M.Sc. Engg. (CSE) Thesis

Devising A New Methodology of Traffic Signal Scheduling for Dhaka City Leveraging Computer Vision and Multi-Objective Optimization

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Candidate's Declaration

I, do, hereby, certify that the work presented in this thesis, titled, "Devising A New Methodology of Traffic Signal Scheduling for Dhaka City Leveraging Computer Vision and Multi-Objective Optimization", is the outcome of the investigation and research carried out by me under the supervision of Dr. A. B. M. Alim Al Islam, Professor, Department of CSE, BUET.

I also declare that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree, diploma or other qualifications.

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The thesis titled "**Devising A New Methodology of Traffic Signal Scheduling for Dhaka City Leveraging Computer Vision and Multi-Objective Optimization**", submitted by Masfiqur Rahaman, Student ID 0421052008, Session April 2021, to the Department of Computer Science and Engineering, Bangladesh University of Engineering and Technology, has been accepted as satisfactory in partial fulfilment of the requirements for the degree of Master of Science in Computer Science and Engineering and approved as to its style and contents on September 24, 2023.

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Abstract

With the rapid increase of population in the current world, there is an increasing demand for efficient transportation systems. Proper vehicle management in road intersections can ameliorate the efficiency of transportation systems to a great extent. In this regard, one of the most important traffic management steps is traffic signal scheduling at road intersections or junctions. Traffic signal scheduling is also one of the fundamental concepts used in Intelligent Transportation Systems. Many research studies have been conducted on adaptive or traffic-responsive signal scheduling covering vehicle detection, optimization, simulation, etc. However, most of the existing studies have been conducted considering the context of developed countries. These studies have not considered various contexts prevalent in developing countries. Examples of such contexts include non-lane-based traffic, heterogeneous traffic, etc. A special focus covering these distinctive contexts of the developing countries is needed to develop a contextually-appropriate traffic signal scheduling, which is yet to be explored in the literature to the best of our knowledge.

To fill the gap in the existing literature, in this study, we propose a new methodology incorporating chronological implementations of computer vision, multi-objective optimization, and simulation for the purpose of developing an efficient traffic signal scheduling mechanism appropriate for Dhaka city. To do so, first, we collect real traffic images from important junctions of Dhaka city and annotate the images by trained human annotators. After a rigorous checking over the annotations, we prepare a complete dataset of 1071 images covering diverse weather and illumination conditions. Then, we perform experimentation on the prepared dataset using state-of-the-art object detection architectures, where YOLOv8n (nano) architecture provides the best inference time (5.3 ms) as well as the second-best mean average precision (68.3 %). Then, we explore three metaheuristics algorithms with two new objectives. Among the three algorithms, we find that real-encoded NSGA-II performs the best. Accordingly, we leverage the best-found model in our rigorous simulation using the simulator, DhakaSim. Our simulation results demonstrate that we can achieve up to 24.1% decrease in average waiting time, 10.4% increase in average vehicle flow rate, and 6.6% increase in average speed.

Chapter 1

Introduction

The growing population of the current world, especially in the cities, is continuously challenging the current transportation infrastructures. As more people are moving towards cities, more vehicles are joining on the streets, resulting in congestion. More congestion means more loss of working hours, more fuel consumption, and more Carbon emissions. Therefore, many governments are constructing roads, highways, flyovers, elevated expressways, etc., to tackle traffic congestion. Though these construction works can facilitate the growing demand for vehicles, they can also invite more vehicles on the streets resulting in more congestion in many cases. Moreover, heavy construction work can harm the ecological balance of a particular area. One alternative to this approach is enable optimal traffic management within the existing transportation systems. This approach is particularly appealing as traffic jams generally occur at the intersections of roads, where traffic lights are deployed to control the flow of cross traffic. Proper signaling at those intersections or junctions can significantly improve the congestion situation not only at the local premises but also throughout the whole transportation system.

1.1 Significance of Traffic Signaling

Traffic signaling is an essential task in the fields of conventional transportation systems as well as in the emerging Intelligent Transportation Systems (ITSs). Accurate traffic signaling is crucial for traffic management and public safety. Traffic counting, localization, and tracking are fundamental tasks in the case of image-based traffic signaling systems.

Many studies have been conducted on adaptive or traffic-responsive signaling. Those studies can be divided into three main parts - i) traffic image analysis, ii) signal optimization, and iii) simulation or experimentation. Among these, traffic image analysis has received attention from researchers with the advancement of Deep Neural Networks and the availability of advanced computations devices [2–5]. Here, accurate image analysis can portray the real condition of traffic in a road network. Alongside image analysis, more and more comprehensive datasets are

(a) Motorized and non-motorized vehicles move alongside

(b) No lane is followed

Figure 1.1: The non-lane-based heterogeneous nature of traffic in Dhaka city

being published, which are crucial for image-based analysis in different contexts [6, 7].

Besides, signal optimization is another appealing area of research for traffic management. In this regard, state-of-the-art metaheuristics algorithms have paved the way for faster signal scheduling [8, 9]. Finally, simulation-based studies gain the attention of researchers due to their convenience of exploration and a huge impact on critical understanding of the real scenarios. Several macro and micro simulators have been proposed in the literature to simulate different types and speeds of vehicles, pedestrian movement, etc., [10–14].

1.2 Traffic Signaling in Dhaka and Similar Contexts

Traffic congestion is much more severe in the cities of developing countries such as Dhaka where population density is very high. There are many reasons for traffic jams in Dhaka city, namely non-lane-based vehicle movement, heterogeneous traffic on the same road, narrow roads, on-road pedestrian movements, violation of traffic by the drivers, lack of necessary road networks, lack of traffic police in the field, etc. It is tough to solve all these problems altogether. However, by utilizing the information available and applying appropriate technologies, we can minimize the extent of impacts of the problems.

To exemplify, in Dhaka, including other cities in developing countries, motorized and non-motorized vehicles move on the same lane (Figure 1.1a). Besides, traffic does not follow the lane (Figure 1.1b). These phenomena lead to heterogeneous and non-lane-based traffic.

In the current situation, there is almost no automated traffic light system actively working in Dhaka city, where only two exceptions could be the Gulshan and Dhaka Cantonment areas. Most of the important junctions in Dhaka, thus, are managed by human traffic police using their hand-generated signals using some communication devices and whistles. In most of such cases, green lights from the traffic signaling systems are not maintained properly, which leads to dissatisfaction and discomfort for drivers and passengers.

1.3 Gaps in the Existing Literature

Many research studies have been conducted in the literature aiming for traffic signaling. Accordingly, different intelligent solutions have been proposed in this regard [15–19]. However, the existing studies have mostly focused on traffic congestion, management, and mitigation for developed countries. Moreover, existing image-based traffic signaling technologies are generally designed for lane-based transportation systems in the developed countries [16–20]. However, in Dhaka city, traffic does not follow the lane. As a direct consequence, severe occlusion can occur where the existing image-based models designed for the developed countries may not work well. Therefore, designing a new image-based traffic signaling technique particularly focusing on the developing countries is of great necessity.

Further, in existing studies on metaheuristics-based approaches, the effect of non-motorized vehicles is not considered when designing the objective function. However, the effect of non-motorized vehicles is crucial in the cases of Dhaka [21]. Moreover, some existing studies have proposed waiting time models for a specific time of a day, which may not work well for the complex traffic conditions of Dhaka [9].

Next, simulation-based models, especially micro-simulation models gained the attention of most of the researchers in transportation management in recent times. However, most of the simulators are designed for lane-based and homogeneous traffic, which is not applicable for the traffic in Dhaka city.

1.4 Our Contribution in This Work

To fill the gaps in the existing literature, we formulate the task of traffic signal scheduling in the context of Dhaka city as a multi-stage development task. Our formulation involves - i) a contextually-appropriate traffic image dataset preparation, ii) vehicle detection using the dataset, iii) applying appropriate multiobjective optimization, and iv) integrating the optimization model in an appropriate simulator. Following this, we make the following set of contributions in this study.

- We propose a new methodology of traffic signal scheduling incorporating chronological implementations of computer vision and multi-objective optimization algorithms to optimize traffic signal scheduling particularly appropriate for Dhaka city in similar contexts.

- We prepare a comprehensive traffic image dataset (n=1071) for Dhaka city, considering different types of vehicles (i.e., motorized and non-motorized) as well as different moving directions of the vehicles (i.e., incoming and outgoing), to develop a benchmark dataset appropriate for the heterogeneous traffic in the Dhaka city.

- We evaluate the performance of existing machine learning models in detecting on-road vehicles based on the benchmark dataset and reveal the strengths as well as limitations of the models for the purpose of identifying a suitable model. Among those models, YOLOv8n (nano) provides the best inference time (5.3 ms) as well as the second-best mean average precision (68.3 %).

- We evaluate the efficacy of three suitable multi-objective optimization algorithms with a novel objective function to optimize traffic signal scheduling based on the outputs of the vehicle detection model selected through the previous evaluation.

- We integrate the best optimization algorithm in the DhakaSim traffic simulator, which is the only existing simulator for simulating the non-lane-based and heterogeneous traffic of Dhaka city. The integration results in up to 24.1% decrease in average waiting time, 10.4% increase in average vehicle flow rate, and 6.6% increase in average speed.

1.5 Organization of This Study

We organize the rest of the thesis book as follows. In Chapter 2, we will discuss the basic concepts and preliminary ideas related to transportation systems. In Chapter 3, we will discuss different signaling approaches developed so far, the application of machine learning, and metaheuristics-based simulation in signal scheduling. In Chapter 4, we will explain the gaps in the literature, our motivation behind doing this research, and our research context. In Chapter 5, we will explain the detailed methodology of our research. In Chapter 6, we will demonstrate the findings of our study. In Chapter 7, we will analyze the findings and their future implications. Finally, in 9, we will explain our conclusion and future work regarding this study.

Chapter 2

Backgrounds and Preliminaries

To understand the importance of intelligent traffic management in Dhaka city, we had to do some background study on the traffic condition of Dhaka. Bangladesh is the 8^{th} largest populated country and it has the 92^{nd} largest land area of the world which means population density is too high. Dhaka is the capital of Bangladesh, where the offices of all the Government and Non-Government Organizations are situated inside the city including a large number of universities and educational institutions. One of the major drawbacks of our transport system is the movement of non-motorized vehicles like rickshaws, carts, slow-moving locally-made transport, etc. More than 2 million people are riding slow-moving transports inside Dhaka city, and only because of that 3.2 million working hours are lost every day.

2.1 Transportation Systems

Transportation system is a crucial element in Urban life. Good transportation systems highly influence the economy as well as the health and well-being of people. Every prosperous and developed city in the world has a good transportation system. There are many crucial components for a good transportation system, such as infrastructures (e.g., roads, highways, bridges, etc.), vehicles, operations and management (e.g., traffic controlling, scheduling, maintenance, etc.), technology (e.g., vehicle tracking, toll collection, etc.), safety measures, etc.

2.1.1 Infrastructure

Infrastructure in transportation systems refers to the physical facilities that enable the movement of people and goods. It includes roads, bridges, tunnels, railways, airports, and ports. Scientifically, infrastructure design considers factors like traffic flow modeling, structural engineering principles, and geotechnical analysis to ensure the durability and safety of these facilities. Besides, simulation-based surveys can also help in better infrastructure design.

There are several traffic simulators designed for this purpose [13, 14, 22, 23]. Among them, DhakaSim [24] is the only existing simulator that is designed and developed for Non-lane-based and heterogeneous traffic in Dhaka city.

2.1.2 Vehicles

Vehicles encompass a wide range of modes, from automobiles to trains, airplanes, ships, and bicycles. Scientifically, vehicle design involves considerations of aerodynamics, materials science, mechanical engineering, and energy efficiency to optimize their performance, safety, and environmental impact. The structural design, mode of usage, and speed of vehicles influence the traffic pattern on roads. For example, buses take more space than cars, though buses can carry more passengers. That is why buses can reduce overall congestion in a traffic system. Then, slow vehicles take more time to reach their destination which can cause long-time congestion in a traffic network. Moreover, in many cases, slow vehicles are unavoidable, especially in developing countries like Bangladesh, India, Kenya, etc. In the streets of Dhaka city, several types of slow vehicles can be seen, such as rickshaws, bicycles, wheelbarrows, etc.

2.1.3 Operations and Management

The efficient operation and management of transportation systems involve scientific principles, such as optimization algorithms and real-time data analysis. Traffic management utilizes computer modeling, signal control theory, and data-driven decision-making to mitigate congestion and enhance traffic flow. In the field of signal control, adaptive signal controlling is a new and evolving field of interest for researchers due to the shortcomings of fixed-time signal controlling.

2.1.4 Technology

Technology plays a critical role in modern transportation. Scientific advancements in information technology, sensors, and communication systems enable real-time traffic monitoring, route optimization, and safety enhancements. Sensors like cameras, vibration modules, and RFID are being used to track and monitor traffic in real-time. Besides, traffic route optimization based on GPS information has been used by many in recent days.

2.1.5 Planning and Design

Transportation planning employs scientific methodologies like Geographic Information Systems (GIS), urban planning principles, and traffic modeling software to design efficient transportation networks. Concepts like traffic demand modeling use statistical techniques to forecast future travel patterns. Many recent studies explore the forecast method for predictive analysis of traffic.

2.2 Traffic Congestion in Dhaka

Traffic congestion is one of the most alarming daily phenomena faced by people in many cities of the world. The situation is even worse in developing countries such as Bangladesh, India, the Philippines, etc. Dhaka, the bustling capital of Bangladesh, is a city that has an unprecedented number of complex transportation challenges. As one of the most densely populated cities in the world, Dhaka faces a constant influx of people and a proliferation of vehicles. These factors have combined to create a transportation system characterized by congestion, time-consuming, and unsafe public transportation.

