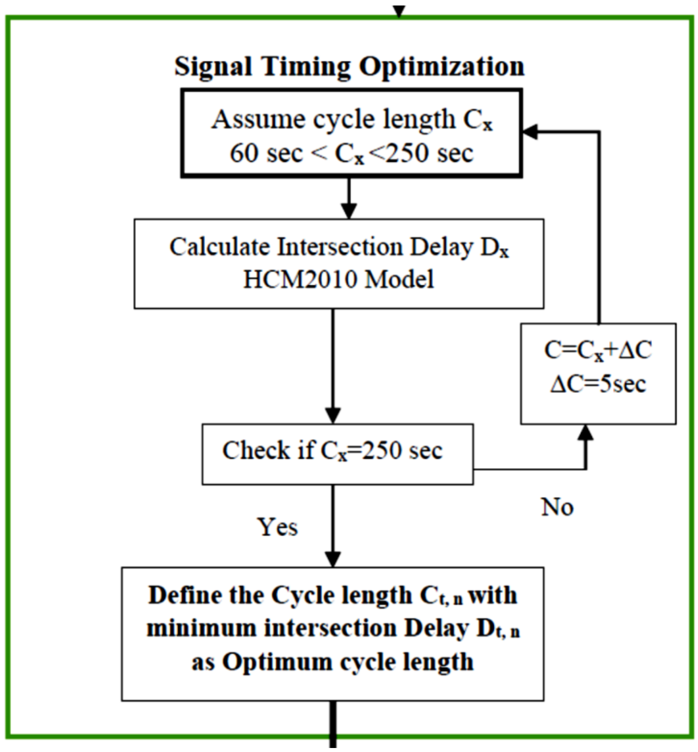

Figure 4.6 Signal timing optimization

The green splits are distributed based on the ratio of critical saturation flow ratio of each phase to the summation of the critical flow ratios of all phases. Assumptions used for signal timing calculations are shown in Table 4.1. By changing lane group combination (LGC), and estimating the optimum cycle length and associated D_a, the lane group combination (LGC) that results in the minimum D_a for each volume distribution is defined as the optimum lane group combination (LGC_o) (as shown in Figure 4.2). Then, by using the next demand combination (as defined in Equation 4.1), the whole process explained previously is repeated to identify LGC_o and associated D_a.

Table 4.1 Lost time parameters

Start-up lost time (l_1)	2 sec/phase
Motorists' use of yellow and all-red clearance interval (e)	2 sec/phase
Length of yellow change interval (y)	3 sec
Length of all red clearance interval (ar)	1.5 sec
Total lost time for phase i (T_{Li})	4.5 sec
Total lost time per cycle (L)	18 sec

4.6 Artificial Neural Network

Artificial Neural Networks are inspired with the biology of a human brain neuron as its name also suggests. Compared to computers, humans can perform complex and various ranges of tasks in an easier way. Researchers tried to incorporate human intelligence into computing machines to enhance their ability in performing complex tasks. Artificial neurons have similarities with the biological neurons like learning from experience, generalization from previous experiences and applying to new data (Figure 4.7).

Neural networks are able to draw complex relationships between any inputs and outputs more easily than the traditional computational methods. Neural networks learn the relationship from the training data and after generalization, it can apply it to any new data.

One type of neural networks is feedforward neural networks, which have the ability to predict the outputs of an unknown function more accurately and can be used as universal predictors. Hornik et al. [72] and Cybenko [73] proved the theory of universal approximates using a multilayered feedforward neural network. The theory states that the network with one hidden layer has the ability to predict any function with a desired accuracy if it has a sufficient number of neurons in the hidden layer.

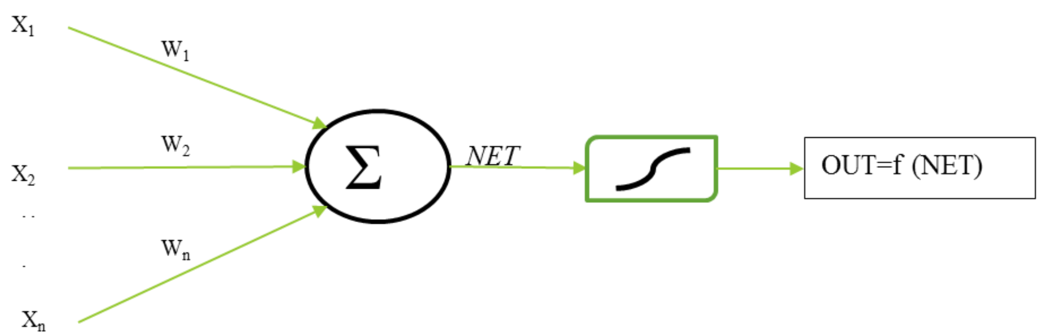

Figure 4.7 First ANN model architecture

4.6.1 Characteristics of neural networks

Due to nonlinearity and the uncertainty of the relation between the demand variation and the optimum lane groups, this study attempts to use artificial intelligence (AI) based models such as ANN. This model was developed in order to predict the optimum lane groups' combination for a typical isolated signalized intersection based on any traffic demand within the domain of the model.

Each neural network has some specific characteristics:

a) Processing elements.

b) Connectivity of processing elements.

c) The signal propagation through the network.

d) Activation functions.

e) Learning and training algorithms.

f) Environment of the performing network.

An example of a typical neural network is shown in Figure 4.8.

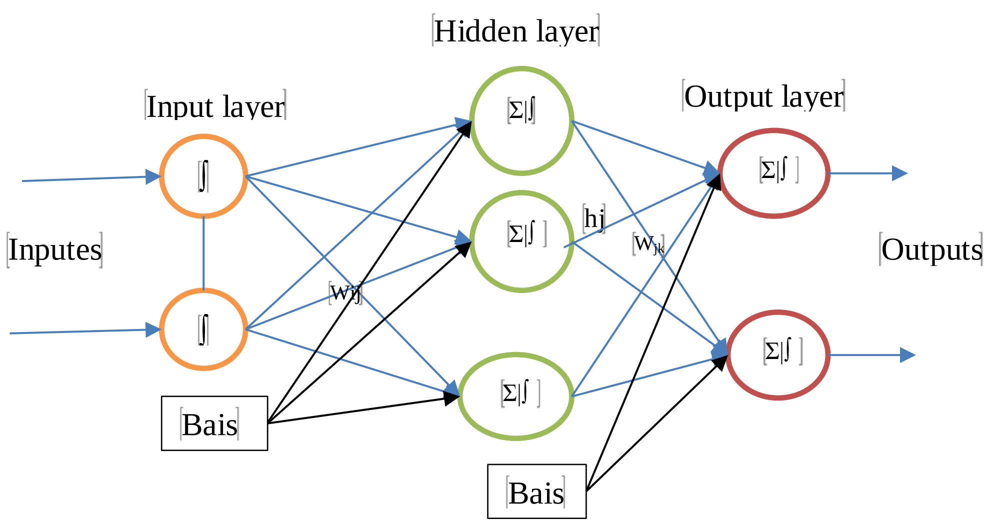

Figure 4.8 Typical neural network architecture

In the network shown in Figure 4.8, there are three layers which the inputs are to pass through. Each layer consists of a specific number of nodes (neurons). In general, any neural network has three types of layers: input, output and hidden.

Nodes in the input layer receive input signals from outside of the network. Nodes in the output layer have to transmit signals as the output outside of the network. All the remaining nodes not belonging to the input and output layers, belong to the hidden layers.

Input nodes receive input signals from sources outside the network. Output nodes transmit signals, which are output values outside the network. All other nodes not belonging to the input/output layers belong to the hidden layers. The nodes of one layer are connected to the nodes of the adjacent layer. This connectivity can be partial or full connectivity. Each node transmits signals of different strengths to its neighboring nodes.

The nodes of one layer are connected to the nodes of the other layer with full or partial connections. Using these connections, the nodes can transfer signals to each other. These connections are different in their strengths; these strengths are called weights of connections. Input signals usually propagate based on specific rules. In the case of multilayered feed forward network, the input signal is transferred through several layers and processed in order to predict the output signal. The processing units or nodes along with their activation functions transform the input values to the output values. It means that each node gets the inputs from the previous layer nodes and supply output to the nodes of the next layer.

4.6.2 Training of a neural network

After building the neural network, the input data is fed into the network through the input nodes, along with the desired output data. The neural networks self-adapt to the data and incite appropriate responses. This process of making the network adapt to the data is known as training of a neural network and the algorithms used for this purpose are known as training algorithms.

After finalizing the neural network structure, the next step is to add the input data to the network through the input nodes, and the corresponding output data to the output nodes. Then, the neural network learns the data and adapt itself to the data and simulate the results. This process in which the network learns the data is known as training of a neural network. Specific algorithms are used for training of a neural network. Training algorithms are classified based on their modeling, learning and validation properties. Each algorithm has its own ability, which determines the amount of nonlinear functions that it can reproduce precisely.

The general structure of the neural network affects the determination of proper learning algorithm and its convergence rate. In multilayered neural networks, the most suitable and most popular training algorithm is back propagation algorithm [74, 75, 76]. The back propagation algorithm is a gradient technique. In this algorithm, the activation functions of the nodes are continuous, tediously growing, constrained, nonlinear and differentiable functions.

The output function of the network is a nonstop, differentiable weight function enabling the search for the local extremes by the "gradient descent" algorithm. The optimum node weights w_{ij} are determined by the rule of gradient descent (delta rule, generalized delta rule) minimizing the error. Each repetition of the algorithm (cycle or epoch defined as the process of transmission of one of a few training pairs through the network whereby the error is calculated) contains two phases (Figure 4.9):

- Propagation of one or a set of input signals onward to the output layer (input values are brought to the network individually).
- Backward pass; in this pass, the error spreads backward to estimate the changes of parameters (weights).

This procedure is repeated for numerous repetitions by using the same training input/output pairs until the error becomes small enough.

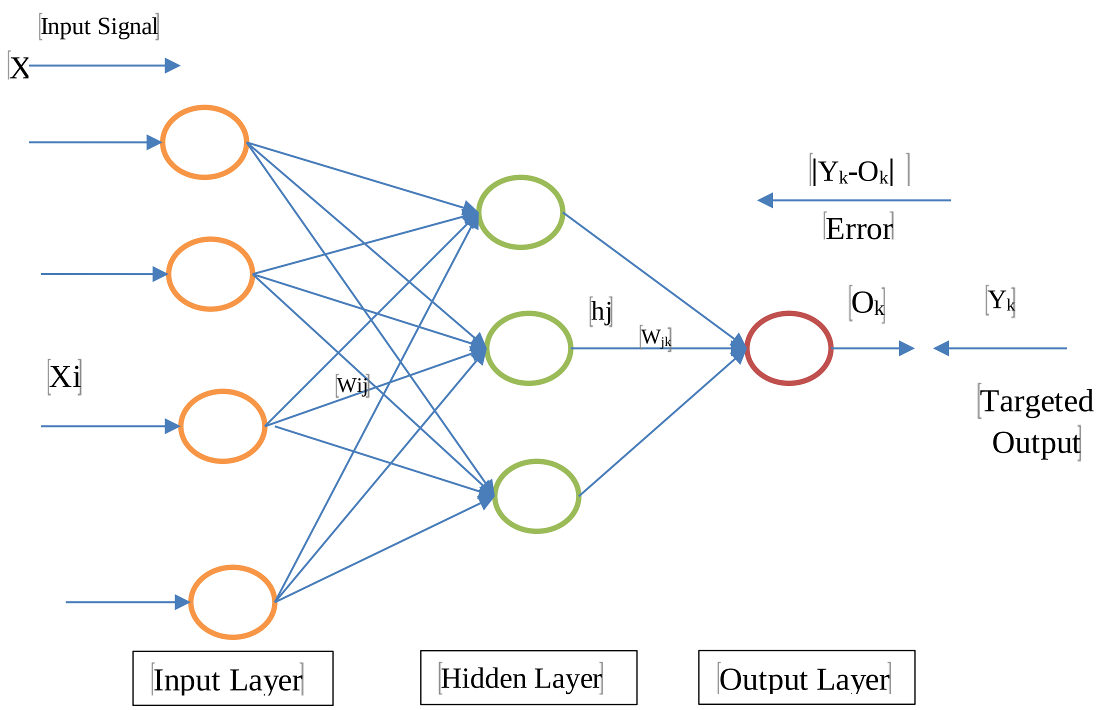

Figure 4.9 Training a Multilayered Network

4.6.3 Sample calculations

To explain the calculation procedure of a neural network, a sample network is given in Figure 4.10.

