An Adaptive and Greener Traffic Signal Coordination Scheme for Transport 4.0

W. A. G. Weerasundara, D. P. D. Udugahapattuwa, T. D. Munasingha, W. D. K. Gunathilake, and Udaya Dampage

***Abstract*—Traffic congestion has become a major concern, aroused as a result of increased population and urbanization. Hence, novel and innovative methods for controlling ever-increasing traffic volumes are essential. Conventional traffic light schemes are the most popular method of controlling traffic, and it is logical and economical to make research endeavors to optimize their existing performance. Despite numerous studies, the aforementioned problem has not been optimally and sufficiently solved. In this research, we introduce an adaptive traffic signaling scheme based on vehicle density to facilitate optimal traffic signal control as well as effective traffic management. We also propose effective coordination of the traffic amongst the junctions. Here, the live video is utilized as an input provided to a deep Q network to provide adaptive phase timings as the output. In the proposed scheme, we introduced per car unit (PCU) as a novel parameter to represent the effect of each vehicle type on traffic conditions. Numerous filed trials on real-time data amply prove that the proposed scheme enhances the average speed of traffic up to 5.597 km/h. The proposed scheme shows an average increment of 175.71% in average mean speed compared to the existing static schemes. Except for the high traffic scenario, for both mid traffic and low traffic scenarios, the proposed scheme shows a considerable improvement in both average densities and maximum densities. In the mid-traffic scenario, the average speed shows an improvement of 3.85 km/h, while in the low traffic scenario, the average mean speed shows an improvement of 7.96 km/h. A reduction in fuel consumption and average delay were also observed, which will lead to a greener Transport 4.0.**

***Index Terms*—Traffic control, video processing, Q-learning, adaptive, coordinated traffic signaling, Per Car Unit (PCU), Transport 4.0**

I. Introduction

One inevitable outcome of increased population and urbanization is traffic congestion. Both the average traffic delay and fuel consumption have a considerable impact on the economy. As both of these factors are dependent on traffic congestion, it is imperative to reduce traffic. Hence, novel and innovative methods of controlling ever-increasing traffic volumes are needed. The traffic light scheme is the conventional and most popular method of controlling traffic, and it is logical and economical to make research endeavors to optimize the performance, as proposed in [1], and improved version in [2]. The outcomes of this paper are an extension of previously published work [2], which is presently an ongoing research project. Reference [3] lists insufficient capacity, unrestrained demand, and non-optimized traffic light delays as the most prominent factors that lead to traffic congestion. This arises because most conventional traffic lighting schemes are based upon a static timing scheme for their operation. Phase timing values are typically an outcome of the study of traffic volumes over a certain time duration utilizing sensor systems. However, due to obvious reasons, the resulting scheme performance is not only inefficient but also does not respond to traffic volume fluctuations. Several works [3]-[6] have endeavored to address the aforementioned problem; however, the author felt that the problem is not yet optimally solved. Here, we propose an adaptive and coordinated traffic light scheme built upon a deep Q–network that can be optimized as per the local traffic environments. The proposed scheme considers the following parameters, namely, the vehicle density, vehicle speed, and the effect of each vehicle type on the traffic in the form of PCU values [7].

The rest of the paper is organized as follows: SECTION II briefly reviews the existing traffic control schemes. SECTION III explains the proposed adaptive and coordinated scheme, followed by SECTION IV, which analyzes the results and performance of the proposed scheme concerning existing schemes, and finally, SECTION V presents the conclusion.

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The authors are with the Department of Electrical, Electronic and Telecommunication Engineering, General Sir John Kotelawala Defence University, Ratmalana, Sri Lanka. (e-mail: gayashanweerasundara@gmail.com, pasinduudugahapattuwa@gmail.com, bm.thamali@gmail.com, wdgkasun@gmail.com, dampage@kdu.ac.lk).

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II. Related Work

Even though considerable attention has been given to the optimization of traffic signaling schemes, thus far, only limited attention has been given to developing practical mechanisms with sufficient performance that are adaptive to local traffic fluctuations. In the following, we briefly review the existing schemes in the literature as per the methods of traffic detection, traffic control, and traffic simulation.