According to a World Bank report, during the years 2009-2018, the average traffic speed in Dhaka dropped from 21 kph to 7 kph [25]. Further, by 2035, the speed is forecasted to drop to 4 kmph, which is slower than the walking speed [25]. To overcome this situation, better traffic management has no alternative. For this purpose, the first step is to ensure traffic-responsive signal scheduling against fixed-time signal scheduling [26]. This step requires traffic information extraction from images of on-road vehicles. To extract information, images can be captured using cameras. Then, we can perform optimization over the extracted information to get an optimized traffic signal scheduling. However, to the best of our knowledge, such a traffic-responsive signal scheduling in the context of Dhaka city is yet to be explored in the literature to the best of our knowledge.

2.3 Traffic Signal Scheduling and Its Impacts

Traffic signal scheduling is unavoidably important for transportation systems. Scheduling algorithms have a significant impact on average speed, congestion volume, and traffic flow rate. Now, we will discuss some common traffic signal scheduling techniques.

2.3.1 Different Types of Controls for Traffic Signal Scheduling

There exist basically three types of signal scheduling options:

1. **Fixed-time traffic signals:** Fixed-time traffic signals operate on a predetermined cycle. In fixed-time signals, each phase (e.g., green, yellow, red) lasts for a fixed duration. Fixed-time signals are based on historical patterns of traffic and remain static throughout operational hours. Fixed-time signals are easy to implement. They are suitable for areas

with stable traffic patterns. However, this signal scheduling system is inefficient in changing traffic conditions which can lead to congestion during peak hours and unnecessary delays.

2. **Actuated traffic signals:** Actuated signals use sensor systems to detect the presence or absence of vehicles. Signals change based on real-time traffic conditions and demand. This system can efficiently adapt to changing traffic conditions, reducing waiting times and improving overall traffic flow. However, the installation and maintenance of sensors is expensive. Besides, it may lead to frequent signal changes in low-traffic areas.

3. **Adaptive traffic signals:** Adaptive signals use advanced algorithms and real-time data to adjust signal timing based on current traffic conditions. They aim to optimize traffic flow dynamically. This method is highly efficient in reducing congestion, maximizing overall speed, minimizing travel times, and improving fuel efficiency. Also, it can respond to unexpected/unknown traffic incidents. However, the initial setup and technology costs can be high and it Requires continuous data collection and processing.

2.3.2 Impact of Traffic Signal Scheduling

Traffic signal scheduling techniques have substantial impacts on both the economy and the better life of individuals. These impacts vary depending on the effectiveness and appropriateness of the signal scheduling techniques employed. Here, we will explore how different signal scheduling techniques can influence these aspects.

1. **Productivity and economic growth:** Efficient traffic signal scheduling, such as adaptive systems, reduces congestion and travel times. This enhances the productivity of individuals and businesses, leading to increased economic growth. Reduced congestion also lowers fuel consumption and transportation costs for both individuals and business organizations.

2. **Trade and commerce:** Well-coordinated traffic signals contribute to the smooth flow of goods, supporting trade and commerce. This is especially vital for urban areas and regions with significant economic activities.

3. **Public transportation** Traffic signal scheduling systems that prioritize public transit can encourage the use of buses, trams, and trains. This reduces traffic congestion and promotes eco-friendly transportation, contributing to a more sustainable economy.

4. **Air quality and well-being:** Effective traffic management, including signal synchronization and adaptive signal scheduling, can reduce traffic congestion and waiting time. This leads to lower emissions of harmful pollutants, improving air quality and public health. Cleaner air can reduce the prevalence of respiratory diseases and improve overall well-being.

2.4 Technical Background

In this section, we discuss the key technical and computational approaches used in this study which involve computer vision and multi-objective optimization.

2.4.1 Computer Vision

Computer vision is like teaching computers how to see, understand, and interpret things around us just like how humans see and interpret things. It involves computers and software to help computers recognize objects, faces, texts, and gestures. Computer vision enables computers to see and interpret visual information which has multitudes of applications including transportation, agriculture, medical imaging, defense, etc.

Computer vision has several important subfields, such as image processing, object detection, object recognition, gesture recognition, human pose estimation, semantic segmentation, etc. Among those, object detection is one of the widely used computer vision tasks that involves identifying one or more objects in an image or video stream. The primary purpose of object detection is to identify objects of interest in an image or video scene including their precise location. There are two broad ways of object detection: traditional methods and deep learning.

Traditional methods of object detection involve hand-crafted feature extraction and using machine learning classifiers, such as support vector machines and random forests. These methods are easy to implement. However, it requires manual feature engineering. With the advent of powerful GPUs and deep learning-based architectures, especially Convolutional Neural Networks, object detection has seen significant advancements. Modern architectures, such as YOLO, SSD, and RCNN [27, 28] leverage deep neural networks to automatically learn features from the data, which results in more accuracy and faster inference time.

2.4.2 Multi-objective Optimization

Multi-objective optimization is a mathematical and computational approach to solve problems that have conflicting objectives. Unlike single objectives, which involve finding a single solution, multi-objective optimization seeks to find a set of solutions that represent a trade-off among multiple objectives. Multi-objective optimization has a wide range of applications involving engineering design, environmental management, healthcare, transportation, etc.

Many algorithms have been proposed in the literature to address multi-objective optimization problems. Pareto-based methods are very popular among those. In Pareto-based methods, solutions are compared using Pareto dominance, where one solution is considered better than another if it is as good as or better in all objectives and strictly better in at least one. Non-dominated Sorting Genetic Algorithm (NSGA-II) [29, 30] is one of the Pareto-based algorithms. NSGA-II is a popular evolutionary algorithm that sorts solutions into non-dominated fronts and uses a crowded comparison operator to maintain diversity in the population. Evolutionary algorithms are also very popular in solving Multi-objective optimization problems. Multi-Objective Genetic Algorithms are evolutionary algorithms designed specifically for solving Multi-objective optimization problems. They use genetic operators like selection, crossover, and mutation to evolve a population of solutions toward Pareto-optimal fronts.

Chapter 3

Related Work

To get optimal signal scheduling, several approaches have been proposed in the literature. Such approaches can be categorized into four parts, such as traffic signaling in general, machine learning for vehicle detection from images, metaheuristics for signal optimization, and traffic simulation.

3.1 Traffic Signal Scheduling

In recent days, automated traffic signal scheduling systems have been widely used for smooth movement of vehicles. In most cases, the duration of signal illumination for each lane (or direction) is determined not based on traffic flow. It is fixed (constant) for all the directions and the period has been set beforehand. In case of heavy traffic flow on a specific lane, the traditional traffic signaling system fails to deal with the movement of vehicles due to fixed-time signaling. Therefore, many emerging technologies have been proposed in the literature to automate the traffic signaling system [31–37].

Such a new networking technology called vehicular ad hoc networking (VANET) has been used to offer a solution for vehicular traffic management [33]. They have introduced a new networking architecture called Named Data Networking (NDN) to implement it in VANET for a robust, efficient, and smart traffic light system. They have developed a dedicated and customized networking architecture for this particular purpose. There exist some RFID-based solutions regarding traffic management [38–43]. Das et al., introduced an RFID system that consists of a small chip and an antenna [41]. Younes et al., proposed a calender-based traffic signaling system based on historical traffic data [44]. They collected traffic data for one year, and then understood the traffic pattern during that year. Based on their understanding, they set traffic rules on SUMO simulator.

Lim et al., proposed a smart traffic light solution based on Wireless Sensor Network (WSN) and VANET [45]. The authors deployed smart cameras at intersections along with image understanding for real-time traffic monitoring and assessment. Here, the cameras can detect and track special vehicles and help prioritize emergency cases. Using their proposed solution, traffic violations can also be identified. They introduced a flexible, adaptive, and distributed control algorithm that uses the information provided by distributed smart cameras to efficiently control traffic signals.

3.2 Machine Learning for Vehicle Detection from Image

Object detection is one of the most important technological breakthroughs in the field of AI. There are mainly two basic types: single-object recognition and multi-object detection with classification. Tasks are evaluated based on training time, inference time, precision, recall, F1-score, etc., [46, 47]. There are basically two techniques involved in detection: i) classical object detection and ii) CNN-based detection.

3.2.1 Classical Object Detection

Some common classical models are HOG, Haar, and LBP [48–50]. HoG, or Histogram of Oriented Gradients, [48] is a feature descriptor used in computer vision and image processing for object detection and recognition tasks. It is particularly effective at capturing the shape and appearance of objects within images. LBP, or Local Binary Pattern, [50] is a texture descriptor used in computer vision and image analysis. It is particularly useful for characterizing the local patterns and textures within an image. LBP has found applications in various fields, including face recognition, texture classification, and object detection.

3.2.2 CNN-based Detection

A CNN-based two-step object detector uses a two-stage approach to locate and classify objects within an image. This approach is commonly used in computer vision tasks and is known for its accuracy and robustness. The first step in a two-step object detector is the Region Proposal Network (RPN). RPN generates a set of candidate object regions, often referred to as ”region proposals.” These region proposals are potential bounding boxes that might contain objects. In the second stage of the two-step object detector, the region proposals generated by the RPN are used for further object classification and bounding box refinement. In recent years, many CNN-based detection architectures have been proposed. In the remainder of this section, we will explain those architectures.

R-CNN [2] is a detection framework that was one of the early successes in using deep learning for object detection tasks. Fast R-CNN [3] is an improved version of the R-CNN object detection framework, designed to address the computational inefficiencies and slow training and inference times of the original R-CNN. Faster R-CNN [4]is an advanced object detection framework that is the improvement of R-CNN and Fast R-CNN to achieve both high accuracy and faster inference speeds.

SSD or Single Shot MultiBox Detector [5], is an object detection algorithm that aims to efficiently detect objects in images or video frames while maintaining high accuracy. It does not rely on multiple stages or region proposals like two-stage detectors (e.g., Faster R-CNN).

YOLO is a pioneering real-time object detection system [51] which revolutionized the field of object detection by providing a fast and efficient way to detect objects in images and video streams. The key idea behind YOLO is to perform object detection in a single pass through the neural network, making it much faster than traditional two-stage detectors like Faster R-CNN. In the latest years, YOLO comes up with different versions including YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, YOLOv7, and YOLOv8 [27, 27, 52].

Recent studies show that object detection algorithms are being used for different vehicle detection tasks. Kausa et al., make use of both classical and CNN-based architectures for vehicle detection using public datasets [53]. Toha et al., proposed DhakaNet which is based on YOLOv5 architecture. This model is capable of detecting 21 types of on-road vehicles using limited computational resources, such as Raspberry Pi [54].

3.2.3 Benchmark Datasets for Vehicle Detection

There are some publicly available benchmark datasets for vehicle detection. Creating such datasets has many challenges and requires highly physical effort. In the remainder of this section, we are going to explain those datasets.

The KITTI dataset is a widely used benchmark dataset in the field of computer vision, particularly for tasks related to autonomous driving and 3D scene understanding [6, 7]. It provides a large collection of sensor data, including images, lidar point clouds, and calibration information, collected from real-world driving scenarios. The KITTI dataset is instrumental in the development and evaluation of algorithms for various autonomous driving tasks.

The Stanford Cars Dataset is a widely used dataset in the field of computer vision, specifically for tasks related to car recognition, classification, and fine-grained categorization [55]. It was created by researchers at Stanford University and provides a comprehensive collection of car images along with detailed annotations. It contains 8,144 training images and 8041 test images. The dataset has 196 different types of cars.

The Tsinghua-Tencent Traffic Sign Dataset is a dataset used in the field of computer vision for traffic sign recognition and detection tasks [56]. This dataset is designed to support research and development in autonomous driving and intelligent transportation systems. The dataset consists of 30,000 samples of traffic signs.

3.3 Metaheuristics for Signal Optimization

Researchers around the world have proposed numerous problem formulation, design of objective functions, and metaheuristics algorithms in the field of signal optimization. In the following subsections, we will discuss each of those.

3.3.1 Decision Variables

A signal optimization problem refers to finding the optimal signal cycle for an intersection of roads. Each cycle refers to a sequence of green time for that particular junction. Most of the research adopted the signal cycle as the decision variable. However, some other studies adopted actuated signal setting parameters as one of the decision variables [52]. In another study, authors considered saturation flow as one of the decision variables which implies a maximum allowed number of vehicles that can pass through the junction [57]. Some other studies considered the path flow of a network as the decision variable.

3.3.2 Objective Function

In every optimization problem, one important thing to consider is the objective function. Researchers are always working to design better objective functions for their intended optimization task in the field of signal scheduling. There are different types of objective functions, such as single-objective function, multi-objective function, etc.

In single objective optimization, there has been work on different objectives, such as: waiting time minimization, travel time minimization, jam length minimization, power minimization, etc. In the waiting time minimization problem, the objective is to minimize the overall delay of vehicles on a network when traveling from a source node to a destination node. One of the first works on this objective function is carried out by Webster et al., [8]. He proposed a waiting function for a single intersection. Besides that, some authors provide a waiting time function for a specific time of day. For example, Tan et al., [9] provided a minimization function for waiting time for the morning peak hour only. On the other hand, Li et al., [21] considered waiting time as the objective function for the whole simulation time.

Travel time minimization is another important objective to be considered which aims to reduce the total travel time of traffic in the network. Though many researchers proposed different functions for this task, one of the influential ones is the measure of average travel time proposed by Gokce et al., [58]. He considered the total travel time divided by the total number of vehicles as the average travel time.