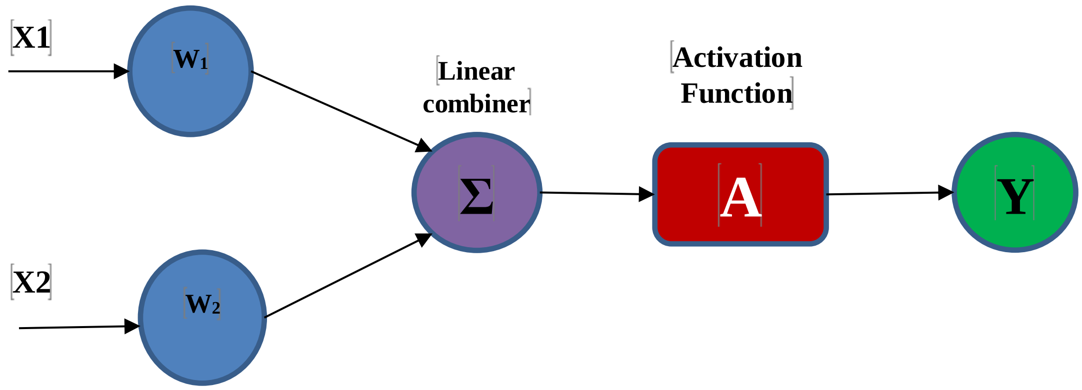

Figure 4.10 Example network

The inputs x_1 and x_2 pass through the nodes of the input layer, and the network assigns randomly the weights w_1 and w_2. The linear combiner calculates the weighted sum of these inputs, Net=w_1*x_1+w_2*x_2. The NET value is constrained by an S curve, such that the output value Y does not exceed a relatively low level. Activation functions are step functions, which are more common; they include sigmoid function, hyper tangent function and identify function. The input transformation process is performed by a logistic curve. By logistic curve, all weak and strong signals can be received and processed, if the threshold value is defined by θ. For example:

If $x1$=0, $x2$=1, $w1$=0.2, $w2$=-0.1, θ=0.2, and the activation function is a step function [Y=0 if NET<θ, else Y=1].

The output is estimated as follows:

NET=$w1$*$x1$+$w2$*x2= 0.2*0+ (-0.1)*1=-0.1 < θ=0.2, So, based on the step function, Y=0.

In the same manner, the output is calculated by the neural network. Based on the training rules, the weights can be changed and adjusted, and then the same procedure is followed using the new weights.

4.6.4 Generalization of the network

The usefulness of a neural network is enhanced while it is possible to be generalized from a limited number of sample data. This means that network algorithm has the ability to interpolate and extrapolate precisely. The artificial neural network is being generalized automatically based on this structure without the use of human intelligence.

4.6.5 Validating the neural network

Each model needs to be validated after development. Similarly, neural network also needs to be validated. The validation process is performed on a trained network using the testing data. Usually, all the data are divided into three parts before training: training data, cross-validation data and testing data. The training data is used for the training of the network, and cross-validation data is used to check the learning of the network during the training process. Testing data is totally different from both training and cross-validation data. The testing data set is the data which is totally new to the network and used for validation of a trained network. If the network estimates the outputs for the testing data precisely, then it means that the neural network can be used for estimating the outputs correctly and the network is validated. The amount of data to be used for training and testing purposes is dependent on the availability of the data, but generally, the training data is 2/3rd of the total data and the remaining data is used for testing the network. The cross-validation data is $1/10^{th}$ of the training data.

4.6.6 Artificial neural network for this research

The relation between the traffic demand and the optimum lane grouping was tried to figure out the complexity of these parameters since we could not get any linear pattern among them. This complexity indicates that nonlinearity of the relation between the demand variation and the optimum lane groups exists. This study attempts to use AI based models, such as ANN, for defining this relationship. This model is developed in order to predict the optimum lane groups' combination for a typical isolated signalized intersection based on any traffic demand within the domain of the model. The neural network is developed using the Matlab environment. A neural network is developed for predicting the optimum lane groups (one per approach). The input layer consists of 12 inputs (12 movement volumes, 3 at each approach).

The output layer is composed of four outputs, one for each approach, for predicting the corresponding optimum lane group. The data obtained from the DLG model are divided into two parts: part for training and part for testing. The total data (total number of volume combination cases) equal to 48895.70% of the data (34230) is used for training of the network and 30% (14665) is used for testing and validation of the neural network.

Then, we tried to find the optimum topology of the network in order to predict the output well and with high accuracy. The optimum topology (number of layers, number of neurons per layer and the type of transfer function) is selected by experience and trial and error procedure. We started our trials from a very simple topology with minimum hidden layers and less number of neurons, and then increased the number of neurons and the number of layers. And finally, we tried to find the optimum topology of the network, which can predict the outputs with reasonable accuracy.

CHAPTER 5

RESULTS AND ANALYSIS

This Chapter includes the main results, contributions and comparative analysis of this research. The first part is a comparative analysis of the approach-based phasing scheme versus the movement-based phasing scheme with both fixed lane grouping (FLG) and dynamic lane grouping (DLG) being discussed and analyzed. The second part of this chapter is discussion about assessing the effectiveness of the DLG strategy with respect to FLG strategy, which is currently being used. The third part of the chapter is a comparative analysis between the DLG model and a microsimulation tool SimTraffic. Also in this part, selection of the optimum lane group of the model is validated using SimTraffic. The last part of this chapter includes the Artificial Neural Network model, which is used as a predicting tool for predicting the appropriate phasing scheme and the optimum lane groups' combination (LGC_o) for any volume combination.

5.1 Comparison of the Phasing Schemes

All signal controlled intersections in Khobar and Dhahran metropolitan area are operated with approach-based phasing scheme. In approach-based phasing scheme, each phase is allocated to all movements of one approach at a time. Approach-based phasing scheme is hazardous in the study area because of the probable improper lane utilization (i.e. vehicles at the right lane make a left turn). In addition to such movement being unsafe, it also reduces the capacity of the intersection by hindering the through movement lane and receiving green time simultaneously. Movement-based phasing scheme can participate in eliminating such behavior of improper lane utilization. For the purpose of this research, both mentioned phasing schemes were investigated. In order to assess the effectiveness of movement-based phasing scheme with respect to the approach-based phasing scheme, two different scenarios were considered:

1. **Phasing schemes with FLG:** Comparison between movement and approach-based phasing schemes when using fixed lane configuration. In this case, traditional lane assignment was made with one lane for left turning movement, one lane for right turning movement and the rest for through movement.
2. **Phasing schemes with DLG:** Comparison of the above-mentioned phasing schemes when using dynamic lane grouping strategy for choosing the optimum lane groups.

5.1.1 Phasing schemes with FLG

In this section, the effects of the two phasing schemes on enhancing the intersection performance are discussed and evaluated with respect to minimizing the intersection delay. Different from the previous section, this time we considered the fixed lane grouping (FLG) condition for both phasing schemes, and for similar randomly selected volume combination cases, the corresponding delays for each scheme were compared and analyzed.

For 10000 randomly selected volume combination cases with fixed lane assignment, both movement-based phasing scheme and approach-based phasing schemes were assessed, respectively. The resultant delays for all the cases were calculated for both phasing schemes. The paired t-test was used to compare the results of the two phasing schemes and assess the difference. The paired t-test is a statistical technique for comparing two sample means. The paired t-test is used when the observations on the two samples are collected in pairs or, in other words, while each pair has similar volume, they have different phasing schemes.

As for each case, the results for both phasing schemes were matched in pairs. So, using t-test is the most appropriate technique to compare the two samples (delay values).

The hypothesis to the test is as follows:

Null Hypothesis: the mean of the differences of the two samples (delay for both phasing schemes) is equal to zero or the phasing schemes do not have significant effects on the intersection performance (Delay):

$$\mu_D=0$$

Alternative Hypothesis: the mean of the differences of the two samples (delay for both phasing schemes) is not equal to zero or the phasing schemes have significant effects on the intersection performance (Delay):

$$\mu_D\neq 0$$

To compare the two phasing schemes under these specific conditions, first, the morning peak traffic volumes were used and analyzed as shown in Table 5.1.

By using the Excel two-way paired t-test function, we found that the probability of the t-value is less than $\alpha = 0.05$, so the null hypothesis can be rejected (Table 5.1).

Table 5.1 Paired t-test results for phasing scheme comparison with FLG

t-Test: Paired Two Samples for Means		
	Movement	*Approach*
t Stat	-78.109	
P(T<=t) one-tail	0	
t Critical one-tail	1.645	
P(T<=t) two-tail	0	
t Critical two-tail	1.960	

We can conclude that with a fixed lane assignment, the type of signal phasing scheme has a significant effect on the intersection performance (average intersection delay).

From the one-way t-test analysis, it can be concluded that the movement-based phasing scheme is more effective than the approach-based phasing scheme in minimizing the average intersection delay.

As this test was performed using only morning peak volume, it cannot be generalized for all the cases.

To generalize the results, different approach volumes were considered and the results were compared in the same manner as the two objective phasing schemes using different intersection volumes. These volumes were selected based on the actual data collected in the morning and evening peaks. Also, different hypothetical volumes were used to assess the effect of the signal phasing scheme in each case. The logic used for selecting the hypothetical volumes was based on changing the ratios between the two opposing approaches' traffic volumes. The ratios were selected from 0.1 to 1 with an increment of 0.1; all possible (100) combinations for four approach volumes were used.

The results obtained from all the cases were individually analyzed and tested for the differences.

For instance, North and East approach volumes are 1500 veh/h and 2000 veh/h, respectively. For the ratios of 0.1 and 0.2 for north-south and west-east, respectively, the volumes of south and west were considered as 150 veh/h and 400 veh/h, respectively. Then, the preferred phasing scheme was assessed and added to the table. In the same way, different volumes were assumed for finding the preferred phasing scheme and the results were tabulated.

Finally, after testing all the above-mentioned cases, the following tabulated results were obtained. The table includes all volume ratios between the opposing approaches and the associated effective phasing scheme (Table 5.2).

Table 5.2 Approach volume variation and phasing schemes

Ratios of opposing volumes with respective appropriate phasing scheme

R(E&W)	R(N&S)	S	R(E&W)	R(N&S)	S	R(E&W)	R(N&S)	S	R(E&W)	R(N&S)	S
0.1	0.1	g	0.2	0.1	g	0.3	0.1	g	0.4	0.1	g
	0.2	g		0.2	g		0.2	g		0.2	g
	0.3	g		0.3	g		0.3	g		0.3	g
	0.4	g		0.4	g		0.4	g		0.4	g
	0.5	g		0.5	g		0.5	g		0.5	g
	0.6	g		0.6	g		0.6	g		0.6	g
	0.7	g		0.7	g		0.7	g		0.7	n.s
	0.8	g		0.8	g		0.8	g		0.8	n.s
	0.9	g		0.9	g		0.9	g		0.9	m
	1	g		1	g		1	g		1	m
0.5	0.1	g	0.6	0.1	g	0.7	0.1	g	0.8	0.1	g
	0.2	g		0.2	g		0.2	g		0.2	g
	0.3	g		0.3	g		0.3	g		0.3	g
	0.4	g		0.4	g		0.4	n.s		0.4	m
	0.5	g		0.5	m		0.5	m		0.5	m
	0.6	m		0.6	m		0.6	m		0.6	m
	0.7	m		0.7	m		0.7	m		0.7	m
	0.8	m		0.8	m		0.8	m		0.8	m
	0.9	m		0.9	m		0.9	m		0.9	m
	1	m		1	m		1	m		1	m
0.9	0.1	g	1	0.1	g						
	0.2	g		0.2	g						
	0.3	n.s		0.3	n.s						
	0.4	m		0.4	m						
	0.5	m		0.5	m						
	0.6	m		0.6	m						
	0.7	m		0.7	m						
	0.8	m		0.8	m						
	0.9	m		0.9	m						
	1	m		1	m						

S-phasing scheme
n.s-not significant
R-stands for Ratio
g-geographic(approach-based) phasing scheme
m-movement-based phasing scheme
N-North Approach volume
S-South Approach volume
E-East Approach volume
W-West Approach volume

In this case, the Major and Minor approaches of the intersection are West-East and North-South, respectively. Figure 5.1 is a 2-dimensional plot for the ratios between the major approach volumes versus the ratios between the minor approach volumes. In other words, it is the graphical representation of Table 5.2.