A. Traffic Detection Methods

Regarding sensors for the detection of vehicle traffic, the existing works have utilized proximity sensors [6], [8] and induction loops [9], [10]. In [9], the loop detector occupancy factor was used to gauge the vehicle speed. The utilization of a piezoelectric sensor incorporated with induction loops was carried out for vehicle classification in [10]. An ultrasonic sensor was utilized to calculate traffic rates in [6], [8]. However, all the aforementioned works cannot detect the type of vehicles unless specific further arrangements are utilized. Furthermore, the determination of typical incidents such as traffic accidents and certain priorities such as ambulances are almost impossible with the sensors utilized in the aforementioned works [6], [8]-[10]. Hence, the authors envisaged that utilization of already available CCTV systems may be the best option to obtain a detailed scenario of the traffic condition. Subsequent video processing was used for vehicle detection in [3], [11]-[13]. The work [11] introduced 3 methods for improving the relevance and quality of training samples, taken for testing and validating deep learning models. The local features of objects were selected as positive samples to train the classifier, also considering positive samples with high color contrast between object and background. Care was taken to select samples to exclusively include targeting objects. Filtering was utilized in [12] to isolate the vehicular data from the background noise in turn to determine the vehicle counting data and relevant classification of vehicles.

B. Traffic Control Methods

The controlling mode can be of three types depending on the type of phase timing values utilized including predefined, vehicle actuated, and adaptive [14]. Considering traffic management systems, TRANSYT (Traffic Network Study Tool) is a fully predefined system that uses offline optimization. Comparatively, SCOOT (Split Cycle and Offset Optimization Technique) and SCATS (Sydney Coordinated Adaptive Traffic System) are fully adaptive systems [15]. An adaptive-type controlling scheme was introduced in [16], utilizing unprocessed high-dimensional sensory information as input to a deep neural network to determine queue length through a continuous reinforcement learning-based agent. In [6], real traffic data were used with a reinforcement learning-based neural network to devise an adaptive controller. However, no categorization was considered for numerous vehicle types; hence, the effect of different vehicle types on traffic density has been neglected.

C. Traffic Simulation Methods

The available testing platforms are numerous and popular, as the creation of real-life scenarios is not economical in practice. This is because the latter may cause traffic accidents and may aggravate traffic congestion. The works [4], [6], [14], [17] selected SUMO [18] selected Paramic [16] selected PTV and [19]-[21] selected VISSIM as the testing platforms. The work in [22] cites the SUMO platform as an open-source traffic simulation platform with net import and demand modeling components. The same was observed to be used to procedurally generate vehicles, routes, traffic light algorithms, and traffic surveillance sensors. When comparing various simulation tools, considering properties such as microscopic/macroscopic model, scaling, user and mode characteristics, statistics output, Intermodality, calibration, API, and source code access [23] show that the SUMO simulator is most suitable for this use case.

D. Traffic Simulation Methods

The passenger car unit (PCU) [7] is a metric that is used in transportation to evaluate the traffic-flow rate on a road or an intersection. The PCU values were calculated according to Eqn. (1),

$$PCU_i = ((V_{car} / V_i) / (A_{car} / A_{car})) \quad (1)$$

where PCU_i is the ith vehicle PCU value, V_{car} is the passenger car speed, V_i is the ith vehicle speed, A_{car} is the passenger car projected area and A_i is the ith vehicle projected area.

When considering inputs, using the existing vehicle count would offset set the impact each vehicle type has on traffic. Using the PCU value, we numerically represented the effect of different vehicles on traffic.