Fuel consumption minimization is another big challenge for the researchers. As the transportation industry is a major contributor to greenhouse gas emissions, researchers are working to reduce its consumption through technological intervention. One way to address this problem is by optimizing traffic signals to reduce both fuel consumption and these harmful emissions. However, finding the best way to do this is quite challenging. Some traffic signal optimization tools like VISSIM [59] try to help by considering factors like travel time, delays, and the number of stoppages. However, they are not always accurate. Thus, researchers are using different fuel consumption models, such as CMEM [60].

3.4 Traffic Simulation

There are mainly two types of simulation models for traffic: i) Macro and ii) Micro models. These models can be used in cooperation with a signal optimization model. Here, the simulator provides the environment where experiments can be run and it also provides the necessary objective/fitness values. Using the objective values, the optimization model can assess the fitness of an individual solution. In the next sections, we will discuss various simulation models for traffic as well as their pros and cons.

3.4.1 Macro Models

Macroscopic modeling is a mathematical way of studying traffic, looking at things like traffic density, traffic flow, and average speed [10]. In the past, considering traffic flow is similar to the flow of fluid, macroscopic models were studied. One of the basic simulation models was Saturn [61]. Similar to Saturn, Visum [62] is another simulation model that has some unique features, such as the history of accidents and public transport differentiation.

Another macroscopic model is TRANSYT [11] which uses an objective function based on delay and number of stoppages experienced by a vehicle. Similar to TRANSYT, Synchro is another macroscopic model [12]. One key feature of Synchro is its use of weight for different phases of simulation. However, both TRANSYT and Synchro can not be used for new optimization algorithms.

3.4.2 Micro Models

In the context of traffic simulation and transportation engineering, microscopic modeling refers to a method of simulating individual vehicles and their interactions within a traffic system at a highly detailed level. This approach involves modeling each vehicle separately, considering its unique characteristics, behaviors, and movements. Microscopic traffic simulations aim to replicate real-world traffic conditions with a high degree of accuracy by taking into account factors such as vehicle types, driver behavior, road geometry, traffic signals, and other elements of the transportation system [63].

Simulation of Urban Mobility (SUMO) [22] is an open-source traffic simulation software which is designed for modeling and simulating urban transportation systems. Due to its simplicity in usage, SUMO has been used extensively in several research studies worldwide. However, the run time of SUMO increases with the size of the network which makes it difficult to use in real-time optimization.

MATSim, which stands for Multi-Agent Transport Simulation [13], is an open-source, microscopic simulation framework designed for modeling and simulating complex transportation systems. MATSim is used in transportation research, urban planning, and policy analysis to study the interactions within a dynamic transportation network.

CORSIM, which stands for CORridor SIMulation [14], is a traffic simulation software. It is designed for the simulation and analysis of traffic flow and congestion within transportation corridors, such as highways, and major roads. CORSIM is a specialized tool that focuses on modeling and optimizing traffic operations within specific corridor segments.

Vissim is a traffic simulation software [23]. It is widely used for modeling, simulating, and analyzing traffic flow, transportation systems, and urban mobility. VISSIM is commonly employed by transportation engineers, urban planners, and researchers to study and optimize transportation networks, assess the impact of various traffic management strategies, and improve road safety. Vissim has the capability to simulate different types of vehicles including bus, truck, rail vehicle, cycle, pedestrian, etc.

Chapter 4

Motivations behind Our Work and Our Research Context

In this section, we demonstrate the limitations of existing studies followed by the motivation behind our study as well as the research context of this study.

4.1 Limitations of the Existing Studies

Most of the existing image-based traffic signaling systems are designed for developed countries, and therefore, they do not consider heterogeneous traffic as experienced in Dhaka city [25]. Moreover, those systems do not perform any multi-objective optimization based on the information extracted from images of heterogeneous traffic for the purpose of optimizing the signal cycle for each lane. In this regard, existing studies perform vehicle tracking from sequences of images only for homogeneous traffic [64]. However, unlike the homogeneous case, severe occlusions take place in heterogeneous traffic conditions, which can hamper the tracking of vehicles. Besides, simulation-based studies employ reinforcement learning on an intersection of roads [65]. However, these studies are mostly designed for homogeneous and lane-based traffic. Further, some research studies explore detecting the presence of vehicles in a simulated environment, which is challenging to implement in real traffic scenarios [66].

Next, VANET [33] solved the traffic congestion issue as well as reduced the waiting time of vehicles in road intersections. However, it is very difficult to cover each lane in a city like Dhaka using such technology. RFID-based solutions also suffer in system performance due to rainy or foggy environments [41–43]. Since Bangladesh has a long rainy season, RFID-based solutions are not suitable for Dhaka city. Then, calendar-based solutions also may not work well for such a complex traffic flow of a mega city like Dhaka [44]. Afterward, Lim et al., [45] did not consider non-motorized vehicles in their WSN-based study. In cities of underdeveloped or developing countries, roads are accommodated with both types of vehicles. Hence, this work may not fit in

(a) Image 1 (b) Image 2 (c) Image 3 (d) Image 4

Figure 4.1: Non-lane-based and heterogeneous traffic of Dhaka city [1].

the context of our problem.

4.2 Our Problem Formulation

We formulate the problem of traffic signal scheduling as a combination of multiple sub-problems. First, we want to prepare a comprehensive traffic image dataset for Dhaka city, considering different types of vehicles (i.e., motorized vs non-motorized) and moving directions of the vehicles (i.e., incoming or outgoing), for the purpose of developing a benchmark dataset appropriate for the heterogeneous traffic in the Dhaka city. Next, we want to evaluate the performance of existing machine learning models in detecting on-road vehicles based on the benchmark dataset and reveal the strengths as well as limitations of the models for the purpose of identifying a suitable model. Then, we want to leverage multi-objective optimization algorithms with a novel objective function for the purpose of optimizing traffic signal scheduling. Finally, we want to integrate the optimization model with DhakaSim traffic simulator to simulate three different road networks and analyze the outcome of the proposed optimization approach.

4.3 Research Context

Our research context is based on traffic in Dhaka, especially the non-lane-based heterogeneous traffic of Dhaka. Due to the nature of traffic in Dhaka, it has a complex traffic structure where motorized and non-motorized vehicles run side by side as shown in Figure 4.1. Due to the imbalance in speed of the two types of vehicles, the overall speed of vehicles slows down.

In this context, we propose a multiobjective optimization approach where we consider the different speeds of vehicles operated in Dhaka. For the purpose of serving the needs of Dhaka, we integrate the DhakaSim [24] traffic simulator in our study. DhakaSim traffic simulator is designed and developed especially focusing on the traffic characteristics of Dhaka city. Therefore, this simulator is the most appropriate one in our study.

Chapter 5

Proposed Methodology

This chapter describes the detailed methodology of this study: traffic data collection, traffic detection, signal optimization, and integration of signal optimization in DhakaSim, etc. Our proposed methodology is demonstrated in Figure 5.1. Besides, the architecture of our proposed system is illustrated in Figure 5.2.

5.1 Dataset Preparation

The first step involved in our study is the preparation of a comprehensive traffic image dataset. During this step, all the necessary procedures are done carefully including data collection, data annotation, data split, etc.

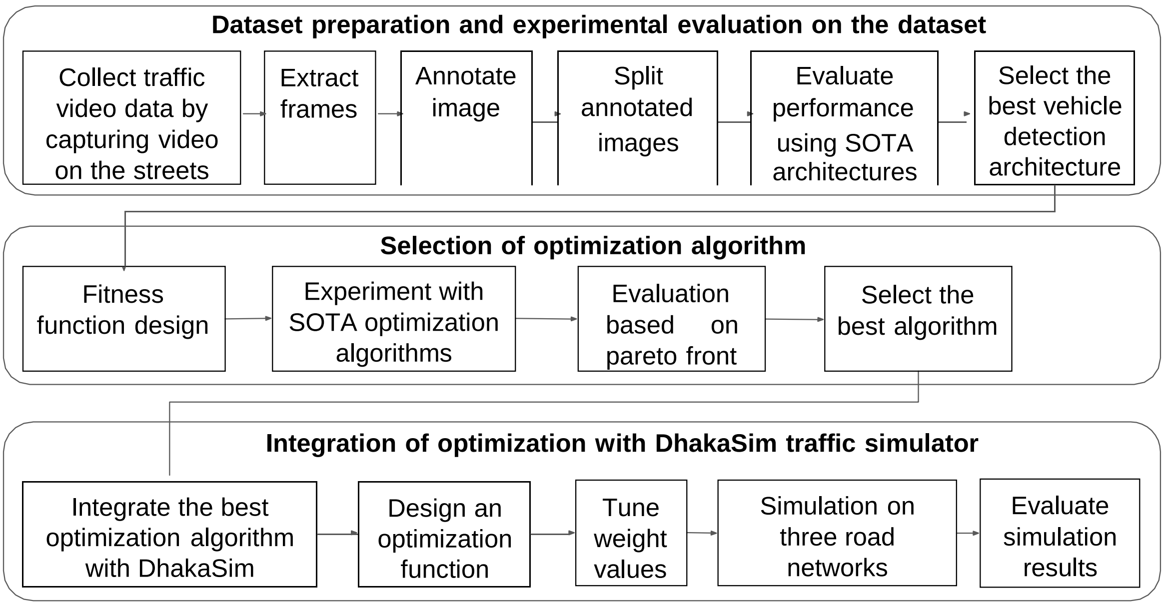


Figure 5.1: Methodology of our proposed approach

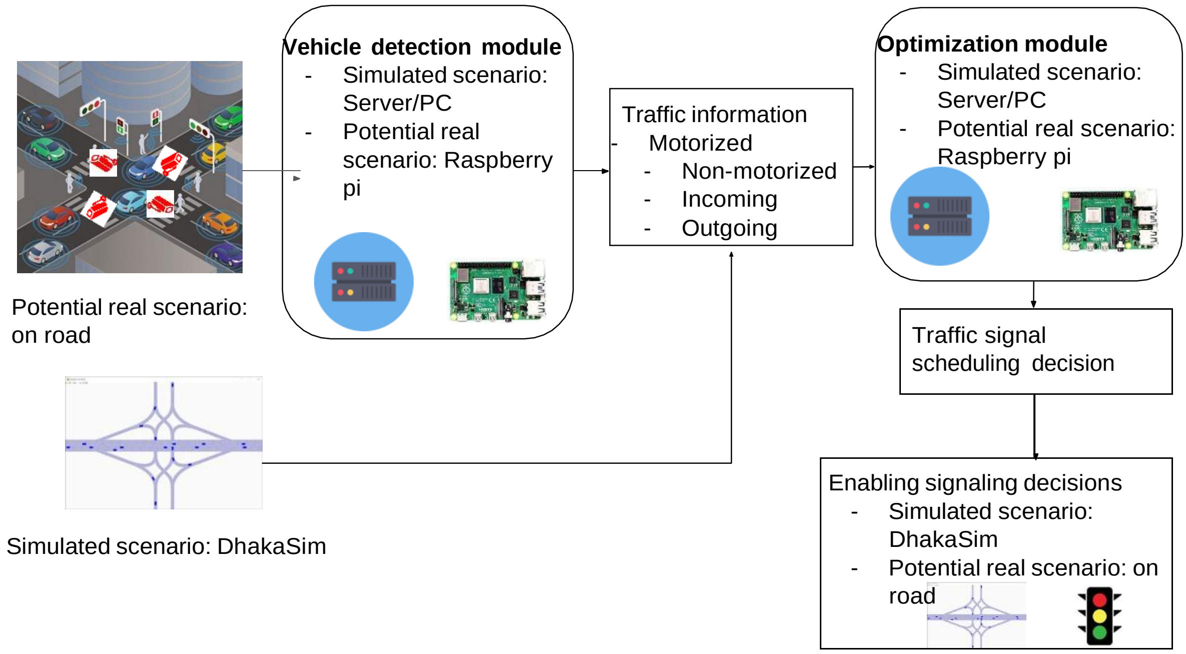


Figure 5.2: Proposed system architecture of our optimized signal scheduling.

5.1.1 Data Collection

We collected 36 video sequences totaling four hours through self-shooting. The data were collected from 8 different locations in Dhaka city having different traffic densities. Besides, diverse weather and illumination conditions are considered during data collection. Snapshots during data collection are shown in Figure 5.3. A detailed description of collected data is shown in Table 6.1. We have taken approval from our institute's "Ethics Committee" prior to conducting the study.

5.1.2 Frame Extraction and Annotation

We extracted frames from the video sequences to annotate them. The frames were extracted at certain intervals ranging from 2 seconds to 10 seconds depending on the average speed of traffic on the road. The reason is that, if we take frames very frequently, the content of each frame will be very much similar. Therefore, we change the interval in proportion to the average speed of vehicles in the video.

We accomplish the task of vehicle detection for four types of vehicles i.e., motorized incoming, motorized outgoing, non-motorized incoming, and non-motorized outgoing. The posture of each type of vehicle is demonstrated in Figure 5.4. We annotate each extracted frame according to the four class labels described above using Labelimg software [67]. Labelimg is a box annotation tool. Using Labelimg, we annotate a vehicle surrounding its boundary and give a label to it i.e., motorized incoming, motorized outgoing, non-motorized incoming, and non-motorized

(a) Capturing image focusing incoming traffic

(b) Metadata collection

Figure 5.3: Data collection from foot overbridge in Banglamotor, Dhaka

(a) Motorized incoming

(b) Motorized outgoing

(c) Non-motorized incoming

(d) Non-motorized outgoing

Figure 5.4: Class labels considered in this study

outgoing.

Though we collected more than four hours of video data, we extracted 1071 frames for annotation and further evaluation. The reason behind this is that each frame takes about 10 minutes on average to annotate. Therefore, for 1071 frames, we spent 10710 minutes or more than 178 hours annotating those frames. As we have time constraints, we could not scale it up to even more. For annotating the images, we recruit annotators who are undergraduate students from Computer Science and Engineering backgrounds.