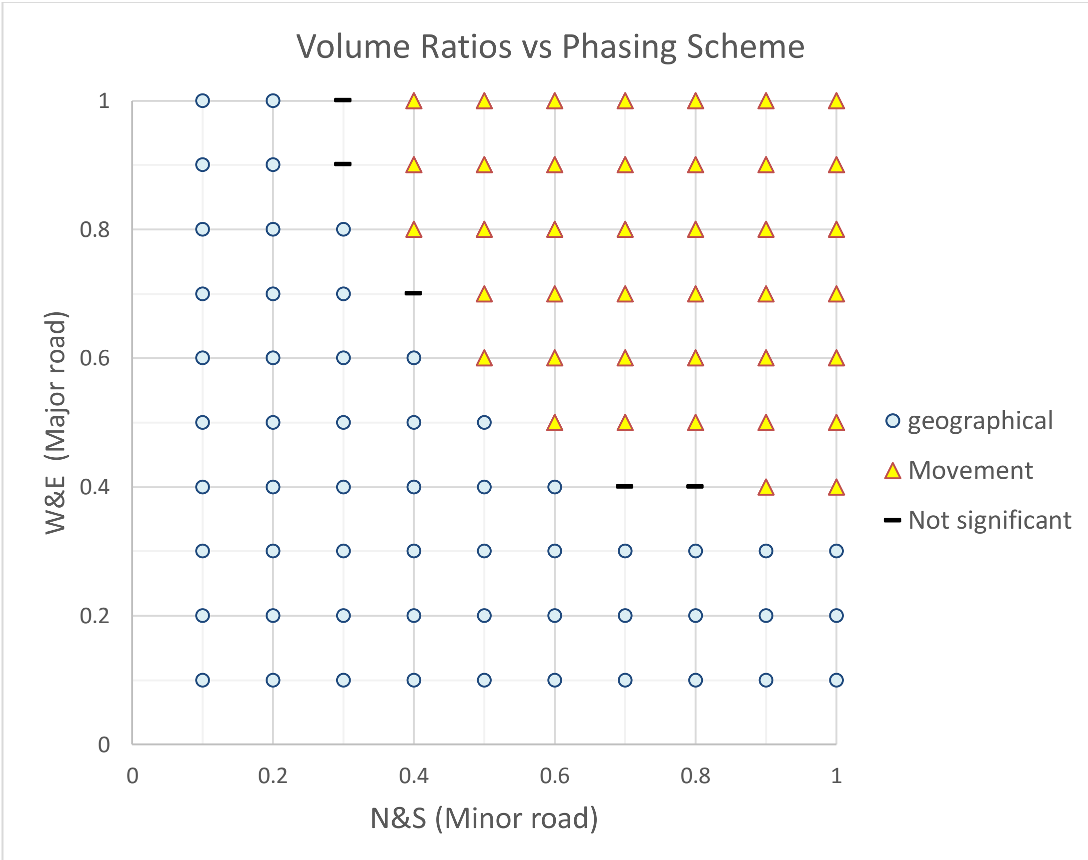

Figure 5.1 Approach volume ratios and phasing schemes

From Table 5.2 and the 2D plot (Figure 5.1), the following results can be concluded:

Approach-based phasing scheme is appropriate when:

1) The ratios of both pairs, major (W&E) and minor (N&S), approach volumes are less than 0.5.
2) The ratio between the approach volumes of the major street is equal or less than 0.3 and the ratio between the approach volumes of the minor street is more than 0.5.

3) The ratio between the approach volumes of the major street is more than 0.5 and the ratio between the approach volumes of the minor street is less than 0.3.
4) The ratios between the approach volumes of the major and minor streets are equal or less than 0.5 and 0.5, respectively.

Movement-based phasing scheme is appropriate when:

1) The ratios of both pairs, major (W&E) and minor (N&S), approach volumes are more than 0.5.
2) The ratio between the approach volumes of the major street is equal to 0.5 and the ratio between the approach volumes of the minor street is more than 0.5.
3) The ratio between the approach volumes of the major street is more than 0.5 and the ratio between the approach volumes of the minor street is equal to 0.5.
4) The ratio between the approach volumes of the major street is more than 0.7 and the ratio between the approach volumes of the minor street is equal to 0.4.
5) The ratio between the approach volumes of the major street is equal to 0.4 and the ratio between the approach volumes of the minor street is more than 0.8.

When using fixed lane assignment at signalized intersections, the type of phasing scheme has significant effects on the performance of the intersection, especially the intersection delay. The type of phasing scheme is dependent on the traffic volumes of each approach and the variation between the two opposing approaches.

Generally, it can be concluded that the movement-based phasing scheme is better with respect to the approach-based phasing scheme when the variation between the opposing approaches' traffic volumes is less. If the variation between the opposing approaches' volumes is higher than the mentioned specific ratios, approach-based phasing scheme can perform well. Simply, if the ratios of both pairs, major (W&E) and minor (N&S), approach volumes are more than 0.5, movement-based phasing scheme is preferred. And if the ratios of both pairs, major (W&E) and minor (N&S), approaches' volumes are equal or less than 0.5, approach-based phasing scheme is preferred. In such cases, Table 5.2 or Figure 5.1 can be used.

Normally, the variation in the opposing approaches' volumes of an intersection is not too much higher. So, movement-based phasing scheme can perform better most of the time than the approach-based phasing scheme.

5.1.2 Phasing schemes with DLG

In this section, the effectiveness of the two phasing schemes (movement and approach) with respect to the objective function, which is minimizing the average vehicle delay, was compared and the results were discussed. For this purpose, we applied the DLG strategy for both phasing schemes and for similar volume combination cases. Then, the corresponding delays for each case were compared pairwise and analyzed.

For 50000 randomly selected volume combination cases with DLG strategy having been applied, both movement-based phasing scheme and approach-based phasing scheme were considered, respectively. The intersection delay for both phasing schemes was calculated for the same volume combination cases using two separate MATLAB models developed for movement and approach-based phasing schemes, respectively. The resultant delay was calculated for both phasing schemes. The paired t-test was used to compare the results of the two phasing schemes and assess the difference. The paired t-test is a statistical technique for comparing two sample means. The paired t-test is used when the observations on the two samples are collected in pairs or, in other words, each pair has a similar condition but this condition may change for the other pairs. (Both samples are matched pairs.)

As for each case, the results for both phasing schemes were matched in pairs, so using t-test is the most appropriate technique to compare the two samples.

The hypothesis to the test is as follows:

Null Hypothesis: the mean of the differences of the two samples (delay for both phasing schemes) is equal to zero or the phasing schemes do not have significant effects on the intersection performance (Delay):

$$\mu_D=0$$

Alternative Hypothesis: the mean of the differences of the two samples (delay for both phasing schemes) is not equal to zero or the phasing schemes have significant effects on the intersection performance (Delay):

$$\mu_D\neq 0$$

By using the Excel test function, we found that the probability of the t-value is less than $\alpha = 0.05$, so the null hypothesis can be rejected (Table 5.3).

Table 5.3 Paired t-test results for phasing scheme comparison with DLG

t-Test: Paired Two Samples		
Phasing scheme	Movement-based	Approach-based
t Stat	178.144	
P(T<=t) one-tail	0	
t Critical one-tail	1.645	
P(T<=t) two-tail	0	
t Critical two-tail	1.960	

Statistically, we can conclude that when we are using the DLG strategy, there is enough evidence to prove that the type of signal phasing scheme has a significant effect on the intersection performance (intersection delay). The results show that in DLG strategy, approach-based phasing scheme is statistically preferred. But according to the data, we cannot always get the minimum delay from the approach-based phasing scheme. Based on the data, the preference for the phasing scheme is so scattered and does not follow a specific threshold. So, in order to find the optimum phasing scheme for any given volume combination, it is recommended to use other powerful tools like machine learning technique rather than using the statistical procedures, although the safety concerns (i.e. misuse of the assigned lanes) with the approach-based phasing scheme still exist and should be considered in the selection of the appropriate phasing scheme.

5.2 Assessment of DLG Strategy with Movement-based Phasing Scheme

This section discusses about assessing the effectiveness of dynamic lane grouping (DLG) strategy with respect to the traditional fixed lane grouping (FLG) strategy using the movement-based phasing scheme.

As stated in the problem statement section, the traditional lane assignment strategy focuses on fixed lane assignment. This strategy has some drawbacks like poor lane and space utilization and long queue formulation at intersections due to limited space for each movement. The recent ITS solution for enhancing the space utilization at signalized intersection is dynamic lane grouping (DLG). In dynamic lane grouping strategy, the optimum lane grouping is selected based on the traffic demand, which produces the minimum intersection delay.

To assess the effectiveness of the proposed DLG strategy for the study intersection, we randomly selected 10000 different volume combination cases (2000 from each total intersection volume) as a study sample. In all these 10000 randomly selected volume combination cases, we applied both FLG and DLG strategies separately. By using the developed model, we calculated the average intersection delay per vehicle for all cases. A sample of 50 randomly selected cases is shown in Figure 5.2.

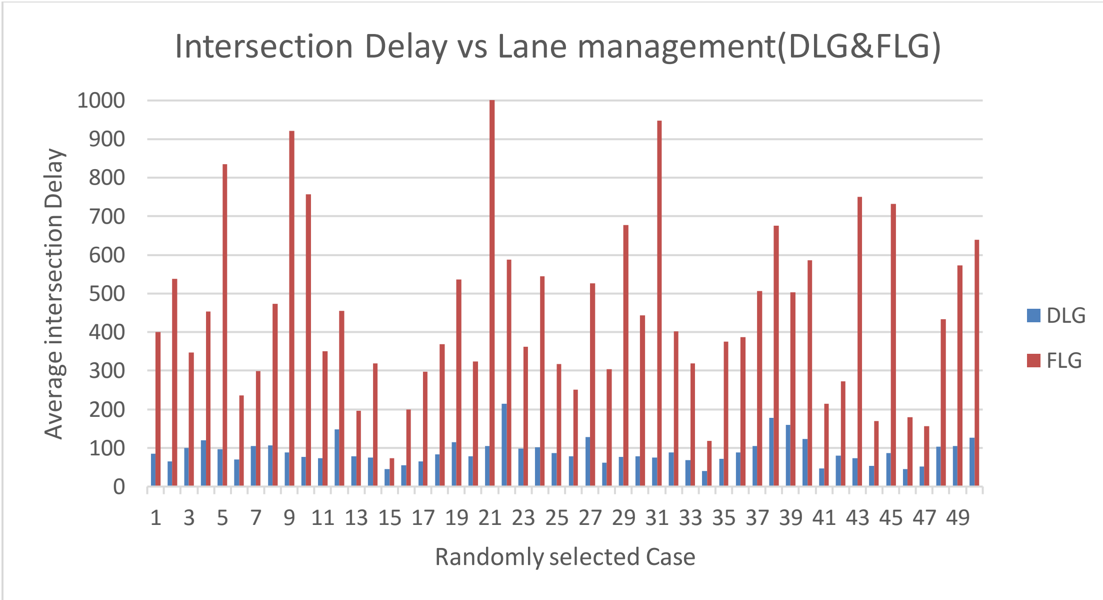

Figure 5.2 Sample cases of intersection delay at DLG& FLG

To compare the results of the two paired t-tests of the intersection delay, we again used the paired t-test statistical technique.