E. Comparison with Related Works

Research	Simulation Method	Type of vehicles	Real-time strategies	Objectives	Constraints
Proposed Solution	Multiple Q-learning Models	Passenger Car, Motorcycles, Three wheelers, bicycles, Heavy goods vehicles, large goods vehicles	Adaptive	Increasing average vehicle speed, Mean queue length minimization	Fixed cycle length, Fixed phase sequence
Wang et al. [24]	Genetic Algorithm	Passenger cars, bicycles	Actuated	Delay Minimization, Safety Maximization	Limit on minimum cycle length, Limit on maximum cycle length, Limit on minimum green phase duration, Phase sequence is selected among phase groups
Li et al. [25]	Heuristic	Passenger Car	Actuated	Delay Minimization	Limit on minimum cycle length, Limit on maximum cycle length, Limit on minimum green phase duration, Limit on maximum green phase duration, Fixed phase sequence
Aslani et al. [26]	Simulation, Reinforcement Learning	Passenger Car, Pedestrians	Actuated	Total travel time minimization, Total vehicle stops minimization, Emission minimization, Fuel consumption minimization	cycle length is not limited, green phase duration is not limited, Fixed phase sequence
Jin and Ma [27]	Simulation, Multi-Agent System, Reinforcement Learning	Passenger Car	Actuated	Delay minimization, Throughput maximization	cycle length is not limited, Limit on minimum green phase duration, Limit on maximum green phase duration, Phase sequence is selected among phase groups

Lee et al. [28]	Simulation, Heuristic	Passenger Car	Actuated	Delay minimization, Throughput maximization	Limit on minimum cycle length, Limit on maximum cycle length, Limit on minimum green phase duration, Limit on maximum green phase duration, Phase sequence is selected among phase groups
Chandan et al. [29]	Simulation, Rule-based	Passenger Car, Transit vehicles, Heavy goods vehicles	Actuated	Delay minimization, Total vehicle stops minimization	cycle length is not limited, Limit on minimum green phase duration, Limit on maximum green phase duration, Fixed phase sequence
Portilla et al. [30]	Model predictive control	Passenger Car, Bicycles	Actuated	Total travel time minimization, Mean queue length minimization	cycle length is not limited, green phase duration is not limited, Fixed phase sequence
Choi et al. [31]	Simulation, Heuristic	Passenger Car	Adaptive	Delay minimization, Throughput maximization, Total travel time minimization, Emission minimization, Fuel consumption minimization, Increasing average vehicle speed	cycle length is not limited, green phase duration is not limited, Fixed phase sequence
Le et al. [32]	Simulation, Heuristic	Passenger Car	Actuated	Throughput maximization	Fixed cycle length, green phase duration is not limited, Fixed phase sequence
Feng et al. [32]	Simulation, Recursive algorithm	Passenger Car	Adaptive	Delay minimization, Mean queue length minimization	Limit on minimum cycle length, Limit on maximum cycle length, Limit on minimum green phase duration, Limit on maximum green phase duration, Phase sequence is selected among phase groups

III. Proposed Adaptive And Coordinated Scheme

A. Location Selection

For this research, a case study was performed in the Horton Plains junction in Colombo, Sri Lanka (6.911472922759695, 79.87734081653434), as shown in Fig. 1 and Fig. 2.

This junction was selected as a case study due to the high level of congestion observed daily and the presence of a variety of traffic flow patterns. Although the junction is a four-way junction, in the presence of a roundabout, a complex traffic light system was implemented.