5.1.3 Data Split and Evaluation

We split the dataset into three parts, namely training, validation, and testing maintaining a 70:15:15 ratio. Following the ratio, we get four types of classes. Our dataset consists of 1071 images having 749 images for training, 161 images for validation, and 161 images for testing.

Evaluation metrics Following the previous works in object detection, we used Mean Average Precision (mAP) as the evaluation metric. mAP is the area under the precision-recall curve as illustrated in Equation 5.1. Here, N is the total number of classes which is four in our case. AP_i is the Average Precision for class i. When mAP is closer to 1, we consider this as a good classifier. Besides, mAP is not sensitive to class imbalance compared to precision and recall. Besides, we also mentioned the precision and recall values as illustrated in Equation 5.2 and 5.3. The next metric we want to consider here is the inference time or Frame Per Second (FPS). In our case, we need less inference time to predict the annotations which implies we need to achieve more FPS.

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i \tag{5.1}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{5.2}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{5.3}$$

5.2 Traffic Detection on Prepared Dataset

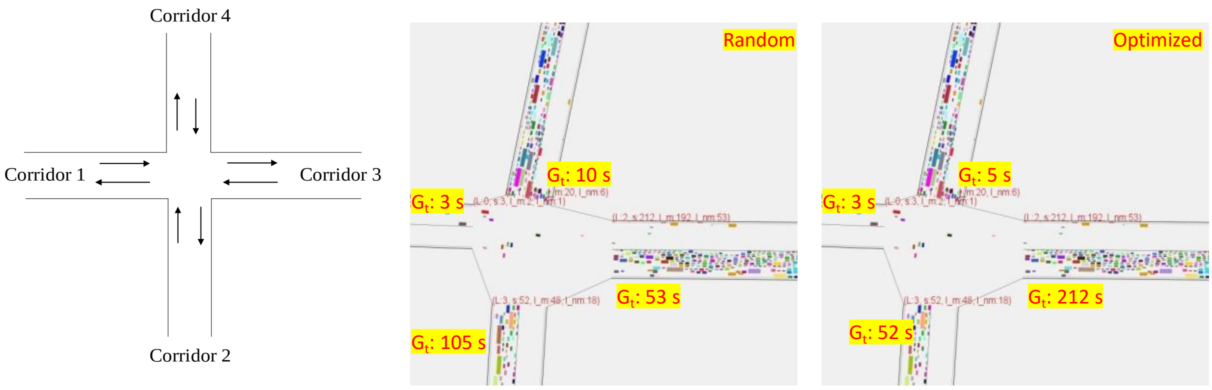
After preparing the dataset, our next step involves detecting vehicles from an image. Here, we choose state-of-the-art object detection architectures namely YOLOv5, YOLOv8, and DhakaNet [27, 28, 54] for the experimentation. Among those architectures, we select the lightweight architectures, such as YOLOv5 medium, YOLOv5 small, YOLOv5 nano, YOLOv8 medium, YOLOv8 small, and YOLOv8 nano for the experimental evaluation.

5.2.1 Experimental Setup

For training the detection models, we use a Windows 10 desktop having a core i7-7700 CPU with a clock speed of 3.6 GHz. The desktop has a main memory of 16 GB. As an accelerator, we use GeForce GTX 1070 GPU having RAM of 8 GB. For each detection model, we train the dataset for 100 epochs having a batch size of 4 and an image size of 768 pixels. Along with the overall mAP, we show the class-wise mAP also so that it can be easy to understand the impact of class imbalance.

5.3 Traffic Signal Optimization

We use jMetal framework and NSGA-II for multi-objective optimization [29, 68]. All the experiments are run on a single intersection as shown in Figure 5.5a. The description of the initial population, fitness function, selection, crossover, and mutation operation are listed below.



(a) A simple schematic view of a traffic network for experiment

(b) Green signal schedule (G_t) with an initial random individual

(c) Green signal schedule (G_t) with an optimized solution

Figure 5.5: A simple schematic view and two simulator views of a signalized intersection in Dhaka-Shahabag road network

5.3.1 Initial Population

We use an array of four real values as the individual where each real value indicates signal timing for each corridor. We initialize this array with random values chosen between 5 seconds and 600 seconds which corresponds to the minimum and maximum jam time respectively. The initial population consists of 50 arrays of such signal timing. The idea behind taking 50 populations comes from previous studies reported having better performance using such configuration [69]. In Figure 5.5b, we demonstrate a random green signal schedule which is the initial individual of our simulation. In Figure 5.5c, we demonstrate an optimized green signal schedule.

5.3.2 Fitness Function

We have two objectives. First, we want to reduce traffic congestion volume. Second, we want to reduce traffic waiting time. These two objectives are inversely proportional, thus creating conflict which is one of the features of the multiobjective optimization problem. We have one constraint which is we can only open one corridor of a junction at a time as shown in Figure 5.5a.

While assessing a signal cycle, we deploy the cycle to the congestion array. We set the speeds of motorized vehicles as 5 units per second and 1 unit per second for human-powered vehicles. Thus, we update all the corridors. At last, the summation of the updated congestion amount is the first objective value of our algorithm. On the other hand, whatever we assign green time in a particular corridor, vehicles of other corridors must stop for that time, which is the waiting time of those vehicles. We use that red time and extra time that is needed to eliminate front vehicles as the second objective value.

In Equation 5.4 and 5.5, we illustrate our two objectives calculated for a signal cycle to complete on an intersection.

$$f_1 = \sum_{i=1}^{L} (n_m(i) + n_{nm}(i)) \tag{5.4}$$

$$f_2 = \sum_{i=1}^{L} \text{Red signal time} \tag{5.5}$$

Here, L signifies the number of links associated with that intersection. $n_m(i)$ and $n_n m(i)$ signify the number of motorized and non-motorized vehicles on intersection i.

5.3.3 Selection

We choose binary tournament selection as the selection operator. The main reason for using binary tournament selection is to strike a balance between exploration and exploitation in the search space, leading to improved convergence and maintaining diversity within the population.

5.3.4 Crossover

We use a simulated binary crossover (SBX) with crossover probability as the inverse of the number of links and distribution index of 20. The reason behind using the SBX crossover operator is that SBX seems to perform well on real encoded GAs [70].

5.3.5 Mutation

We use polynomial mutation as the mutation operator. We choose mutation probability as the inverse of the number of links or corridors. We explore three mutation distribution indexes, i.e., 1, 20, and 100.Adopting these indexes, we run each of the experiments for 1,00,000 iterations. Further, for the mutation distribution index of 100, we run more iterations (10,00,000 and 1,00,00,000, to be more specific) so that we can confirm more exploration to ensure getting rid of the local optima, if any. The idea behind exploring variations of mutation indexes is that a previous study found that it is better to use strong mutation (mutation index $>$ 20) rather than smooth mutation [71].

5.4 Integration of Different Traffic Signal Scheduling Techniques with Simulator

In this section, we discuss how we integrate the fixed-time traffic signal scheduling and optimization-based signaling in DhakaSim [24] traffic simulator. The purpose of integration is to understand how fixed time signals and optimized signals can affect or behave in real traffic scenarios, especially in the case of Dhaka city.

5.4.1 Justification of Selecting DhakaSim

DhakaSim [24] is the only simulator available, to the best of our knowledge, that can simulate real traffic conditions in Dhaka city. The traffic condition of Dhaka is non-lane-based and heterogeneous. Moreover, there are different types of roadside objects that scatter on the streets, such as pedestrians crossing the road, parked buses, tea stalls, waste materials, etc. In this circumstance, the average speed of traffic is highly affected which needs to be considered when implementing and deploying any signal system. The recent version of DhakaSim considers those roadside objects in its implementation.

5.4.2 Integration of Fixed Time Traffic Signal Scheduling in DhakaSim

The integration of fixed-time signaling is very simple to implement in the case of DhakaSim. For an intersection in the road network, we enforce a fixed green time for each link. For example, if there are four links connecting with an intersection, then a fixed-time traffic signal scheduling approach will generate 30, 30, 30, 30 as a signal cycle that implies the first link will get a green time of 30 seconds and incoming traffic on this link will cross the intersection. Next, after the completion of green time on the first signal, the second link will get 30 seconds and traffic on this link will cross the intersection. Gradually, the remaining four links will finish the green time, and traffic on the corresponding link will cross the intersection. This completes the full cycle. After completion of the full cycle, the process again assigns the same signal cycle for that intersection. Note that this algorithm runs over each intersection in the road network.

5.4.3 Integration of Optimized Signal Scheduling in DhakaSim

From the experimentation on different multi-objective optimization algorithms, we find the state-of-the-art binary encoded NSGA-II performs best among the other alternatives. When selecting the appropriate optimization algorithm we need to consider the inference time, as the online optimization which we are performing here is one of the hardest of its kind due to the limited time to get the optimized result. Therefore, we select this model for future experimentation on the DhakaSim simulator. The integration is quite simple. As we know, the simulation of DhakaSim works on a road network. We select three road networks: Shahbagh and its surrounding area, Miami, and Riyadh for this experiment Our proposed methodology of integration is illustrated in Figure 5.1.

First, DhakaSim sends traffic information and junction information to the optimization model. The traffic information consists of the number of motorized and non-motorized vehicles incoming towards the intersection for all links connecting with that junction. For example, if there are three links connecting with an intersection, then DhakaSim will send three pairs of information to the optimization model. Upon receiving the information the optimization module can understand that there are three links associated with that intersection and will also get the required vehicle count for both motorized and non-motorized vehicles.

Second, the optimization model starts running the model using the information gathered with a population size of 50, maximum evaluation of 10000, SBX crossover operator, polynomial mutation, and fitness function mentioned in the last chapter. It is noted that we can not increase the maximum evaluation further in integration in DhakaSim, as it takes much time to get the result. The optimization model returns a set of solutions (population size) consisting of optimized signal cycles consisting of green time for each link of the intersection. The best solution is selected from the pareto front based on an objective function which is described in the later subsection. For example, if the optimizer returns 5, 15, 60, 30 as a signal cycle that implies, the first link will get a green time of 5 seconds, and incoming traffic on this link will cross the intersection. Next, after the completion of green time on the first signal, the second link will get 15 seconds and traffic on this link will cross the intersection. Gradually, the remaining four links will finish the green time, and traffic on the corresponding link will cross the intersection. This completes the full cycle. After completion of the full cycle, the process starts from the first step. Note that this algorithm runs over each intersection in the road network.

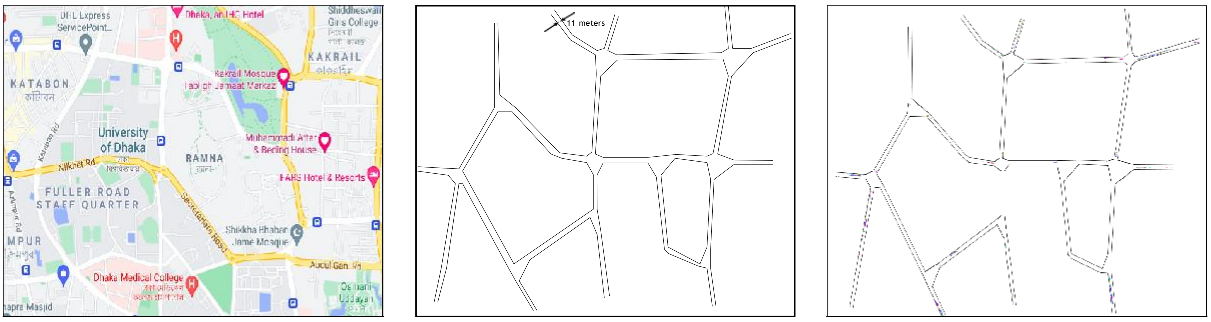
5.4.4 Selection of Signal Cycle from the Pareto Front

The optimization model returns a Pareto front of solutions. Each point in the Pareto front is optimized. However, we have to select one single point from the front and get the corresponding signal cycle for that point. In doing this, we defined an objectives function that takes a weighted sum of the two objectives. We vary the weights for the objectives and compare the performance. The objective function is described in equation 5.7. Besides, we normalize the two objectives using Equation 5.6 so that individual absolute value may not affect the weighted sum calculation.