The hypothesis to the test is as follows:

Null Hypothesis: the mean of the differences of the two samples (delay for both phasing schemes) is equal to zero or the phasing schemes do not have significant effects on the intersection performance (Delay):

$$\mu_D=0$$

Alternative Hypothesis: the mean of the differences of the two samples (delay for both phasing schemes) is not equal to zero or the phasing schemes have significant effects on the intersection performance (Delay):

$$\mu_D\neq 0$$

By using the Excel two-way paired t-test function, we found that the probability of the t-value is less than the significance level $\alpha = 0.05$, so the null hypothesis can be rejected (Table 5.4).

Table 5.4 Paired t-test for DLG and FLG

t-Test: Paired Two Samples for Means	
t Stat	-171.051
P(T<=t) one-tail	0
t Critical one-tail	1.645
P(T<=t) two-tail	0
t Critical two-tail	1.960

From the statistical analysis of the t-test results, we can conclude that the DLG strategy has significant effects on the intersection performance (decreasing the intersection delay) with respect to the base condition, which is fixed lane grouping (FLG). As the conclusion is valid for all the cases, it can therefore be generalized.

5.3 Comparison of the DLG model with Microsimulation Models

Microsimulation models are computerized analytical tools that perform highly detailed analysis of activities such as highway traffic flowing through an intersection. Traffic microsimulation models simulate the behavior of individual vehicles within a predefined road network and are used to predict the likely impact of changes in more detail. SimTraffic is one of these traffic microsimulation models.

In this section, SimTraffic was used to validate the results of the DLG model for two things: intersection delay and prediction of optimum lane group combination (LGC_o). Intersection delay was calculated by SimTraffic for different volume combination cases with optimum lane groups predefined by the DLG model. Intersection delay by the model was calculated based on HCM2010 model. The resultant delay values calculated by SimTraffic were compared with the ones calculated by the MATLAB model for the same cases. SimTraffic was used to validate the prediction of optimum lane groups by the DLG model. For this purpose, first, the delay was calculated using SimTraffic for all possible lane group combinations, and the optimum lane group combination was defined based on the minimum intersection delay. Then, the optimum lane group combination defined by SimTraffic was compared to the one defined by the developed model.

Intersection delay was calculated using both DLG model and SimTraffic for similar volume combinations. For the analysis, 30 randomly selected volume combinations from 5 previously mentioned total intersection volumes were considered to compare the delay using both tools. Table 5.5 includes the maximum (v/c) ratios for the intersection and the intersection delay estimated using both DLG model and SimTraffic, respectively.

Table 5.5 Intersection delay by DLG model and SimTraffic

Case No.	v/c Ratio (Intersection)	Model HCM (sec/veh)	SimTraffic (sec/veh)	Delay Ratio (Model/SimTraffic)
1	0.83	36.5	36.5	1.0
2	0.83	42.0	42	1.0
3	0.83	36.5	39.2	0.9
4	0.84	44.2	44.1	1.0
5	0.85	43.9	62.5	0.7
6	0.85	42.5	44.4	1.0
7	0.86	40.1	37.7	1.1
8	0.86	40.3	49.2	0.8
9	0.87	56.8	66.1	0.9
10	0.88	46.6	59.2	0.8
11	0.88	60.7	92.8	0.7
12	0.89	46.7	59	0.8
13	0.89	48.7	111.7	0.4
14	0.89	54.9	71.7	0.8
15	0.89	59.6	144.9	0.4
16	0.90	51.8	105.8	0.5
17	0.90	62.2	91.1	0.7
18	0.90	55.7	86	0.6
19	0.90	55.9	75.9	0.7
20	0.90	60.3	62.7	1.0
21	0.90	57.7	79.8	0.7
22	0.91	47.2	102.4	0.5
23	0.95	87.2	212.3	0.4
24	0.95	76.2	214.3	0.4
25	0.96	79.6	166.6	0.5
26	0.96	90.9	211	0.4
27	0.98	84.8	204.4	0.4
28	0.98	95.4	239.2	0.4
29	1.01	104.6	317.5	0.3
30	1.01	99.4	284.2	0.3

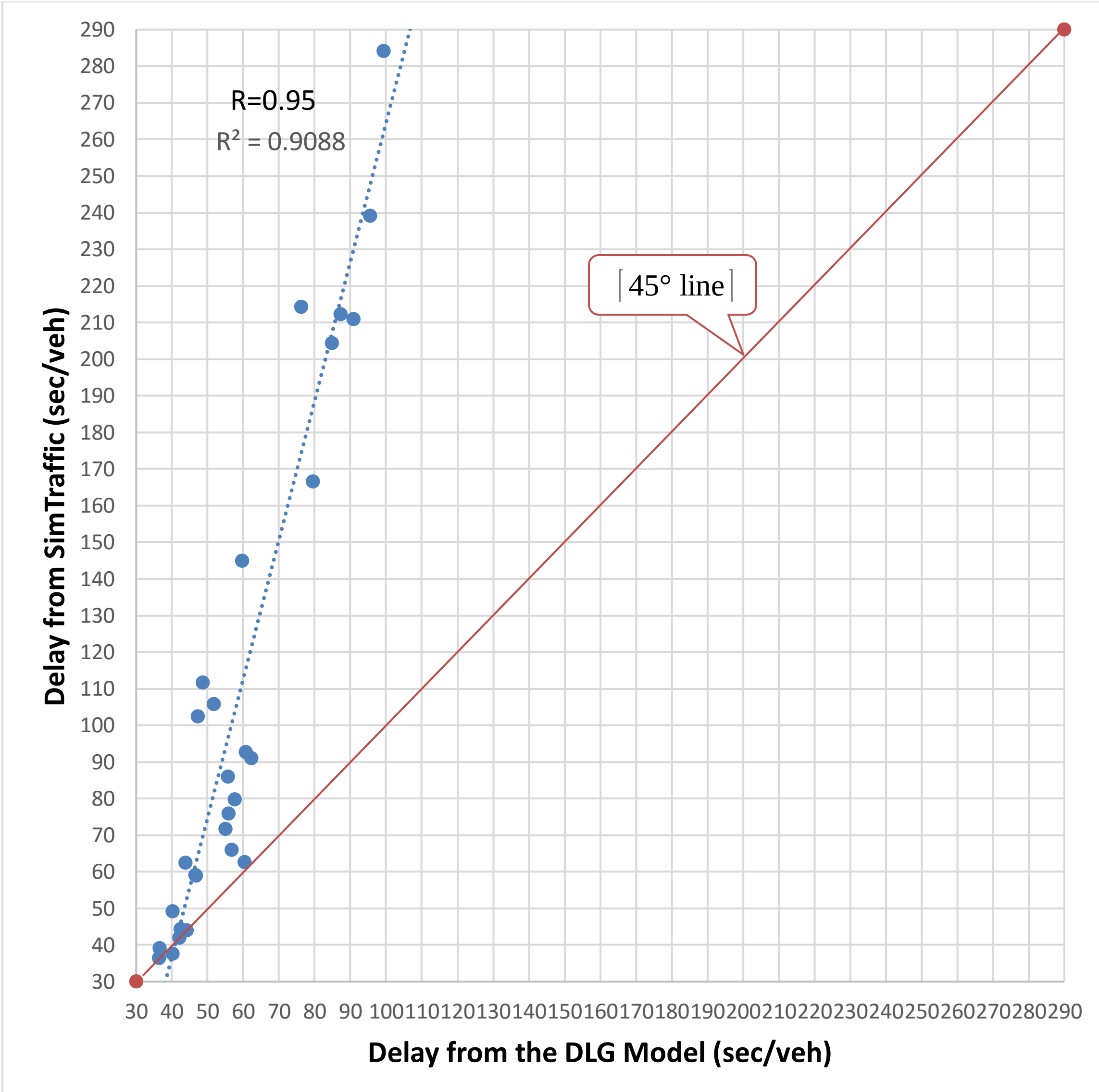

Figure 5.3 Intersection delay by DLG model vs. SimTraffic (sec/veh)

From the above graphs and the tabulated data, it is obvious that the DLG model (which calculates the delay based on HCM2010 procedure) underestimates the intersection delay compared to SimTraffic. The main reasons for this underestimation are as follows:

- Some of the assumptions for the DLG model constrain the delay estimation. For instance, the initial queue in the DLG model is assumed to be zero.

- The model is using deterministic procedures while SimTraffic uses stochastic procedures, which are more accurate.
- In the case of oversaturation, both SimTraffic and HCM methodologies are weak in delay estimation [77].

However, the intersection delay values from the model and SimTraffic are identical, which are less than 50 sec/veh, and in these cases, the traffic conditions are undersaturated (v/c<1). But in the other cases, the traffic situations are oversaturated (v/c) and the delay values from the model are less than that from SimTraffic. From the plot, it is shown that generally, the coefficient of correlation R=0.95 and the coefficient of determination R^2 is 0.91, which shows a proper matching of the results from both models. Both models follow the same increasing direction in the calculation of the delay.

5.3.1 Validation of the optimum DLG selection model

In this section, validation of the DLG model in defining the optimum lane group is discussed. Optimum lane groups predicted by the DLG model were validated by SimTraffic. For this purpose, having a specific volume combination, the intersection delay was estimated using SimTraffic for all the possible lane groups' combinations. Based on the estimated intersection delays, the LGC with minimum delay was defined as the optimum. This new optimum LGC was then compared with the optimum LGC from the DLG model. Based on the typical intersection layout for each volume case, there are 6*6*3*3=324 possible lane group combinations, and it is necessary to calculate the delay for all the 324 combinations. In order to make this calculation simple and less time consuming, it was assumed that the optimum lane group of one approach is only being affected by the opposing approach lane group in case of a similar volume distribution. The optimum lane group is not affected by the other two approaches' lane groups while the volume conditions remain similar.

To validate this assumption, we considered two approaches (North and South) to find the optimum lane group combinations for them and to find out the effects of the lane groups of the other two approaches (East and West). For one volume combination, the optimum lane group combinations for North and South approaches was defined by keeping the other two approaches with fixed lane groups. This process was repeated for the three difference cases of the West and East approaches' lane groups. First, we considered the optimum lane groups for East and West, and then we considered the randomly selected lane groups in the East and West approaches. Based on the SimTraffic results, the optimum lane group combination for North and South was defined in all the three cases. Finally, the same lane group combination was defined for North and South approaches in all the three cases. Based on this result, it can be concluded that the optimum lane group of one approach is affected only by the opposing approach's lane group in case of combination. The optimum LGC for the whole intersection can be obtained by combining the two combinations of each two opposing approaches' optimum LGCs. In this case, the optimum LGC for North and South is (1 and 1) (Table 5.6).