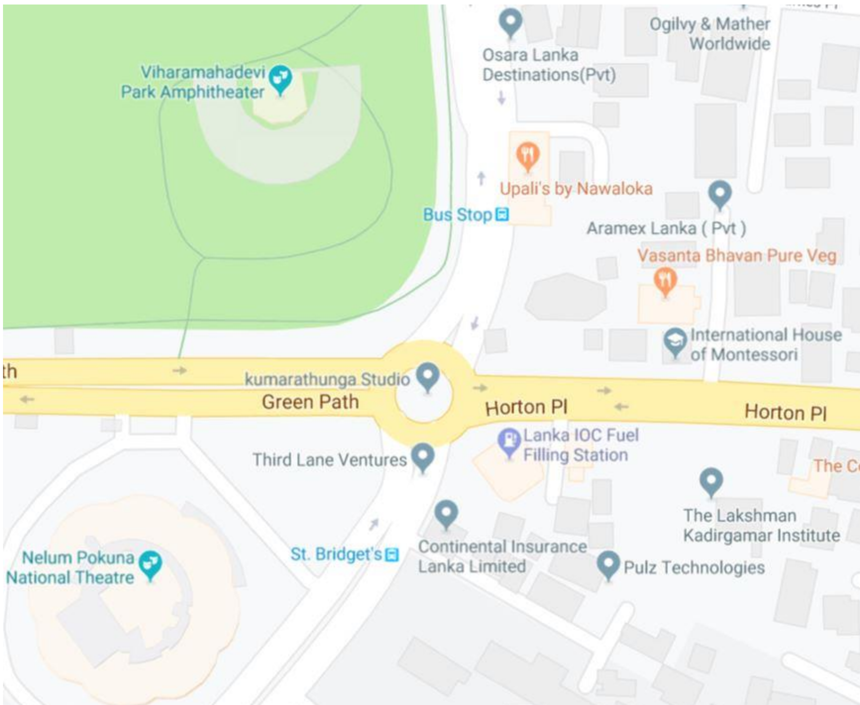

Fig. 1. Horton plains junction.

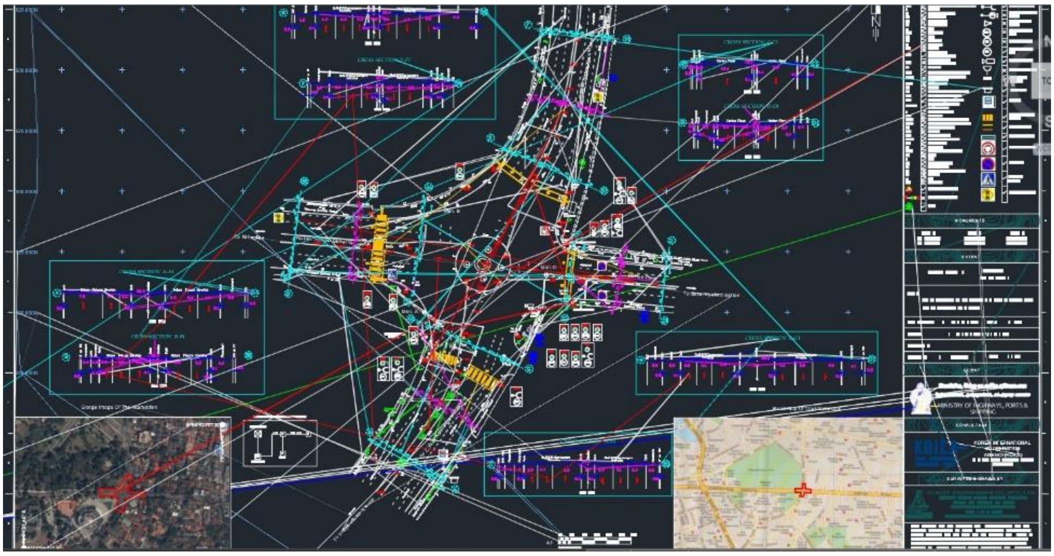

Fig. 2. Horton plains junction AutoCAD design.

TABLE I: STATICAL TIMINGS

Horton Place/C W W Kannangara Mw - Time Allocation for Several Periods			
Time slots	Entry to Horton Pl from Public Library side	Exit from Horton Pl to Green path & R/T	Entry & Exit from C W W Kannangara Mw
0600–0700	12	20	20
0700–0930	20	40	25
0930–1145	15	40	20
1145–1430	15	45	25
1430–1630	15	45	40
1630–1930	20	50	60
1930–2100	12	25	25
2100–0600	10	15	20

B. Data Collection

The data for the research were sourced from both primary and secondary means sourced from research papers, journals, websites [33]-[37], and standard archives such as State Development, Construction Corporation (SD & CC) and Municipal Council, Colombo (CMC), Sri Lanka and field surveys. The research team obtained access to live CCTV feeds from 4 CCTV cameras located at the Horton Plains junction. Manual counting and image processing were utilized to obtain the vehicle density data of each lane. Data were collected for four days per week, selecting two weekdays and weekends, for a total duration of 3 consecutive weeks.