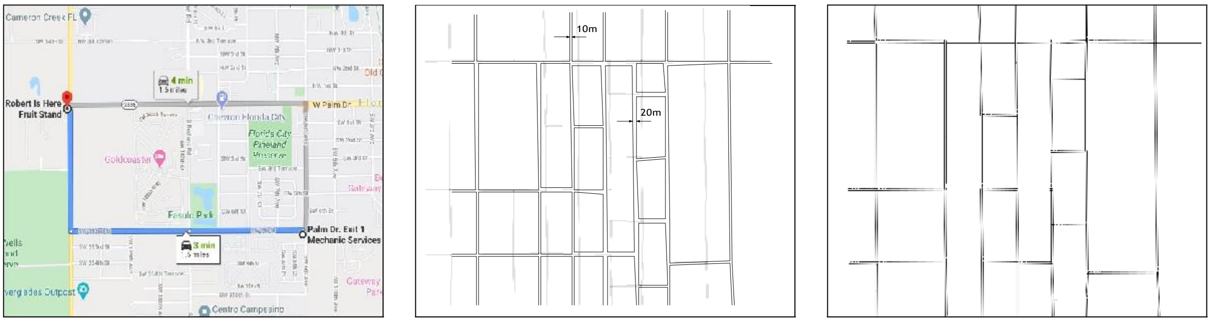
$$f_i(normalized) = \begin{cases} \frac{f_i - f_i(min)}{f_i(max) - f_i(min)}, & \text{if } f_i(max) - f_i(min) \neq 0 \\ 0, & \text{if } f_i(max) - f_i(min) = 0 \end{cases} \tag{5.6}$$

$$F(f_1, f_2) = w \times f_1(normalized) + (1 - w) \times f_2(normalized) \tag{5.7}$$

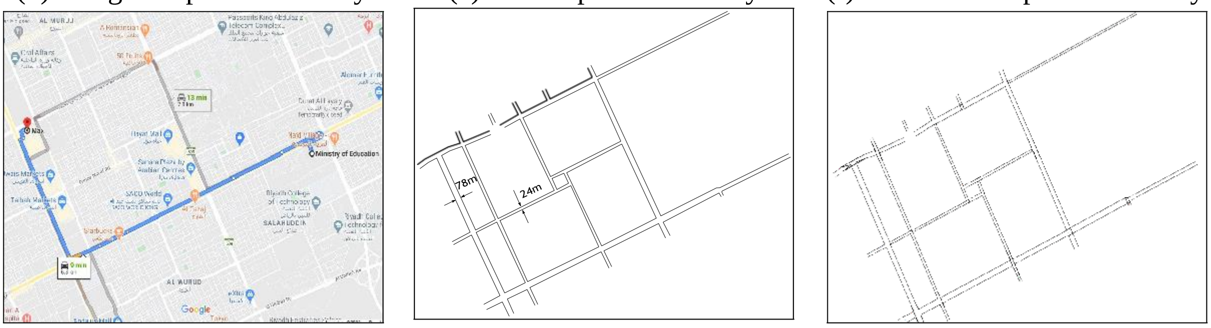
From the weighted sum values for each Pareto optimal point, we select the minimum sum values, as this is a minimization problem. The signal cycle corresponding to the minimum weighted value of the Pareto optimal point is then used for the next signal cycle.



(a) Google map of Dhaka city (b) GIS map of Dhaka city (c) Simulated map of Dhaka city



(d) Google map of Miami city (e) GIS map of Miami city (f) Simulated map of Miami city



(g) Google map of Riyadh city (h) GIS map of Riyadh city (i) Simulated map of Riyadh City

Figure 5.6: Simulation environment and topologies used in our simulations

5.4.5 Experimental Setup

Here, we describe the experimental setup for the experiments to be carried out.

Parameters of Experiment

We tweak some key parameters during our experimentation, such as the weight of objectives (w), green time for fixed signaling, minimum and maximum green time for optimized signaling, etc.

Road Networks

For the evaluation of our proposed optimized signal scheduling in comparison with fixed signal scheduling, we perform experiments on three road networks of Dhaka, Miami, and Riyadh respectively. Dhaka is the representative of a developing country which is our primary target network. The reason for selecting Miami and Riyadh is to observe the effect of optimized signaling on road networks of developed countries. The road networks are shown in Figure 5.6.

Evaluation Metric

To assess the performance of both fixed and optimized signaling, we implement two evaluation metrics: i) average speed of vehicles and ii) average waiting time of vehicles in the network. The average speed of a vehicle defines the average speed of all the vehicles in the network from a source node to a destination node. This metric has a unit of kilometers per hour. The average waiting time of a vehicle defines how much time a vehicle has to wait due to traffic jams in the network. This metric has a unit of seconds. Our purpose in this study is to gain as much average speed as possible as well as less average waiting time as possible.

5.4.6 Our Considerations and Assumptions - Prerequisites behind This Study

In most of the cases, traffic signal in Dhaka city fails due to the high volume-by-capacity ratio ($v/c > 1$) [72]. Therefore, vehicles can not achieve their expected high speed. Moreover, vehicles face long waiting times in junctions because of such a high volume-by-capacity ratio. It needs to be noted that, in our study, we also consider a similar scenario (high volume-by-capacity ratio with $v/c > 1$) to mimic the traffic scenario of Dhaka city. Thus, our study mainly explores how far the on-road experience could be improved even in the presence of high volume-by-capacity ratio.

Chapter 6

Findings

In this section, we discuss the findings on dataset preparation, vehicle detection from images, signal optimization leveraging metaheuristics approaches, and analysis of the integration of optimization with the DhakaSim traffic simulator.

6.1 Dataset Preparation

Our dataset contains 1071 annotated images. The distribution of the class labels is demonstrated in Table 6.2. From the distribution, it is clear that our dataset has a class imbalance where the count of motorized vehicles dominates non-motorized. This is very much natural for traffic on the roads of Dhaka where non-motorized vehicles move very infrequently on important roads and highways. Rather, non-motorized vehicles can be seen on local streets of residential areas. In Figure 6.1, we show some sample images from our prepared dataset.

6.2 Vehicle Detection

The outcome of vehicle detection for different detection models is shown in Table 6.3. Here, we can see that YOLOv8m gets the best mAP, however, it has the highest inference time. Also, it is clear that models having higher mAP have higher inference time.

In our case, we need to consider both mAP and inference time as traffic detection should be accurate as well as faster. Therefore, we draw a scatter plot of mAP and inference time, which is shown in Figure 6.2. Here, our goal is to find a point that has higher mAP and less inference time. The red colored dot fulfills this requirement. The point has a mAP of 68.3 and an inference time of 5.3 ms. the point corresponds to the YOLOv8n (nano) model, which is comparatively lightweight.

(a) Image 1 (b) Image 2 (c) Image 3 (d) Image 4

(e) Image 5 (f) Image 6 (g) Image 7 (h) Image 8

(i) Image 9 (j) Image 10 (k) Image 11 (l) Image 12

(m) Image 13 (n) Image 14 (o) Image 15 (p) Image 16

Figure 6.1: Sample images from our prepared traffic image dataset. Locations from where these images are taken include: Science lab, Banani, Dhaka Cantonment, Bangla Motor, and Bijoy Sarani.

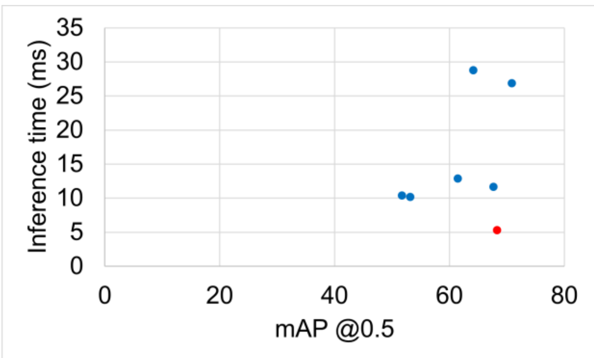


Figure 6.2: Scatter plot of inference time and Mean Average Precision (mAP) for different models. Red colored dot has higher mAP as well as lower inference time.

Table 6.1: Description of the collected data

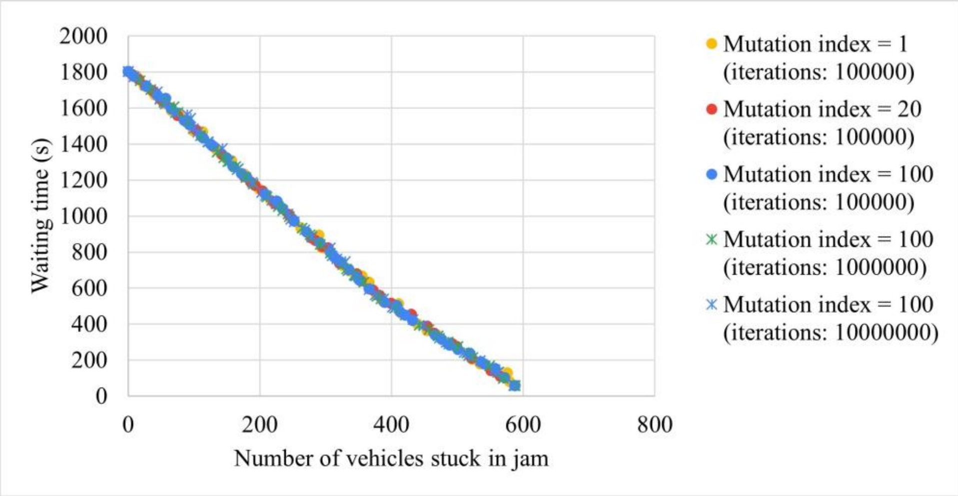
Serial no.	Location	Duration (minutes)	Start time	Weather	Direction of traffic coming from
1	Dhaka Cantonment	10	9:23 AM	Sunny	South
2		20	9:30 AM	Sunny	North
3	Dhaka Cantonment	10	10:00 PM	Rainy	North
4	Nikunja-2	10	11:08 AM	Sunny	South
5		10	11:19 AM	Sunny	North
6	Banani	10	11:08 AM	Sunny	South
7		3	11:19 AM	Sunny	North
8		2	11:25 AM	Sunny	North
9		3	11:28 AM	Sunny	North
10	Bijoy Sarani	10	12:53 PM	Sunny	North
11	Bangla Motor	10	1:17 PM	Sunny	South
12	Science Lab	5	3:49 PM	Cloudy	South
13		7	3:55 PM	Cloudy	North
14		9	4:05 PM	Cloudy	North
15		3	4:15 PM	Cloudy	South
16	Science Lab	20	6:30 PM	Night	North

Table 6.2: Class-wise distribution and split of the annotated dataset. For dataset split, 70:15:15 ratio is maintained.

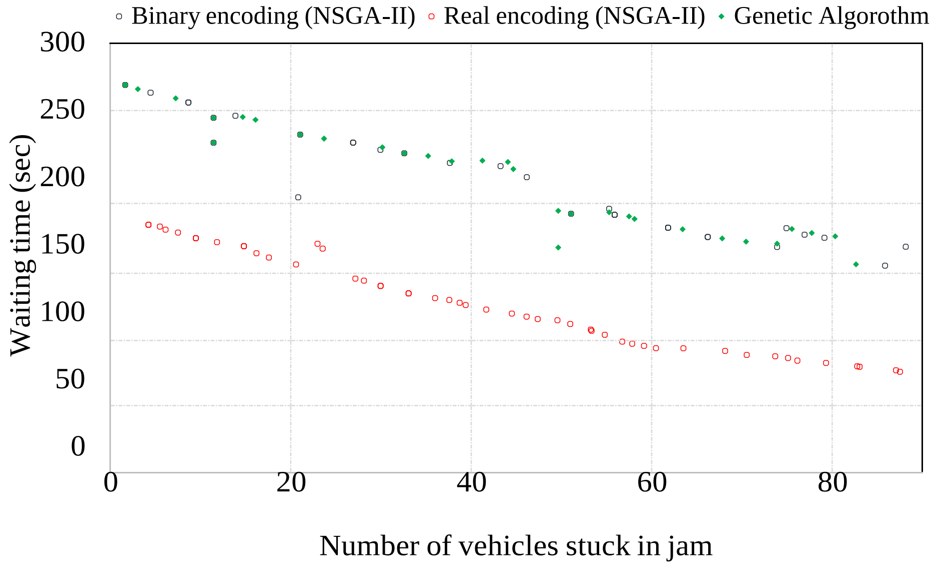
Class	Vehicle count	Dataset split	Image count
Motorized incoming	16053	Total number of images	1071
Motorized outgoing	10745	Training	749
Non-motorized incoming	1302	Validation	161
Non-motorized incoming	1949	Testing	161

Table 6.3: Performance evaluation using state-of-the-art lightweight architectures on our prepared dataset. MI: “Motorized Incoming”, MO: “Motorized Outgoing”, N-MI: “Non-Motorized Incoming”, and N-MO: “Non-Motorized Outgoing”

Model	Class-wise mAP@0.5 (%)				mAP @0.5 (%)	mAP@ 0.5:0.95 (%)	P (%)	R (%)	Inference time (ms)	FPS
	MI	MO	N-MI	N-MO						
YOLOv8m [27]	81.1	75.8	54.9	71.3	70.8	38.8	76.4	64	26.9	37.175
YOLOv8s [27]	78.8	73.9	49.7	68	67.6	36.5	76.4	58.9	11.7	85.47
YOLOv8n [27]	74.7	66.8	59	72.6	68.3	38.9	77.6	58.7	5.3	188.679
YOLOv5m [28]	78	73.5	41.7	63.2	64.1	33.6	72.1	58.2	28.8	34.722
YOLOv5s [28]	76	70.8	38.4	60.6	61.4	31.2	72.8	54.4	12.9	77.519
YOLOv5n [28]	71.8	66	23.4	51.1	53.1	25.2	58.9	49.5	10.2	98.039
DhakaNet [54]	71.4	65.3	17.6	52.5	51.7	23.8	25.9	66.2	10.4	96.154



(a) Pareto front for different mutation distribution index in NSGA-II



(b) Pareto front for different metaheuristic algorithms

Figure 6.3: Experimental results on different metaheuristic algorithms

6.3 Signal Optimization

As previous studies found that mutation distribution can influence the performance of optimization, we explore three mutation distribution indexes: 1, 20, and 100. We evaluate these settings with the NSGA-II algorithm by calculating the Pareto front for each setting. The result is shown in Figure 6.3a. Here, on the x-axis, we have traffic jam volume (number of vehicles stuck in jam) and on the y-axis, we have waiting time. As we see, the Pareto fronts are quite similar looking for all the distribution indexes and iterations. Hence, mutation distribution indexes have no impact on the performance of NSGA-II in our problem.

We compare three metaheuristics algorithms among which Binary encoded NSGA-II is one of the state-of-the-art [73]. Among the three algorithms, we first experiment with a state-of-the-art binary encoded NSGA-II. In the paper, they used 10-bit for the encoding. The Pareto front for this setting is evaluated and shown in black colored dots in Figure 6.3b. Next, we evaluate our proposed real-encoded NSGA-II. The Pareto front of this setting is shown in Figure 6.3b with red-colored dots. The performance is quite bad compared to state-of-the-art binary-encoded NSGA-II. Finally, we evaluate the genetic algorithm. The Pareto front is shown in Figure 6.3b in a green-colored diamond-shaped object and the performance is quite similar to state of the art.