Table 5.6 Optimum LGC for North and South

Optimum lane groups for North and South Approaches

Case	No	Delay	Lane groups W	N	E	S
1	1	33.6	3	1	2	1
	2	37	3	2	2	1
	3	45.1	3	3	2	1
	4	35.9	3	1	2	2
	5	37.6	3	2	2	2
	6	46.5	3	3	2	2
	7	56.6	3	1	2	3
	8	56.6	3	2	2	3
	9	57.9	3	3	2	3
2	1	61.7	1	1	1	1
	2	93.1	1	2	1	1
	3	171	1	3	1	1
	4	66.2	1	1	1	2
	5	97.6	1	2	1	2
	6	177.2	1	3	1	2
	7	199.4	1	1	1	3
	8	188.6	1	2	1	3
	9	207.7	1	3	1	3
3	1	47.1	2	1	3	1
	2	89.9	2	2	3	1
	3	171.1	2	3	3	1
	4	63.3	2	1	3	2
	5	94.8	2	2	3	2
	6	171.4	2	3	3	2
	7	200.8	2	1	3	3
	8	199.3	2	2	3	3
	9	216	2	3	3	3
Optimum LGC for North and South Approaches by SimTraffic					**1**	
Optimum LGC for North and South Approaches by DLG Model					**1**	
Case 1 Optimum lane groups are considered for east and west approaches. Case 2&3 Random lane groups are considered for east and west approaches.						

To find the LGC for East and West approaches, the intersection delay is estimated for all possible LGCs (the possible combinations for East & West are 6*6=36) (Table 5.7).

The optimum lane group combination of East and West was defined based on the minimum intersection delay, which is (2, 3). The optimum lane group combination for the whole intersection is (3, 1, 2, 1), which shows the lane groups of West, North, East and South approaches, respectively.

Table 5.7 Optimum LGC for East and West

Optimum lane groups for East and West Approaches

No	Delay	Lane groups				No	Delay	Lane groups			
		W	N	E	S			W	N	E	S
1	33.6	3	1	2	1	19	61.6	4	1	1	1
2	42.6	3	1	1	1	20	107.4	4	1	2	1
3	34.1	3	1	3	1	21	335.7	4	1	3	1
4	116.6	3	1	4	1	22	510	4	1	4	1
5	34.2	3	1	5	1	23	116.3	4	1	5	1
6	49.3	3	1	6	1	24	335.7	4	1	6	1
7	61.7	1	1	1	1	25	77.5	5	1	1	1
8	49.9	1	1	2	1	26	71.5	5	1	2	1
9	61.9	1	1	3	1	27	41.7	5	1	3	1
10	194.9	1	1	4	1	28	44.8	5	1	4	1
11	124.6	1	1	5	1	29	44.8	5	1	5	1
12	194.6	1	1	6	1	30	77.1	5	1	6	1
13	62.5	2	1	1	1	31	43.1	6	1	1	1
14	41	2	1	2	1	32	35.3	6	1	2	1
15	60.9	2	1	3	1	33	34.2	6	1	3	1
16	292	2	1	4	1	34	171.9	6	1	4	1
17	119.5	2	1	5	1	35	34.2	6	1	5	1
18	256.7	2	1	6	1	36	113.4	6	1	6	1
Optimum LGC for East and West Approaches by SimTraffic						**1**					
Optimum LGC for East and West Approaches by DLG Model						**1**					

As the optimum lane group defined by the DLG model is also the same lane group combination (3, 1, 2, 1), so we can conclude that the SimTraffic also defines the same optimum lane group combination similar to the DLG model.

5.4 Artificial Neural Network

Feed forward backpropagation neural networks were developed using the Matlab environment. Here in this research, three separate neural network models were developed: first, for predicting the appropriate phasing scheme (approach of movement based) with FLG strategy, one model for predicting the appropriate phasing scheme (approach of movement based) with DLG, and one neural network model was developed for predicting the optimum lane groups (one per approach).

5.4.1 ANN Model for Phasing scheme FLG

This model was developed for selecting the proper phasing scheme for any volume combination in FLG case. A total number of 110000 volume combinations data were used for developing the model, with an optimized topology that gives 96% accuracy of the testing data. The characteristics of the model are shown below.

- Model type : Feed forward backpropagation (FFBP)
- Training algorithm: Levenberg-Marquardt
- Calculation environment: Matlab
- Data division: Random
- Problem type: Prediction

- Selecting the topology: Trial and error
- Performance measure: Accuracy

The input layer consists of 12 inputs (12 movement volumes, 3 at each approach) for all the models. The outputs of the phasing scheme network are one phasing scheme (Table 5.8).

Table 5.8 Phasing scheme ANN details

Inputs	Outputs	Total data	% of Training data	% of Testing data	Accuracy
12	1	110000	70%	30%	96%

The optimum topology (number of layers, number of neurons per layer and the type of transfer function) was selected by experience and trial and error procedure. We started our trials from a very simple topology with minimum hidden layers and less number of neurons, and then increased the number of neurons and the number of layers. And finally, we tried to find the optimum topology of the network, which can predict the outputs with reasonable accuracy.

The optimum topology for the phasing scheme network is two hidden layers with 12 and 12 neurons at each layer, respectively, with one output (Figure 5.4). The accuracy of the model is 96% of the testing data (new data beyond the training data).

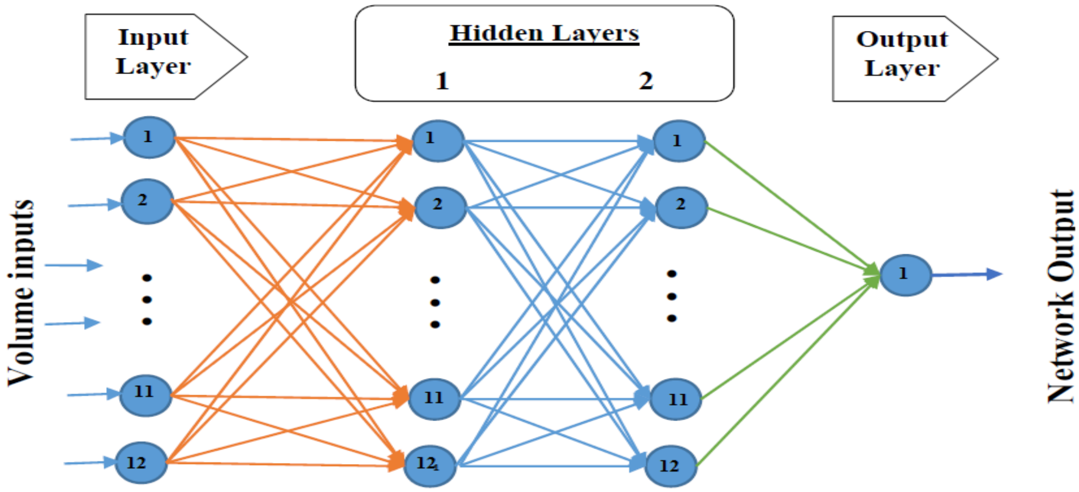

Figure 5.4 Topology of ANN for Phasing Scheme FLG

5.4.2 ANN model for phasing scheme DLG

This model was developed for selecting the proper phasing scheme for any volume combination in the DLG case. A total number of 50000 randomly selected volume combinations data were used for developing the model, with an optimized topology that gives 90% accuracy of the testing data. The characteristics of the model are shown below.

- Model type : Feed forward backpropagation (FFBP)
- Training algorithm: Levenberg-Marquardt
- Calculation environment: Matlab
- Data division: Random
- Problem type: Prediction
- Selecting the topology: Trial and error
- Performance measure : Accuracy

The input layer consists of 12 inputs (12 movement volumes, 3 at each approach). The outputs of the phasing scheme network are one phasing scheme (Table 5.9).

Table 5.9 Phasing scheme ANN details

Inputs	Outputs	Total data	% of Training data	% of Testing data	Accuracy
12	1	50000	70%	30%	90%

The optimum topology (number of layers, number of neurons per layer and the type of transfer function) was selected by experience and trial and error procedure. We started our trials from a very simple topology with minimum hidden layers and less number of neurons and, then increased the number of neurons and the number of layers. And finally, we tried to find the optimum topology of the network, which can predict the outputs with reasonable accuracy.

The optimum topology for the phasing scheme network is three hidden layers with 12 neurons in each layer with one output (Figure 5.5). The accuracy of the model is 90% of the testing data (new data beyond the training data).

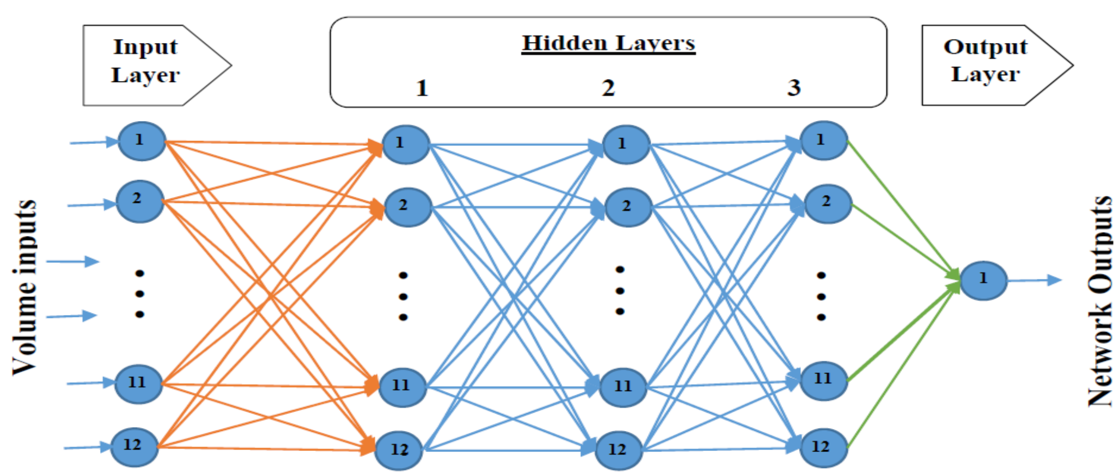

Figure 5.5 Topology of ANN for Phasing Scheme FLG

5.4.3 ANN model for optimum LG

This model was developed for predicting the optimum LG combination for any volume combination. A total number of 50000 randomly selected volume combinations data were used for developing the model, with an optimized topology that gives 92% accuracy of the testing data. The characteristics of the model are shown below.

- Model type : Feed forward backpropagation (FFBP)
- Training algorithm: Levenberg-Marquardt
- Calculation environment: Matlab
- Data division: Random
- Problem type: Prediction
- Selecting the topology: Trial and error
- Performance measure: Accuracy

The input layer consists of 12 inputs (12 movement volumes, 3 at each approach, and the output layer for the optimum lane groups is composed of four outputs, one for each approach, predicting the corresponding optimum lane group (Table 5.10). The outputs of the LG network were normalized by converting them to binary numbers, so for all the four lane groups, we have 10 binary digits as the outputs of the model. The DLG model was applied in different volume combinations. The data obtained from the DLG model were divided into two parts, part for training and part for testing.

Table 5.10 LGC ANN details

Inputs	Outputs	Total data	% of Training data	% of Testing data	Accuracy
12	10 (4)	50000	70%	30%	92%

Then, we tried to find the optimum topology of the network in order to predict the output well and with high accuracy. The optimum topology (number of layers, number of neurons per layer and the type of transfer function) was selected by experience and trial and error procedure. We started our trials from a very simple topology with minimum hidden layers and less number of neurons, and then increased the number of neurons and the number of layers. And finally, we tried to find the optimum topology of the network, which can predict the outputs with reasonable and desired accuracy.

The optimum topology of the optimum lane group network was selected based on the same procedure, a network with 3 hidden layers and 12, 12 and 10 neurons in each layer, respectively (Figure 5.6). From the validation of the model, we got an accuracy of 91-92% of the testing data.