6.4 Integration with Simulator

We run seven simulations for fixed signaling mode and nine simulations for optimized signaling mode having different weight values and green time combinations. Each simulation takes 20 seconds and 50 seconds on average to execute for fixed and optimized signaling. Fixed and optimized mode of simulation has inference time of 2 ms and 5 ms respectively. Results for each simulation are shown in Table 6.4, 6.5, and 6.6. Here, mode defines the mode of the experiment (e.g., fixed and optimized). Weight defines weight values for each objective in the objective function. We have two objectives, thus two weight values. In fixed mode, there is no weight associated. Green time defines green cycle length. For example, in fixed mode, a green time of 5 seconds implies that in an intersection having four links, each link will get 5 seconds of green time. In optimized mode, the green time can vary between 5 seconds and 600 seconds. Finally, average speed and average waiting time are our evaluation metrics. To get a broader picture, we also need to observe the average speed, waiting time, and vehicle flow rate for all the links in the network. Therefore, we draw three bar charts for each network containing average speed vs. link, average waiting time vs. link, and vehicle flow rate vs. link.

6.4.1 Performance on Dhaka Road network

From Table 6.4, we see in Experiment 2 of fixed mode, we get 4.9 km/h average speed having 268.9 seconds average waiting time of vehicles. On the other side, in optimized mode, in Experiment 7 and 9, we get 6.3 km/h average speed and 251 seconds waiting time. This average speed is very close to a recent statistic, which is published in a reputed national daily in Bangladesh [74]. According to the statistics, in the last 10 years until 2018, the average speed of traffic in Dhaka dropped from 21 km/h to 7 km/h. Moreover, by 2035, the speed is expected to drop to 4 km/h, which is slower than the walking speed.

Following the above simulation results, to better understand the simulation outcomes, we draw a scatter plot of average speed and average waiting time, which is shown in Figure 6.5a. Here, blue dots represent fixed signaling and red dots represent optimized signaling. It is clear from this plot that optimized signaling can provide more average speed as well as less waiting time compared to fixed signaling for the Dhaka road network, which is a representative of non-lane-based heterogeneous traffic.

In Figure 6.6, blue bars represent fixed signaling and red bars represent optimized signaling. We can see that optimized signaling gets more speed in almost all the links compared with fixed signaling. Also, optimized signaling has more overall average speed (horizontal red dots) on all links compared with fixed signaling. Next, optimized signaling has less average waiting time for almost all the links compared with fixed signaling. Moreover, optimized signaling has less overall average waiting time (horizontal red dots) on all links compared with fixed signaling. Finally, optimized signaling has more average vehicle flow rate for almost all the links compared with fixed signaling. Moreover, optimized signaling has a higher overall average vehicle flow rate (horizontal red dots) on all links compared with fixed signaling.

6.4.2 Simulation in Different Other Signal Scheduling Scenarios

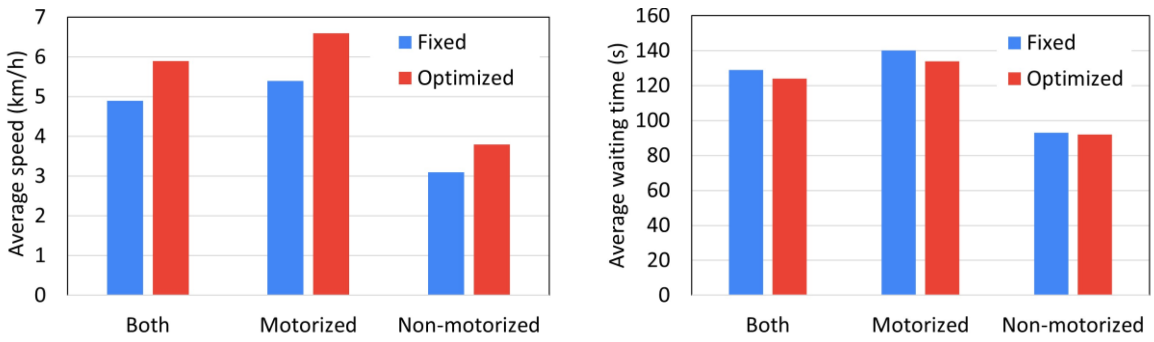
We integrate random, biased-random, and single-objective traffic signal scheduling in our DhakaSim traffic simulator to compare their performances against that of our proposed methodology. Before presenting the performances of these three alternative scheduling methodologies, we discuss each of the alternative traffic signal scheduling methodologies below.

1. **Random traffic signal scheduling:** In random traffic signal scheduling, each link of an intersection gets a random green signal timing. The timing is chosen from a specific duration range. Here, we consider two duration ranges having integer values in our experimentation. The two ranges are [5, 10] and [5, 600]. To elaborate, the range of [5, 10] implies that the signal timing for each link in an intersection will be an integer value within the range from 5 to 10.

2. **Biased-random traffic signal scheduling:** In biased-random traffic signal scheduling, each link of an intersection gets a green signal timing, which we derive through multiplying a random number and a bias. Here, we adopt the fraction of vehicle counts along a link of an intersection as the bias. Similar to the previous case, we consider two duration ranges ([5, 10] and [5, 100]) for generating the random numbers.

3. **Single-objective case in traffic signal scheduling:** In single-objective traffic signal scheduling, each link of an intersection gets a green signal timing based on a weighted combination of the number of vehicles stuck in jam and the waiting time of those vehicles in the intersection. We multiply the weighted combination by 10, as the green signal timing of 10 provides the best average speed and waiting time for the fixed mode of signal scheduling. In Equation 6.1, 6.2, and 6.3, we demonstrate how green signal timing is generated in single-objective traffic signal scheduling in this way. Here, j_l and w_l represent the number of vehicles in link l and the waiting time of vehicles at link l respectively.

The simulation outcomes for the above three alternative traffic signal scheduling are presented in Table 6.7. Here, we find the best average speed and waiting time of 6.1 km/h and 271.6 s



(a) Average speed for motorized, non-motorized, and both

(b) Average waiting time for motorized, non-motorized, and both

Figure 6.4: Average speed and waiting time for motorized, non-motorized, and both types of vehicles

respectively for the biased-random mode. However, it is worth mentioning that these results come out only when the maximum value of green signal timing is judiciouly chosen (10 s in this case). Otherwise, if the maximum value of green signal timing is not properly chosen, the performance can severely degrade. This situation gets evident from the subtantially degraded performance in the case of setting the maximum value of green signal timing to 600 s. On the other side, the average speed and waiting time for the random and single-objective case is worse compared to random-biased and very close to fixed signal scheduling for the Dhaka-Shahabagh road network as shown in Table 6.4.

6.4.3 Comparison of Performances for Motorized and Non-motorized Vehicles

For the case of the best combinations of Fixed and Optimized modes (i.e., Experiment 2 and 7 in Table 6.4), we further explore our simulation results to perform a comparative analysis between speed and waiting time for motorized and non-motorized vehicles. In Figure 6.4, we show the speed and waiting time for three different cases: motorized, non-motorized, and combining both the types vehicles. As per the figure, non-motorized vehicles exhibit less average waiting time and less speed compared to that of motorized vehicles in both fixed and optimized traffic signal scheduling. There can be two reasons behind this phenomenon. First, in Dhaka, non-motorized traffic is smaller in size compared to motorized ones. Owing to the smaller sizes, non-motorized vehicles can quickly pass through along traffic jams, which can lead to less waiting time. Second, due to low average speed, non-motorized vehicles have to pass through more time on-motion before arriving a junction. This renders relatively less time for the non-motorized vehicles to arrive in a traffic jam, even after having lower average speed.

Table 6.4: Simulation outcomes for Dhaka-Shahabagh road network.

Mode	No.	Weight (w1, w2)	Green time (s)	Average speed (km/h)	Average waiting time (s)
Fixed	1	-	5	1.7	509.4
	2	-	10	**4.9**	**268.9**
	3	-	15	4.2	328.5
	4	-	60	2.67	380.6
	5	-	120	2.07	405.2
	6	-	360	1.93	468.5
	7	-	600	1.65	518.6
Optimized (our proposed)	1	0.9., 0.1	[5, 600]	3.03	350.45
	2	0.8, 0.2	[5, 600]	3.28	393.8
	3	0.7, 0.3	[5, 600]	3.24	365.21
	4	0.6, 0.4	[5, 600]	3.3	352.9
	5	0.5, 0.5	[5, 600]	3.8	409.12
	6	0.4, 0.6	[5, 600]	5.9	263
	7	0.3, 0.7	[5, 600]	**6.3**	267
	8	0.2, 0.8	[5, 600]	5.6	253
	9	0.1, 0.9	[5, 600]	5.5	**251**

$$j_l(normalized) = \begin{cases} \frac{j_l - j_l(min)}{j_l(max) - j_l(min)}, & \text{if } j_l(max) - j_l(min) \neq 0 \\ 0, & \text{if } j_l(max) - j_l(min) = 0 \end{cases} \tag{6.1}$$

$$w_l(normalized) = \begin{cases} \frac{w_l - w_l(min)}{w_l(max) - w_l(min)}, & \text{if } w_l(max) - w_l(min) \neq 0 \\ 0, & \text{if } w_l(max) - w_l(min) = 0 \end{cases} \tag{6.2}$$

$$G(j_l, w_l) = 10 \times (1 + (0.3 \times j_l(normalized) + 0.7 \times w_l(normalized))) \tag{6.3}$$

6.4.4 Performance on Miami Road Network

From Table 6.5, we see in simulation no. 1 of fixed mode, we get 27.2 km/h average speed having 75.8 seconds average waiting time of vehicles. On the other side, in optimized mode in Experiment 8 and 6, we get 27.7 km/h average speed and 46.4 seconds waiting time. To better understand the simulation outcomes, we draw a scatter plot of average speed and average waiting time, which is shown in Figure 6.5b. Here, blue dots represent fixed signaling and red dots represent optimized signaling. It is clear from this plot that optimized signaling can provide more average speed as well as less waiting time compared to fixed signaling for the Miami road

Table 6.5: Simulation outcomes for Miami road network.

Mode	No.	Weight (w1, w2)	Green time (s)	Average speed (km/h)	Average waiting time (s)
Fixed	1	-	5	**27.2**	**75.8**
	2	-	10	23.4	112.5
	3	-	15	21.2	130.7
	4	-	60	12.6	408.7
	5	-	120	8.8	481.8
	6	-	360	4.7	502.8
	7	-	600	3.6	545.4
Optimized (our proposed)	1	0.9., 0.1	[5, 600]	26.3	52.9
	2	0.8, 0.2	[5, 600]	26.8	58
	3	0.7, 0.3	[5, 600]	26.2	51.7
	4	0.6, 0.4	[5, 600]	27	52.3
	5	0.5, 0.5	[5, 600]	26.8	65.6
	6	0.4, 0.6	[5, 600]	26.3	**46.4**
	7	0.3, 0.7	[5, 600]	27.5	56.8
	8	0.2, 0.8	[5, 600]	**27.7**	56.8
	9	0.1, 0.9	[5, 600]	26.9	62.2

Table 6.6: Simulation outcomes for Riyadh road network.

Mode	No.	Weight (w1, w2)	Green time (s)	Average speed (km/h)	Average waiting time (s)
Fixed	1	-	5	**28.5**	**173.2**
	2	-	10	25.1	197.2
	3	-	15	23.2	209.1
	4	-	60	17.5	323.4
	5	-	120	13.4	426.8
	6	-	360	10.4	768.9
	7	-	600	11.2	838.9
Optimized (our proposed)	1	0.9., 0.1	[5, 600]	25.2	206.4
	2	0.8, 0.2	[5, 600]	24.5	201.1
	3	0.7, 0.3	[5, 600]	24.8	175.6
	4	0.6, 0.4	[5, 600]	25.9	188.8
	5	0.5, 0.5	[5, 600]	25.6	197.8
	6	0.4, 0.6	[5, 600]	**28.9**	**161.2**
	7	0.3, 0.7	[5, 600]	27.9	170.6
	8	0.2, 0.8	[5, 600]	27.1	185.3
	9	0.1, 0.9	[5, 600]	27.9	196.7

Table 6.7: Simulation outcomes in other signal scheduling scenarios for Dhaka-Shahabagh road network.

Mode	Weight	Green time (s)	Average speed (km/h)	Average waiting time (s)
Random	-	[5, 10]	4.9	286.7
	-	[5, 600]	1.8	457.1
Biased-random	-	[5, 10]	**6.1**	**271.6**
	-	[5, 600]	2	438.2
Single-objective case	0.3, 0.7	Multiplication factor of 10	4.9	290

network, which is representative of lane-based homogeneous traffic.

In Figure 6.7, blue bars represent fixed signaling and red bars represent optimized signaling. We can see that optimized signaling gets more speed in almost all the links compared with fixed signaling. Also, optimized signaling has more overall average speed (horizontal red dots) on all links compared with fixed signaling. Next, optimized signaling has less average waiting time for almost all the links compared with fixed signaling. Moreover, optimized signaling has less overall average waiting time (horizontal red dots) on all links compared with fixed signaling. However, in the Miami road network, optimized signaling gets less average vehicle flow rate for almost all the links compared with fixed signaling. Also, optimized signaling has less overall average vehicle flow rate (horizontal red dots) on all links compared with fixed signaling.

6.4.5 Performance on Riyadh Road Network

From Table 6.6, we see in simulation no. 1 of fixed mode, we get 28.5 km/h average speed having 173.2 seconds average waiting time of vehicles. On the other side, in the optimized mode in Experiment 6, we get 28.9 km/h average speed and 61.2 seconds waiting time. To better understand the simulation outcomes we draw a scatter plot of average speed and average waiting time, which is shown in Figure 6.5c. Here, the blue dot represents fixed signaling and red represents optimized signaling. It is clear from this plot that optimized signaling can provide more average speed as well as less waiting time compared to fixed signaling for the Riyadh road network, which is a representative of lane-based homogeneous traffic.