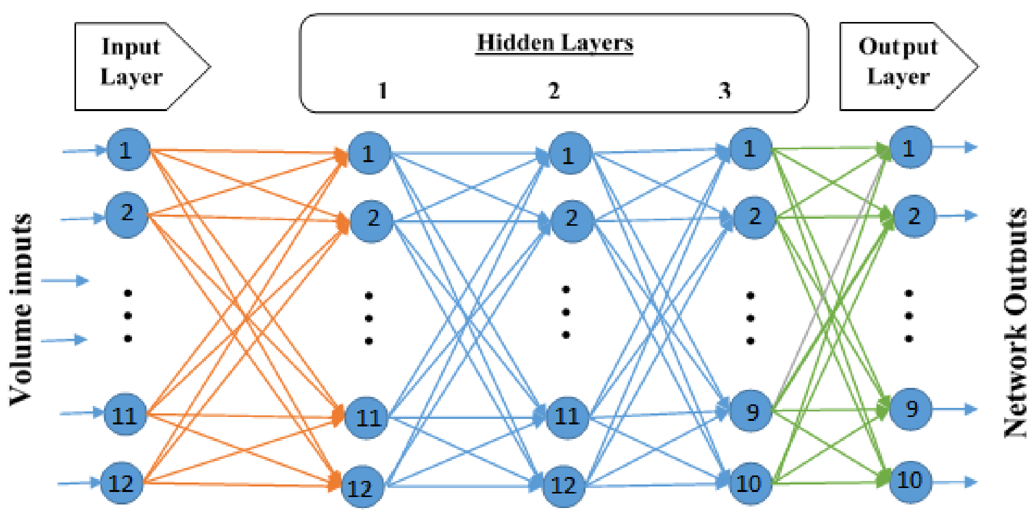

Figure 5.6 LGC ANN topology

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

DLG strategy is also one of the effective intelligent transportation system (ITS) lane management strategies for traffic congestion control. Different types of phasing schemes are used for intersection signalization, the most commonly used signal phasing schemes are approach and movement-based phasing schemes.

From this study, it is concluded that when fixed lane grouping (FLG) is used at a signalized intersection, the type of phasing scheme has a significant effect on the intersection performance. The most appropriate phasing scheme can be defined based on the ratio between the opposing approaches' traffic demands of the intersection.

Generally, it can be concluded that in the case of FLG, movement-based phasing scheme is better with respect to the approach-based phasing scheme when the variation between the opposing approaches' traffic volume is less. If the variation between the opposing approaches' volumes is higher than the mentioned specific ratios, approach-based phasing scheme can perform well. To be more specific, if the ratios of both pairs, major (W&E) and minor (N&S), approach volumes are more than 0.5, movement-based phasing scheme is preferred. And if the ratios of both pairs, major (W&E) and minor (N&S), approaches' volumes are equal or less than 0.5, approach-based phasing scheme is preferred. In other cases, Table 5.2 or Figure 5.1 can be used as a look-up table for the preferred phasing scheme.

When movement-based phasing scheme is used, the dynamic lane grouping (DLG) strategy is more effective in enhancing the intersection performance with respect to FLG strategy by decreasing the average delay.

According to the results of this study, when the DLG strategy is applied at signalized intersections, generally approach-based phasing scheme is preferred. But still, more studies are required for specific conditions to verify the optimum phasing scheme. As the approach-based phasing scheme has in addition to safety concerns because of wrong lane utilization, the intersection capacity will be highly affected. So, there is still the favor for movement-based phasing scheme to be preferred with respect to approach-based phasing scheme.

The neural network models are time efficient prediction tool. As the parameters for this study are more and the relation among them is complex, three separate neural networks were developed: two for predicting appropriate phasing scheme at FLG and DLG conditions, respectively and with one network for predicting the optimum lane group combination of movement-based phasing scheme. The inputs of all ANN models are traffic volumes per movement.

Application of the DLG strategy needs to use other technologies like variable message signs (VMS), pre-signals and in vehicle notification system to transfer information to the driver. It is highly recommended that in applying this strategy, driver familiarity should be ensured.

As a future work, it is recommended to develop an ANN model which is supposed to be able to predict the proper phasing scheme, in addition to optimum lane groups' combination. Further studies are recommended to enhance the safety and application limitations of the DLG strategy at a signalized intersection.

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APPENDICES

Appendix A

Intersection layout and typical data in Synchro and SimTraffic Interface

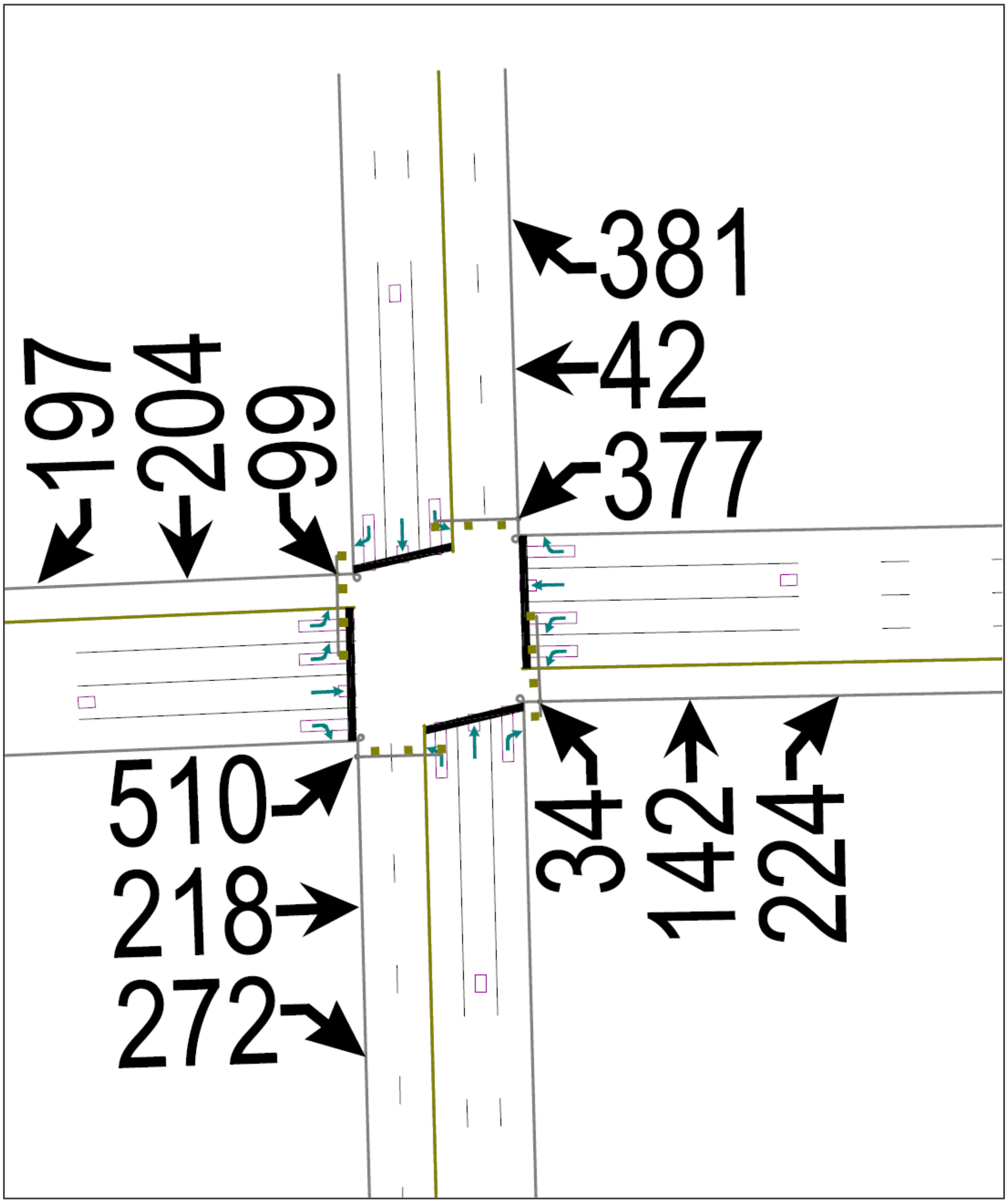

Figure 8.1 Intersection layout In Synchro

Appendix B

DLG Model Mat lab Code

Below text is the MATLAB code for the dynamic lane grouping at signalized intersection with movement based phasing scheme. With running this coded algorithm in MATLAB environment for any volume combination, intersection delay optimum lane groups, cycle length and green splits can be estimated.

```
% Load the defined volume for each approach

LoadLanesVolumData;

 % Load the rest defined variables

loadOtherVariablesData();

lanesDelay = {1:4};

allDelay = (1:4);

fourLanesGroup = {laneGroup1, laneGroup2, laneGroup3, laneGroup4, laneGroup5,

laneGroup6};

threeLanesGroup = {threeLanesGroup1, threeLanesGroup2, threeLanesGroup3};

minMaxCR = [];

minMaxCR_Print = [];

minMinID_Print = [];

IDFromMinMaxCR = [];

minMinID = [];

CRFromMinMinID = [];

Index = 0;

index2 = 0;

zeorsIndex = 0;
```

```
cycleLengthDrawData_ID = [];
laneGroupsDrawData_ID = [];
cycleLengthDrawData_CR = [];
laneGroupsDrawData_CR = [];
CPFromMinMinID = [];
    minCapacityRatio = 1000000;
    %minIntersectionDelay = 1000000;
    minCapacityRatioLane = 1;
    minIntersectionDelayLane = 1;
    index = index + 1;
    index2 = index2 + 1;
    %lanesGroupMaxCapacitRation = [];
    lanesGroupMinIntersectionDelay = [];
    lanesGroupCombination1 = {};
    lanesGroupCombination2 = {};
    lanesGroupCombination3 = {};
    lanesGroupCombination4 = {};
    lanesGroupCL = [];
    lanesGroupCR1 = [];
    lanesGroupCR2 = [];
    lanesGroupCR3 = [];
    lanesGroupCR4 = [];
    lanesGroupGREE1 = [];
```

```
lanesGroupGREE2 = [];
lanesGroupGREE3 = [];
lanesGroupGREE4 = [];
compinations = [];
leftVolume1 = [];
throughVolume1 = [];
rightVolume1 = [];
leftVolume2 = [];
throughVolume2 = [];
rightVolume2 = [];
leftVolume3 = [];
throughVolume3 = [];
rightVolume3 = [];
leftVolume4 = [];
throughVolume4 = [];
rightVolume4 = [];
finalIndex = 0;
totalApproach1Volum = 1388;
totalApproach2Volum = 630;
totalApproach3Volum = 1412;
totalApproach4Volum = 611;
App1LaneGroupNum = [];
App2LaneGroupNum = [];
```

```
    App3LaneGroupNum = [];
    App4LaneGroupNum = [];
    %skipThisLaneGroup = false;
    randomData = [];     % For randomly selecting the volume ratios of each movement.
    randIndex = 1;
  for trails = 1:1:2
   rnd1L = rand*.72;
   rad1T = rand*(0.8 - rnd1L);
   for i1 = rnd1L
       leftVolum1= floor (rnd1L * totalApproach1Volum);
       for j1 = rad1T
           throughVolum1 = floor (rad1T * totalApproach1Volum);
           rightVolum1 = totalApproach1Volum - leftVolum1 - throughVolum1;
      rnd2L = rand*.72;
      rad2T = rand*(0.8 - rnd2L);
       for i2 = rnd2L
       leftVolum2= floor (rnd2L * totalApproach2Volum);
        for j2 = rad2T
  throughVolum2 = floor (rad2T * totalApproach2Volum);
rightVolum2 = totalApproach2Volum - leftVolum2 - throughVolum2;
         rnd3L = rand*.72;
         rad3T = rand*(0.8 - rnd3L);
         for i3 = rnd3L
```

```
leftVolum3 = floor (rnd3L * totalApproach3Volum);
for j3 = rad3T
throughVolum3 = floor (rad3T * totalApproach3Volum);
rightVolum3 = totalApproach3Volum - leftVolum3 - throughVolum3;
rnd4L = rand*.72;
rad4T = rand*(0.8 - rnd4L);
for i4 = rnd4L
leftVolum4 = floor (rnd4L * totalApproach4Volum);
for j4 = rad4T
throughVolum4 = floor (rad4T * totalApproach4Volum);
rightVolum4 = totalApproach4Volum - leftVolum4 - throughVolum4;
rnd1LData {randIndex} = rnd1L;
rnd1TData {randIndex} = rad1T;
rnd1RData {randIndex} = 1 - rnd1L - rad1T;
rnd2LData {randIndex} = rnd2L;
rnd2TData {randIndex} = rad2T;
rnd2RData {randIndex} = 1 - rnd2L - rad2T;
rnd3LData {randIndex} = rnd3L;
rnd3TData {randIndex} = rad3T;
rnd3RData {randIndex} = 1 - rnd3L - rad3T;
rnd4LData {randIndex} = rnd4L;
rnd4TData {randIndex} = rad4T;
rnd4RData {randIndex} = 1 - rnd4L - rad4T;
```

```
randIndex = randIndex + 1;

compIndex = 0;

TEMPlanesGroupCR1 = [];
TEMPlanesGroupCR2 = [];
TEMPlanesGroupCR3 = [];
TEMPlanesGroupCR4 = [];
TEMPlanesGroupGREE1 = [];
TEMPlanesGroupGREE2 = [];
TEMPlanesGroupGREE3 = [];
TEMPlanesGroupGREE4 = [];
TEMPcompinations = [];
TEMPlanesGroupCL = [];
TEMPlanesGroupMinIntersectionDelay = [];
                TEMPApp1Lanes = [];
                TEMPApp2Lanes = [];
                TEMPApp3Lanes = [];
                TEMPApp4Lanes = [];
for app1Lanes = 1:6          %lane groups for 1st approach (west)
group1 = fourLanesGroup {app1Lanes};
 [group1, shared, skip] = sharedLaneFunction (group1, leftVolum1, throughVolum1,
rightVolum1);
```

```
if shared == false
group1 = volumeDistributionFunction (group1, leftVolum1, throughVolum1,
rightVolum1);
end
if skip == false
for app2Lanes = 1
group2 = threeLanesGroup {app2Lanes};
[group2, shared, skip] = sharedLaneFunction (group2, leftVolum2, throughVolum2,
rightVolum2);
if shared == false
group2 = volumeDistributionFunction (group2, leftVolum2, throughVolum2,
rightVolum2);
end
if skip == false
for app3Lanes = 3
group3 = fourLanesGroup {app3Lanes};
[group3, shared, skip] = sharedLaneFunction (group3, leftVolum3, throughVolum3,
rightVolum3);
if shared == false
group3 = volumeDistributionFunction (group3, leftVolum3, throughVolum3,
rightVolum3);
end
if skip == false
```

```
for app4Lanes = 1
 group4 = threeLanesGroup {app4Lanes};
 [group4, shared, skip] = sharedLaneFunction (group4, leftVolum4, throughVolum4,
rightVolum4);
 if shared == false
group4 = volumeDistributionFunction (group4, leftVolum4, throughVolum4,
rightVolum4);
        end
        if skip == false
compIndex = compIndex + 1;
allVolums = {group1, group2, group3, group4};
 [calc, CL, CR1, CR2, CR3, CR4, GREE1, GREE2, GREE3, GREE4] =
calculations(allVolums);
tempCapAndDel = calc;
%comText = strcat(num2str(app1Lanes), num2str(app2Lanes), num2str(app3Lanes),
num2str(app4Lanes));
%str = sprintf('%d', comText);
%TEMPcompinations{compIndex} = comText;
TEMPApp1Lanes(compIndex) = app1Lanes;
TEMPApp2Lanes(compIndex) = app2Lanes;
TEMPApp3Lanes(compIndex) = app3Lanes;
TEMPApp4Lanes(compIndex) = app4Lanes;
TEMPlanesGroupMaxCapacitRation(compIndex) = tempCapAndDel(1);
```

```
TEMPlanesGroupMinIntersectionDelay(compIndex) = tempCapAndDel(2);
TEMPlanesGroupCL(compIndex) = CL;
TEMPlanesGroupCR1(compIndex) = CR1;
TEMPlanesGroupCR2(compIndex) = CR2;
TEMPlanesGroupCR3(compIndex) = CR3;
TEMPlanesGroupCR4(compIndex) = CR4;
                                TEMPlanesGroupGREE1(compIndex) = GREE1;
                                TEMPlanesGroupGREE2(compIndex) = GREE2;
                                TEMPlanesGroupGREE3(compIndex) = GREE3;
                                TEMPlanesGroupGREE4(compIndex) = GREE4;
end
        end
    end
      end
               end
           end
                  end
              end
finalIndex = finalIndex + 1;
[miIDValue,minMinID_Index] = min (TEMPlanesGroupMinIntersectionDelay);
lanesGroupMinIntersectionDelay(finalIndex) = miIDValue;
%lanesGroupMaxCapacitRation(finalIndex) =
TEMPlanesGroupMaxCapacitRation(minMinID_Index);
```

```
%compinations{finalIndex} = TEMPcompinations{minMinID_Index};
 lanesGroupCL(finalIndex) = TEMPlanesGroupCL(minMinID_Index);
 lanesGroupCR1(finalIndex) = TEMPlanesGroupCR1(minMinID_Index);
lanesGroupCR2(finalIndex) = TEMPlanesGroupCR2(minMinID_Index);
lanesGroupCR3(finalIndex) = TEMPlanesGroupCR3(minMinID_Index);
lanesGroupCR4(finalIndex) = TEMPlanesGroupCR4(minMinID_Index);
 lanesGroupGREE1(finalIndex) = TEMPlanesGroupGREE1(minMinID_Index);
lanesGroupGREE2(finalIndex) = TEMPlanesGroupGREE2(minMinID_Index);
lanesGroupGREE3(finalIndex) = TEMPlanesGroupGREE3(minMinID_Index);
lanesGroupGREE4(finalIndex) = TEMPlanesGroupGREE4(minMinID_Index);
 leftVolume1(finalIndex) = leftVolum1;
leftVolume2(finalIndex) = leftVolum2;
leftVolume3(finalIndex) = leftVolum3;
leftVolume4(finalIndex) = leftVolum4;
throughVolume1(finalIndex) = throughVolum1;
throughVolume2(finalIndex) = throughVolum2;
throughVolume3(finalIndex) = throughVolum3;
throughVolume4(finalIndex) = throughVolum4;
 rightVolume1(finalIndex) = rightVolum1;
rightVolume2(finalIndex) = rightVolum2;
rightVolume3(finalIndex) = rightVolum3;
rightVolume4(finalIndex) = rightVolum4;
App1LaneGroupNum(finalIndex) = TEMPApp1Lanes(minMinID_Index);
```

```
App2LaneGroupNum(finalIndex) = TEMPApp2Lanes(minMinID_Index);
App3LaneGroupNum(finalIndex) = TEMPApp3Lanes(minMinID_Index);
App4LaneGroupNum(finalIndex) = TEMPApp4Lanes(minMinID_Index);
                    end
                  end
                end
              end
            end
          end
        end
      end
    end
      %finalIndex
      %lanesGroupMinIntersectionDelay
      %[minCapacityRatioLaneValue,minMaxCR_Index]=
min(lanesGroupMaxCapacitRation);
      %[miIDValue,minMinID_Index] = min(lanesGroupMinIntersectionDelay);
 %MinimumInterSectionDelay = miIDValue;
 data1 = [lanesGroupMinIntersectionDelay', App1LaneGroupNum',
App2LaneGroupNum', App3LaneGroupNum', App4LaneGroupNum', leftVolume1',
throughVolume1', rightVolume1', leftVolume2', throughVolume2', rightVolume2',
leftVolume3', throughVolume3', rightVolume3', leftVolume4', throughVolume4',
rightVolume4', lanesGroupCL', lanesGroupGREE1',lanesGroupGREE2',
```

```
lanesGroupGREE3',lanesGroupGREE4', lanesGroupCR1', lanesGroupCR2',
lanesGroupCR3', lanesGroupCR4' ];
filename1 = 'minimumIntersectionDelayData1.xlsx';
   xlswrite(filename1, data1, 1);
       data2 = [rnd1LData', rnd1TData', rnd1RData', rnd2LData', rnd2TData', rnd2RData',
rnd3LData', rnd3TData', rnd3RData', rnd4LData', rnd4TData', rnd4RData'];
      filename2 = 'randomData.xlsx';
      xlswrite(filename2, data2, 1);

%data1 = [lanesGroupMinIntersectionDelay, str2double(compinations), leftVolume1];
%filename1 = 'minimumIntersectionDelayData1.xlsx';
%xlswrite(filename1, lanesGroupMinIntersectionDelay, 1);
      %filename2 = 'minimumIntersectionDelayData2.xlsx';
      %xlswrite(filename2, str2double(compinations), 1);

%filename3 = 'minimumIntersectionDelayData3.xlsx';
      %xlswrite(filename3, leftVolume1, 1);

%filename4 = 'minimumIntersectionDelayData4.xlsx';
      %xlswrite(filename4, throughVolume1, 1);

%filename5 = 'minimumIntersectionDelayData5.xlsx';
      %xlswrite(filename5, rightVolume1, 1);
```

```
%filename6 = 'minimumIntersectionDelayData6.xlsx';
    %xlswrite(filename6, leftVolume2, 1);
%filename7 = 'minimumIntersectionDelayData7.xlsx';
    %xlswrite(filename7, throughVolume2, 1);
 %filename8 = 'minimumIntersectionDelayData8.xlsx';
    %xlswrite(filename8, rightVolume2, 1);
%filename9 = 'minimumIntersectionDelayData9.xlsx';
    %xlswrite(filename9, leftVolume3, 1);
%filename10 = 'minimumIntersectionDelayData10.xlsx';
    %xlswrite(filename10, throughVolume3, 1);
%filename11 = 'minimumIntersectionDelayData11.xlsx';
    %xlswrite(filename11, rightVolume3, 1);
%filename12 = 'minimumIntersectionDelayData12.xlsx';
    %xlswrite(filename12, leftVolume4, 1);
%filename13 = 'minimumIntersectionDelayData13.xlsx';
    %xlswrite(filename13, throughVolume4, 1);
%filename14 = 'minimumIntersectionDelayData14.xlsx';
    %xlswrite(filename14, rightVolume4, 1);
%filename15 = 'minimumIntersectionDelayData15.xlsx';
    %xlswrite(filename15, lanesGroupCL, 1);
%filename16 = 'minimumIntersectionDelayData16.xlsx';
    %xlswrite(filename16, lanesGroupGREE1, 1);
```

```
%filename17 = 'minimumIntersectionDelayData17.xlsx';
    %xlswrite(filename17, lanesGroupGREE2, 1);
%filename18 = 'minimumIntersectionDelayData18.xlsx';
%xlswrite(filename18, lanesGroupGREE3, 1);
%filename19 = 'minimumIntersectionDelayData19.xlsx';
    %xlswrite(filename19, lanesGroupGREE4, 1);
%xlswrite(filename,lanesGroupMinIntersectionDelay,1);
 %xlswrite(filename, lanesGroupMinIntersectionDelay,'C:C');
    %xlswrite(filename,compinations,2);
    %xlswrite(filename,lanesGroupCL,3);
    %xlswrite(filename,lanesGroupGREE1,4);
    %xlswrite(filename,lanesGroupGREE2,5);
    %xlswrite(filename,lanesGroupGREE3,6);
    %xlswrite(filename,lanesGroupGREE4,7);
    %xlswrite(filename,lanesGroupCR1,8);
    %xlswrite(filename,lanesGroupCR2,9);
    %xlswrite(filename,lanesGroupCR3,10);
    %xlswrite(filename,lanesGroupCR4,11);

    %LG1 = lanesGroupCombination1{minMinID_Index};
    %LG2 = lanesGroupCombination2{minMinID_Index};
    %LG3 = lanesGroupCombination3{minMinID_Index};
    %LG4 = lanesGroupCombination4{minMinID_Index};
```

```
    %CycleLength = lanesGroupCL(minMinID_Index);
    %CR1 = lanesGroupCR1{minMinID_Index};
    %CR2 = lanesGroupCR2{minMinID_Index};
    %CR3 = lanesGroupCR3{minMinID_Index};
    %CR4 = lanesGroupCR4{minMinID_Index};

    %GreenTime1 = lanesGroupGREE1(minMinID_Index);
    %GreenTime2 = lanesGroupGREE2(minMinID_Index);
    %GreenTime3 = lanesGroupGREE3(minMinID_Index);
    %GreenTime4 = lanesGroupGREE4(minMinID_Index);
%leftVolum;
%throughVolum;
%rightVolum;
%minMaxCR;
%minMaxCR_Print;
%minMinID_Print;
%IDFromMinMaxCR;
%minMinID;
figure
x = minMinID(:,1);
y = minMinID(:,2);
z = minMinID(:,3);
a=size(minMinID);
```

```
b=a(:,1);

xlin=linspace(min(x),max(x),b);

ylin=linspace(min(y),max(y),b);

[X,Y]=meshgrid(xlin,ylin);

Z = griddata(x,y,z,X,Y);

surf(X,Y,Z);

zlim([20 60]);

xlabel('Percentage of left turn vehicles');

ylabel('Percentage of through vehicles');

zlabel('Average Intersection Delay (s/v)');

colorbar


figure

x = CPFromMinMinID(:,1);

y = CPFromMinMinID(:,2);

z = CPFromMinMinID(:,3);


a=size(CPFromMinMinID);

b=a(:,1);

xlin=linspace(min(x),max(x),b);

ylin=linspace(min(y),max(y),b);

[X,Y]=meshgrid(xlin,ylin);

Z = griddata(x,y,z,X,Y);
```

```
surf(X,Y,Z);
zlim([.5 1]);
xlabel('Percentage of left turn vehicles');
ylabel('Percentage of through vehicles');
zlabel('Maximum Capacity Ratio (V/c)');
colorbar
figure;
x = cycleLengthDrawData_ID(:,1);
y = cycleLengthDrawData_ID(:,2);
z = cycleLengthDrawData_ID(:,3);

a=size(cycleLengthDrawData_ID);
b=a(:,1);
xlin=linspace(min(x),max(x),b);
ylin=linspace(min(y),max(y),b);
[X,Y]=meshgrid(xlin,ylin);
Z = griddata(x,y,z,X,Y);
surf(X,Y,Z);
zlim([50 100]);
xlabel('Percentage of left turn vehicles');
ylabel('Percentage of through vehicles');
zlabel('Cycle Length (s)');
colorbar
```

```
figure;
x = laneGroupsDrawData_ID(:,1);
y = laneGroupsDrawData_ID(:,2);
z = laneGroupsDrawData_ID(:,3);

a=size(laneGroupsDrawData_ID);
b=a(:,1);
xlin=linspace(min(x),max(x),b);
ylin=linspace(min(y),max(y),b);
[X,Y]=meshgrid(xlin,ylin);
Z = griddata(x,y,z,X,Y);
surf(X,Y,Z);

xlabel('Percentage of left turn vehicles');
ylabel('Percentage of through vehicles');
zlabel('Lane Group Number');
colorbar;

figure
x = minMaxCR(:,1);
y = minMaxCR(:,2);
z = minMaxCR(:,3);
```

```
a=size(minMaxCR);
b=a(:,1);
xlin=linspace(min(x),max(x),b);
ylin=linspace(min(y),max(y),b);
[X,Y]=meshgrid(xlin,ylin);
Z = griddata(x,y,z,X,Y);
surf(X,Y,Z);
zlim([.5 1]);
xlabel('Percentage of left turn vehicles');
ylabel('Percentage of through vehicles');
zlabel('Maximum Capacity Ratio (V/c)');
colorbar;
figure
x = IDFromMinMaxCR(:,1);
y = IDFromMinMaxCR(:,2);
z = IDFromMinMaxCR(:,3);

a=size(IDFromMinMaxCR);
b=a(:,1);
xlin=linspace(min(x),max(x),b);
ylin=linspace(min(y),max(y),b);
[X,Y]=meshgrid(xlin,ylin);
Z = griddata(x,y,z,X,Y);
```

```
surf(X,Y,Z);
zlim([20 60]);
xlabel('Percentage of left turn vehicles');
ylabel('Percentage of through vehicles');
zlabel('Average Intersection Delay (s/v)');
colorbar
  figure;
x = cycleLengthDrawData_CR(:,1);
y = cycleLengthDrawData_CR(:,2);
z = cycleLengthDrawData_CR(:,3);
 a=size(cycleLengthDrawData_CR);
b=a(:,1);
xlin=linspace(min(x),max(x),b);
ylin=linspace(min(y),max(y),b);
[X,Y]=meshgrid(xlin,ylin);
Z = griddata(x,y,z,X,Y);
surf(X,Y,Z);
zlim([50 100]);
xlabel('Percentage of left turn vehicles');
ylabel('Percentage of through vehicles');
zlabel('Cycle Length (s)');
colorbar
```

```
figure;
x = laneGroupsDrawData_CR(:,1);
y = laneGroupsDrawData_CR(:,2);
z = laneGroupsDrawData_CR(:,3);
a=size(laneGroupsDrawData_CR);
b=a(:,1);
xlin=linspace(min(x),max(x),b);
ylin=linspace(min(y),max(y),b);
[X,Y]=meshgrid(xlin,ylin);
Z = griddata(x,y,z,X,Y);
Surf(X,Y,Z);
xlabel('Percentage of left turn vehicles');
ylabel('Percentage of through vehicles');
zlabel('Lane Group Number');
colorbar;
```