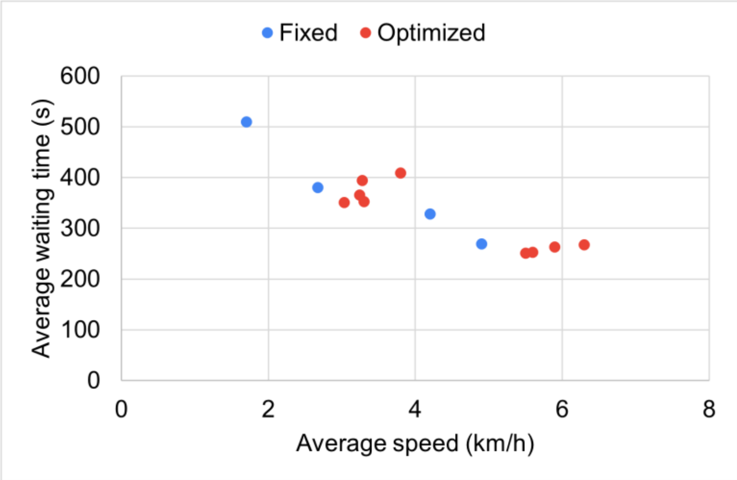
In Figure 6.8, blue bars represent fixed signaling and red bars represent optimized signaling. We can see that optimized signaling gets more speed in some of the links compared with fixed signaling. Also, optimized signaling has slightly more overall average speed (horizontal red dots) on all links compared with fixed signaling. Next, optimized signaling has likely similar average waiting time for almost all the links compared with fixed signaling. Similarly, optimized signaling gets almost identical vehicle flow rate for almost all the links compared with fixed signaling.

Table 6.8: Performance of our proposed optimized signaling against fixed signaling in three evaluation metrics.

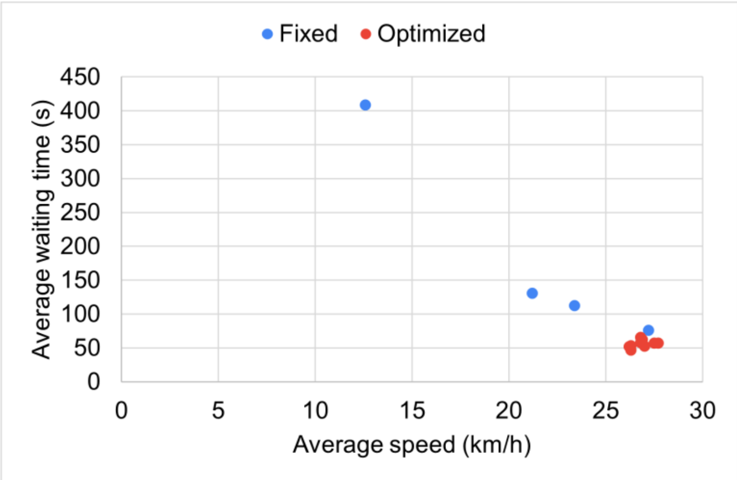
Name of road network	Performance of optimized signal scheduling with respect to fixed signal scheduling (%)		
	Average speed (km/h)	Average waiting time (s)	Average vehicle flow rate (vehicle/hr)
Dhaka-Shahabagh	6.6	-24.1	10.4
Miami	3.1	-23.1	-2.7
Riyadh	2.0	4.7	0.5

6.4.6 Comparison of Performance on All Road Networks

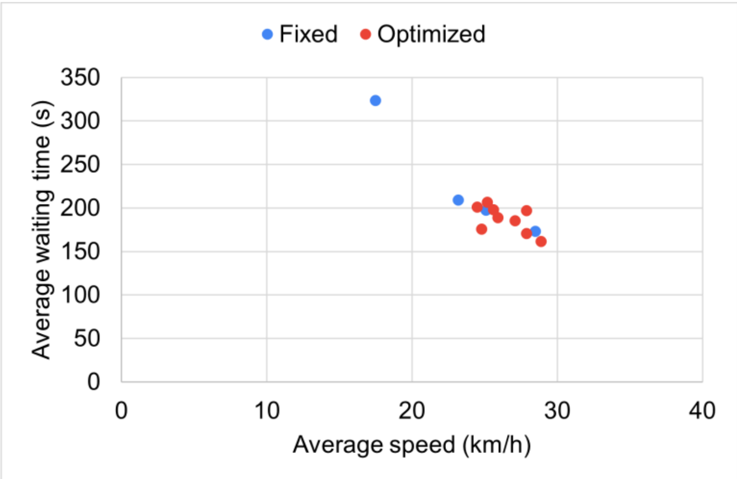
In Table 6.8, we demonstrate the change in performance after integrating the optimized signal scheduling in DhakaSim. Among the three toad networks, using optimized signal scheduling, Dhaka-Shahabagh network has 6.6.% increase in average speed, 24.1% decrease in average waiting time, and 10.4% increase in average vehicle flow rate against fixed-time signal scheduling. However, in Miami road network, average flow rate decreases by 2.7%. In Riyadh road network, average waiting time increases by 4.7%. Though in both Miami and Riyadh, there is a performance degradation for one metric, we find significant performance gains in the other two metrics. The overall results on the three road networks indicate that our proposed optimized signal scheduling has the capability to generalize in road networks of developed countries.



(a) Dhaka-Shahbagh road network.

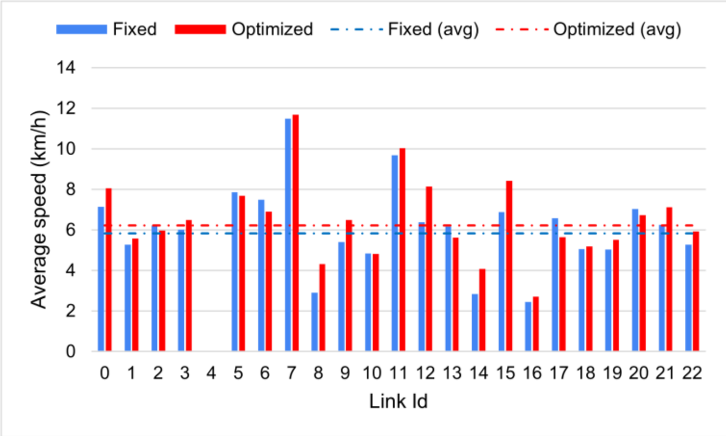


(b) Miami road network.

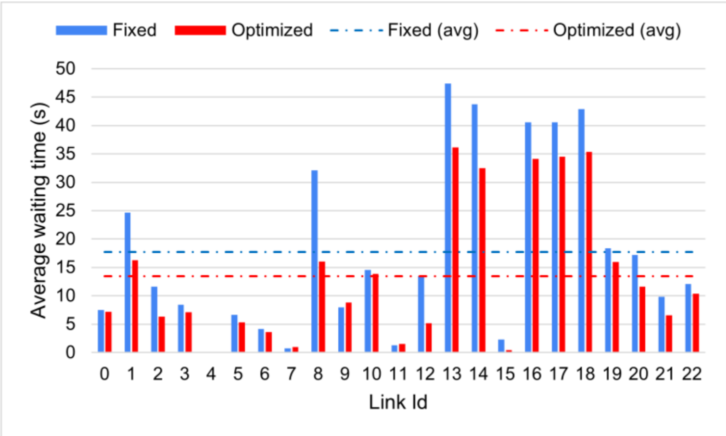


(c) Riyadh road network.

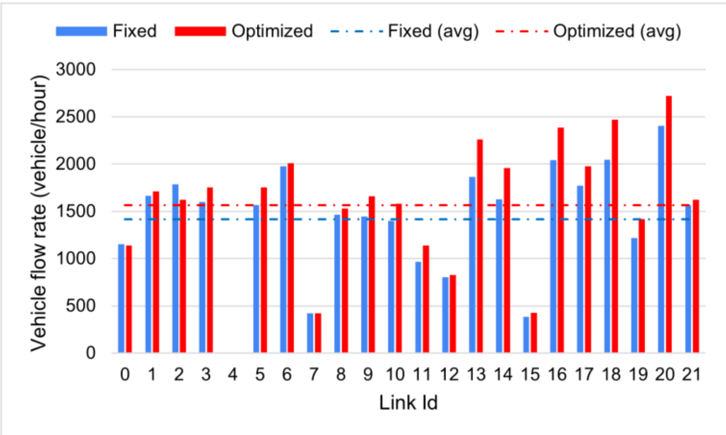
Figure 6.5: Scatter plots of evaluation metrics based on different road networks.



(a) Average speed on all links

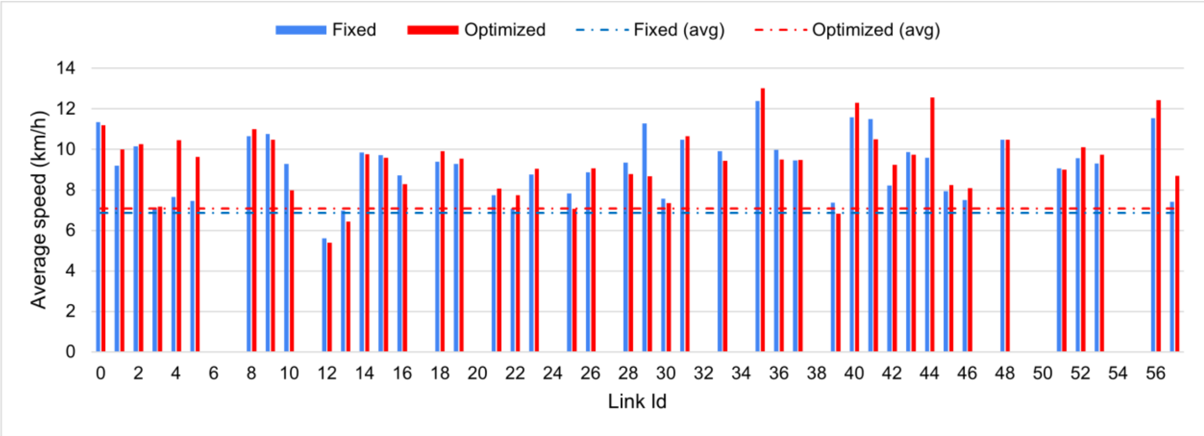


(b) Average waiting time on all links

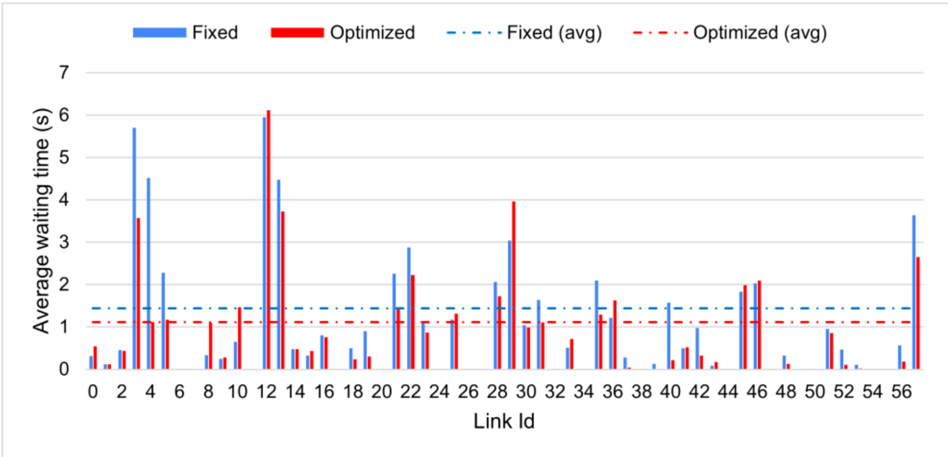


(c) Vehicle flow rate

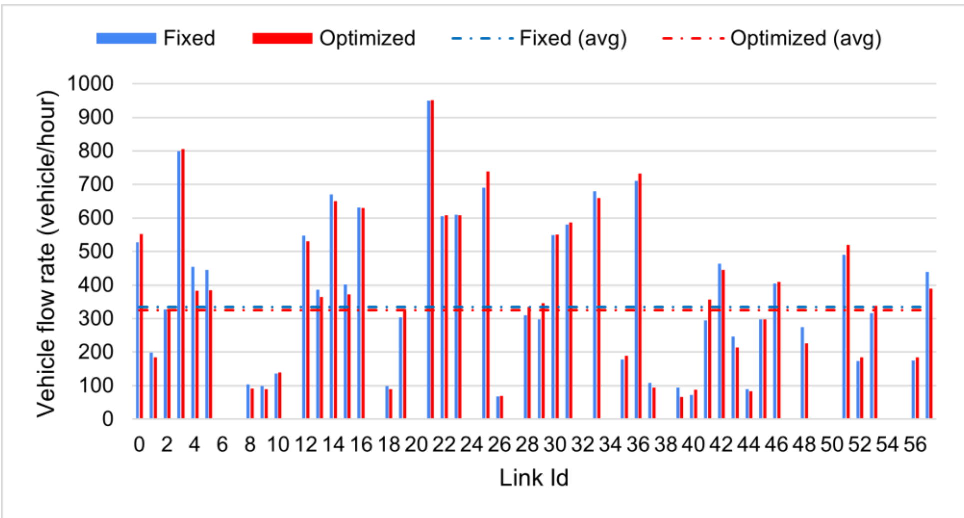
Figure 6.6: Speed, waiting time, and flow rate on Dhaka-Shahabagh road network.