Appendix C

Artificial Neural Network

(For predicting Optimum lane group combination)

```
trainning_input=(xlsread('trainning_input_data'))';

trainning_output=(xlsread('trainning_output_data'));

testing_input=(xlsread('testing_input_data'))';

testing_output=(xlsread('testing_output_data'));

res=zeros(34230,10);

vec=trainning_input;

res(:,1:3)=de2bi(trainning_output(:,1));

res(:,4:5)=de2bi(trainning_output(:,2));

res(:,6:8)=de2bi(trainning_output(:,3));

res(:,9:10)=de2bi(trainning_output(:,4));

res=res';

res1=trainning_output';

   w=testing_input;

actual(:,1:3)=de2bi(testing_output(:,1));

actual(:,4:5)=de2bi(testing_output(:,2));

actual(:,6:8)=de2bi(testing_output(:,3));

actual(:,9:10)=de2bi(testing_output(:,4));

actual=actual';

actual1=testing_output';

net=newff(vec,res, [12,12,10], {'tansig','tansig','logsig'},'trainlm', 'learngdm','mse');
```

```
 % Define learning parameters
net.trainParam.epochs=90000;   % Maximum number of epochs to train ,  Training stops
when the condition occu
net.trainParam.goal = 1e-9;%Performance goal  ,Training stops when the condition occur
net.trainParam.lr=0.15;%Learning rate
%net.trainParam.mc=0.6;%Momentum constant
%net.trainParam.lr_inc=1.05; %Ratio to increase learning rate
%net.trainParam.lr_dec=0.7; %       Ratio to decrease learning rate%
net.trainParam.max_fail=206;  %Maximum validation failures ,Training stops when the
condition occur
%net.trainParam.max_perf_inc=1.04; %  Maximum performance increase%
% net.trainParam.min_grad=1e-10; %Minimum performance gradient ,Training stops
when the condition occur
 %net.trainParam.show=300;  %Epochs between displays (NaN for no displays)
 %net.trainParam.time=inf;%Maximum time to train in seconds  ,Training stops when the
condition occur
     net = train(net,vec,res);
    for i=1:14665
       predictedtesting(:,i) = sim(net,w(:,i));
end
for i=1:34230
        predictedtraining(:,i) = sim(net,vec(:,i));
 end
```

```
tr=(xlsread('trainning_output_data'));
tt=(xlsread('testing_output_data'));
y=round(predictedtesting');
x=abs(round(predictedtraining'));
r=zeros(34230,4);
x(x>1)=1;
y(y>1)=1;
r(:,1)=bi2de(x(:,1:3));
r(:,2)=bi2de(x(:,4:5));
r(:,3)=bi2de((x(:,6:8)));
r(:,4)=bi2de(x(:,9:10));
l(:,1)=bi2de(y(:,1:3));
l(:,2)=bi2de(y(:,4:5));
l(:,3)=bi2de(y(:,6:8));
l(:,4)=bi2de(y(:,9:10));
completerusulttraning=[r tr];
result1train=(tr==r);
result1train=sum(sum(result1train));
completerusulttest=[l tt];
result1test=(l==tt);
result1test=sum(sum(result1test));
performance_traning=((result1train)/(34230*4))*100
performance_testing=((result1test)/(14665*4))*100
```

Appendix D

Typical Intersection location Map

This map shows the location of the intersection under study at Dhahran city, Eastern province KSA.(From google map)

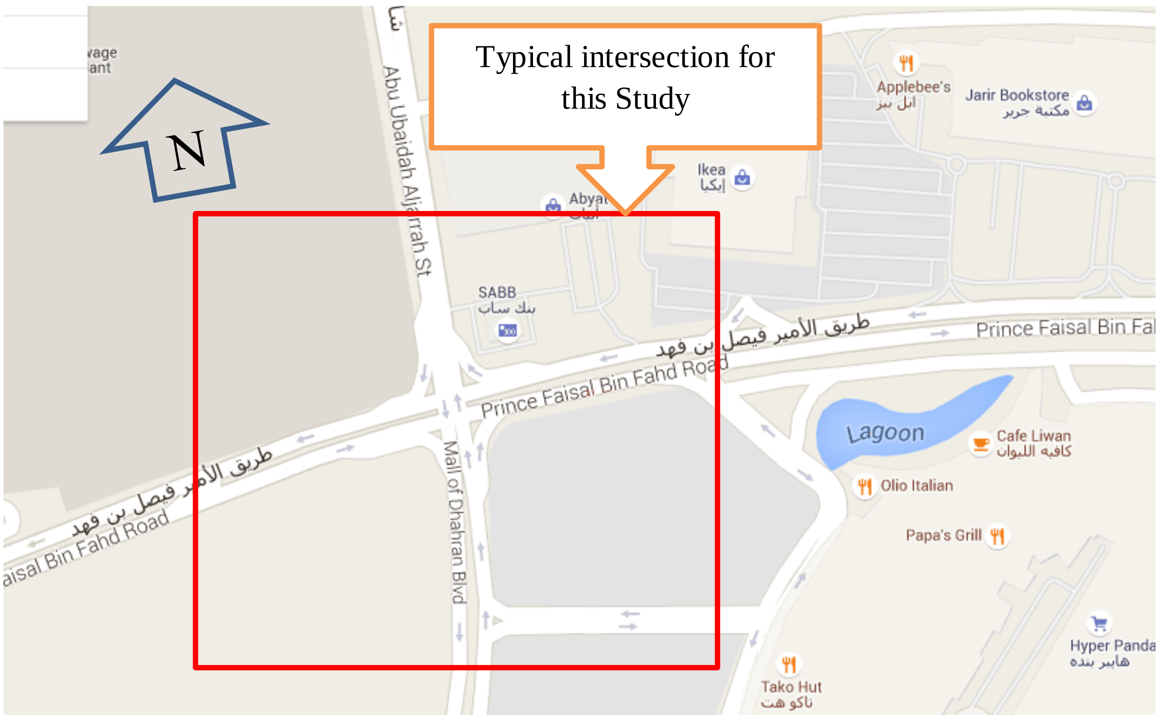

Figure 8.2 Typical Study Intersection

Vitae

Name	: Hekmatullah Habibi
Nationality	: Afghan
Date of Birth	: 10/10/1988
Email	: hekmat8352@gmail.com , g201403900@kfupm.edu.sa
Address	: Kabul City, Afghanistan
Academic Background	: Bachelor of Science in Civil Engineering from Kabul University, Kabul Afghanistan. Received the honor of the top graduating student in year 2010 from Kabul University Engineering Faculty