(a) Average speed on all links

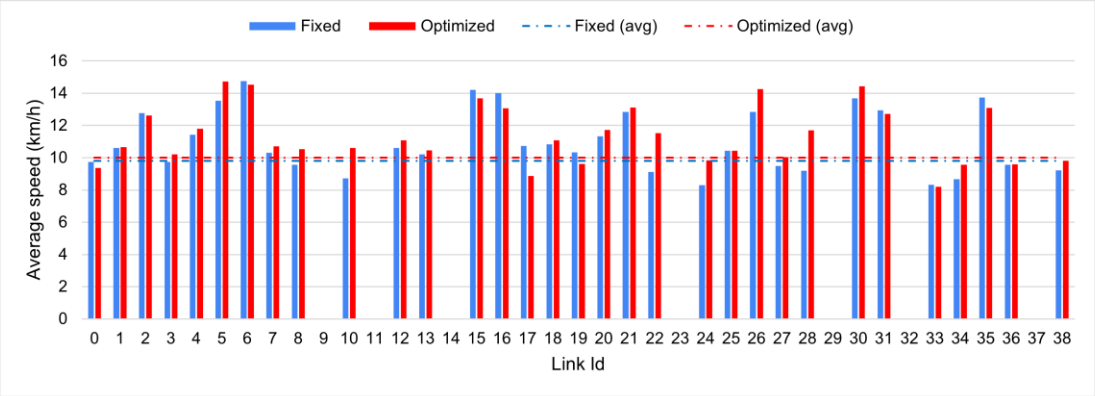


(b) Average waiting time on all links

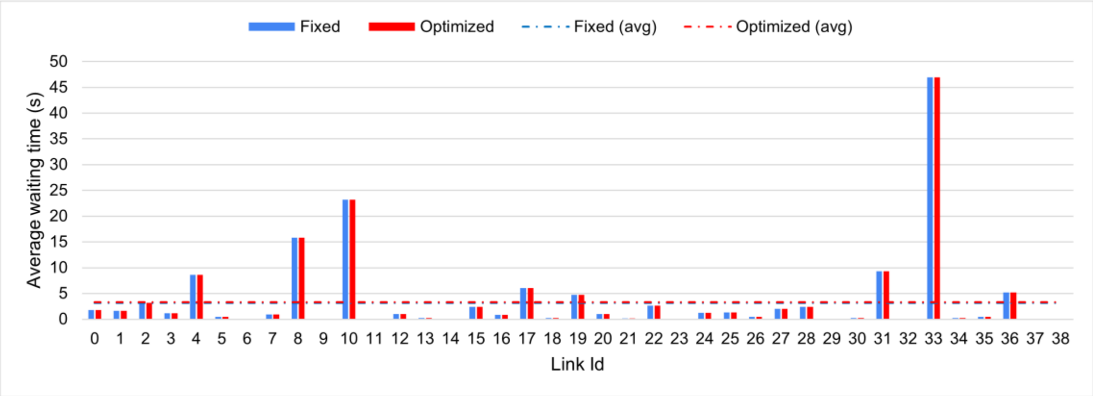


(c) Vehicle flow rate

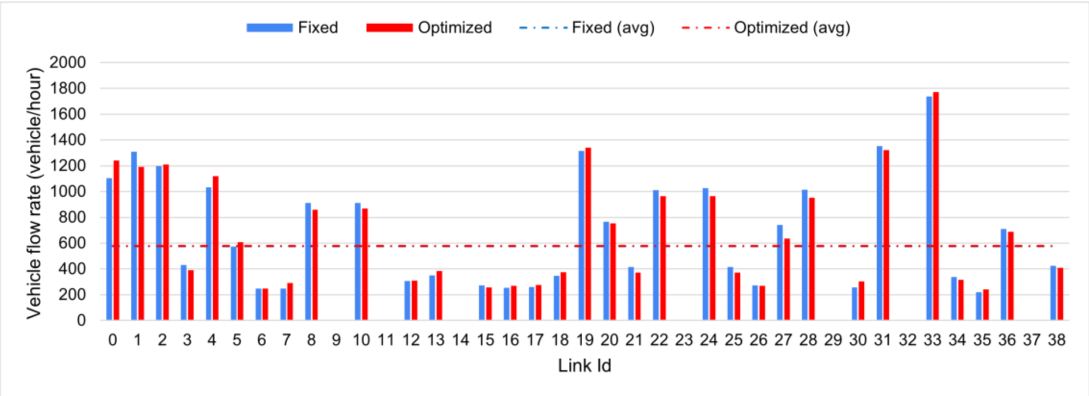
Figure 6.7: Speed, waiting time, and flow rate on Miami road network.



(a) Average speed on all links



(b) Average waiting time on all links



(c) Vehicle flow rate

Figure 6.8: Speed, waiting time, and flow rate on Riyadh road network.

Chapter 7

Discussion

Traffic signal scheduling is an important task in the field of transportation. Keeping this in mind, we formulate the problem as a chronological implementation of dataset preparation, experimentation with computer vision algorithms, optimization, and simulation. During the study period, we explore the existing studies done so far in the relevant field and design our work filling the gap in the literature. In this section, we discuss the contributions made to this study followed by how we fill the gap in the literature.

7.1 Our Contributions

In this study, we propose a new methodology of traffic signal scheduling leveraging computer vision, multiobjective optimization, and simulation. Alongside the proposed methodology, we prepare a comprehensive traffic image dataset for Dhaka city consisting of 1071 images with annotations. When preparing the dataset, we consider diverse weather and illumination conditions. Next, we evaluate the performance of existing machine learning models in detecting on-road vehicles based on the benchmark dataset and identify YOLOv8 (nano) as the most suitable model based on the evaluation results. Then, we perform experiments with three multiobjective optimization algorithms and find binary encoded NSGA-II as the best model. Finally, we integrate the optimization model with the DhakaSim traffic simulator. Our simulation results in up to 24.1% decrease in average waiting time, 10.4% increase in average vehicle flow rate, and 6.6% increase in average speed for optimized signal scheduling on Dhaka-Shahabagh road network.

7.2 Comparison with Existing Studies

Prior research studies also attempted to detect vehicles on roads using state-of-the-art object detection architectures. For example, Sang et al., [75] performed vehicle detection using a benchmark traffic image dataset named BIT-vehicle dataset. They proposed a modified YOLOv2 architecture named YOLOv2-vehicle. YOLOv2-vehicle achieved higher precision compared to state-of-the-art architectures on the above-mentioned dataset. Liu et al., and Wang et al., [76, 77] proposed new architecture for vehicle detection based on Faster RCNN. They performed the experiments on the DETRACT dataset. Nguyen et al., and Jahan et al., [78, 79] worked on YOLOv4 and YOLOv3 respectively. Among them, Jahan et al., proposed their own dataset having 2240 training images and 560 testing images [79]. They found a modified YOLOv3 which gave higher precision compared to YOLOv3. Among the studies discussed above, most of the studies are based on benchmark traffic image datasets. We found only two studies where authors prepared the dataset on their own. Moreover, those studies did not consider optimization and simulation for traffic which is crucial for accurate traffic signal scheduling. In contrast to that, our approach proposed a complete path of signal scheduling including dataset preparation, optimization, and simulation.

Some prior studies attempted to perform optimization [80–82] for traffic signal scheduling. They used different state-of-the-art simulators, such as Matlab, SATURN, Cellular Automata, etc. However, most of the simulation-based studies consider a single objective which is highly unlikely for the complex traffic of Dhaka city. We find two multiobjective optimization-based work done by Nguyen et al., and Armas et al., [83, 84] based on SUMO and MatSim simulator. However, none of these work considered any computer vision-based study or preparation of traffic image dataset. Labib et al., [85] performed computer vision-based traffic detection work along with single objective optimization on a single junction. However, for such a complex traffic flow in Dhaka, we need a multi-objective approach for optimization along with a complete road network consisting of multiple junctions. In comparison, we prepared a traffic image dataset of 1071 images. Next, we perform vehicle detection experiments using our prepared dataset and find YOLOv8 nano as the best architecture. We also perform multi-objective optimization along with DhakaSim traffic simulator on three different road networks.

7.3 Limitations of This Study

In this study, we follow a chronological implementation of a traffic image dataset, computer vision algorithms, multi-objective optimization, and simulation to develop an efficient traffic signal scheduling model. Although we achieved improvements in average speed, average waiting time, and average vehicle flow rate for Dhaka-Shahbagh, there are still scopes of improvement for the traffic network of developed countries so that the proposed model can be generalized. Besides, the size of the traffic image dataset can be extended as found in other existing studies [54, 79]. Next, we use the state-of-the-art object detection model and one vehicle detection model [54]. This can be improved by experimenting with more existing vehicle detection models. Afterwards, we experiment with classical metaheuristics algorithms for signal optimization which can be

Table 7.1: Comparison of our study with existing literature

Research study	Image dataset preparation	Computer vision	Optimization	Simulation	Type of network
Sang et al., [75]	-	YOLOv2	-	-	-
Xu et al., [86]	-	Modified YOLOv3	-	-	-
Liu et al., [76]	-	Faster RCNN	-	-	-
Wang et al., [87]	-	CS-CNN	-	-	-
Wang et al., [77]	-	Faster RCNN	-	-	-
Nguyen [78]	-	YOLOv4	-	-	-
manugmai and Nuthong [88]	Yes (n=914)	CNN	-	-	-
Jahan et al., [79]	Yes (n=2800)	YOLOv3	-	-	-
Tan et al., [80]	-	-	Single-objective	Matlab	Road network
Teklu et al., [81]	-	-	Single-objective	SATURN	Road network
Saanchez et al., [89]	-	-	Single-objective	Cellular Automata	Road network
Guan et al., [82]	-	-	Single-objective	SATURN	Road network
Gokce et a;., [90]	-	-	Single-objective	Vissim	Road network
Brian Park et al., [91]	-	-	Single-objective	CORSIM	Road network
Nguyen et al., [83]	-	-	Multi-objective	SUMO	Road network
Armas et al., [84]	-	-	Multi-objective	Matsim	Road network
Labib et al., [85]	-	OpenCV	Single-objective	Vissim	Single junction
Our proposed approach	Yes (n=1071)	YOLOv8 nano	Multi-objective	DhakaSim	Road network

improved if we can work with more specialized metaheuristics algorithms. Finally, to get more robust results on simulation, we need to explore more traffic networks of developing and developed countries.

Chapter 8

Future Work

In the future, we plan to address the following issues.

1. We plan to address the limitations of this study by collecting more traffic images from other important junctions in Dhaka. It is worth mentioning that other datasets [54] for Dhaka have higher number of images, however, they are yet to consider the directions of vehicles as we do in this study.

2. We plan to explore more vehicle detection architectures so that the current performance can be ameliorated.

3. We plan to experiment with more specialized metaheuristics algorithms so that the optimization performance can be improved.

4. We plan to extend this research to higher number of signalized intersections in real traffic in Dhaka city.

5. We plan to provide DhakaSim with traffic signal scheduling as a simulator as a service so that interested researchers can explore the simulator as well as our proposed traffic signal scheduling solution.

6. We plan to consider pedestrian and crosswalking in our future simulations.

7. In our study, the experiments done on optimization using different mutation indexes are based on numerical simulation. This might be the reason for not finding any significant changes in the performance in response to a variation in the mutation index. In the future, we plan to integrate real simulation for this experiment so that more dynamics can be considered.

8. We plan to explore more on how we can choose the maximum value of the green signal timing duration range in a more intelligent way for random and biased-random traffic signal scheduling.

9. We plan to explore the detection and tracking of right-turn and left-turn by vehicles in Dhaka city. In doing so, we plan to prepare a new dataset considering the right-turn and left-turn of vehicles and integrate it with our optimization module.

Chapter 9

Conclusion

In this study, we propose a new signal scheduling method with chronological implementation of computer vision, multiobjective optimization, and simulation. During this study, first, we collect real traffic images and videos from different important junctions of Dhaka city. We consider diverse weather and illumination conditions during the data collection process. Using the collected images and extracted frames from videos, we annotate the images with four class labels. At the end of annotation and rigorous checking, we prepared a traffic image dataset of 1071 images. Next, using the dataset, we perform experimentation to detect vehicles using state-of-the-art object detection architectures. Our experimental evaluation finds YOLOv8n (nano) as the best model which achieves 68.3% mAP and 5.3 ms inference speed.

Next, we experiment on a signalized intersection having four connected links, based on two objectives (e.g., traffic congestion and waiting time) leveraging three multiobjective optimization algorithms: i) binary-encoded NSGA-II, ii) real-encoded NSGA-II, and iii) genetic algorithm. Our experimental results show that binary-encoded NSGA-II provides the best Pareto front. Then, we integrate the best optimization model which is binary-encoded NSGA-II in DhakaSim traffic simulator to evaluate the optimization model's efficacy on simulated road networks. We experiment with three road networks: i) Dhaka-Shahabagh, ii) Miyami, and iii) Riyadh. The reason behind experimenting with the last two networks is to understand the generalizability of the optimization algorithm. Experimental results indicate that our proposed optimization-based signal scheduling achieves up to 24.1% decrease in average waiting time, 10.4% increase in average vehicle flow rate, and 6.6% increase in average speed.

Our prepared traffic image dataset is one of the first of its kind which considers motorized and non-motorized traffic in separation along with direction of traffic flow. The dataset can contribute significantly in the field of transportation by providing opportunities for other researchers to conduct their intended study. Furthermore, DhakaSim is the only available simulator specially designed for non-lane-based heterogeneous traffic. We integrate the optimization model in DhakaSim which is the first of its kind to the best of our knowledge. Our simulation results indicate that if optimization-based traffic signal scheduling is employed on the field, it can improve the average speed, waiting time, and vehicle flow rate of the network.

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