TABLE II: VEHICLE COUNTS IN FOUR DAYS OVER ONE WEEK

Date		06/01/2021 Wednesday Vehicle Counts	08/01/2021 Friday Vehicle Counts	09/01/2021 Saturday Vehicle Counts	10/01/2021 Sunday Vehicle Counts
From Public Library Road	Outgoing	5260	6006	3072	2916
	Incoming	5478	6254	2082	2268
From Town Hall Road	Outgoing	6242	7022	3204	3456
	Incoming	7270	7722	3948	3846
From Horton Place Road	Outgoing	6080	5916	1968	1794
	Incoming	6812	7474	3162	3054
From Museum	Outgoing	6752	6276	3600	3456
	Incoming	5774	5864	2652	2454

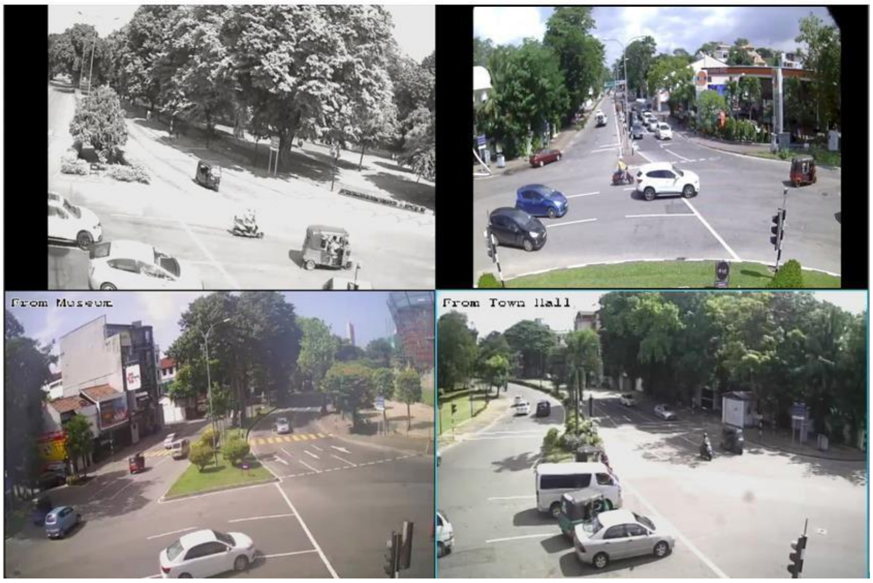

Fig. 3. CCTV feed.

C. Procedure

The overall process consists of two phases: vehicle detection and traffic analysis.

1) Vehicle detection: For vehicle detection, we used CCTV inputs as our methods of observation. When using the video feed to detect and extract traffic information, we tested several machine learning models. From the CCTV footage, we extracted different frames and manually labeled different vehicle classes to create a dataset of local vehicles. We trained several popular machine learning architectures using the datasets depicted in Table III.

TABLE III: TRAINING PARAMETERS

Model	Training time	Accuracy	Prediction time
Yolo_v4_conv	11 h 33 m 13 s	96.3665	1.1
ssd_inception_v2_coco	12 h 40 m 11 s	83.2187	1.6
Ssd_mobilenet_v2_coco	13 h 12 m 51 s	81.4452	1.7
Faster_rcnn_inception_v2_coco	14 h 03 m 36 s	89.4781	1.9

The above models were pretrained initially with COCO datasets, and then using transfer learning, the final layers were trained using the local vehicle datasets. The models were tested on a live CCTV stream. From the above results, the YOLOv4 architecture shows superior performance among the models that we tested. For the vehicle detection model, we used the YOLOv4 architecture and retrained the model completely using the local datasets. Finally, the trained model was tested with a live CCTV stream, and the following results were obtained, as presented in Table IV.

TABLE IV: TEST RESULTS FOR THE LIVE CCTV DATA

Model	Yolo_v4_empty
Training time	23 h 18 m 42 s
Accuracy	99.4329
Prediction time	1.2

The dataset consisted of 5 classes, namely, buses, three-wheeler, motorcycles, cars, and vans. Each category consisted of 300 to 500 images. Using the vehicle detection model, traffic information such as vehicle count, vehicle speed, and vehicle density was obtained for each lane. These data were passed into traffic analysis models.

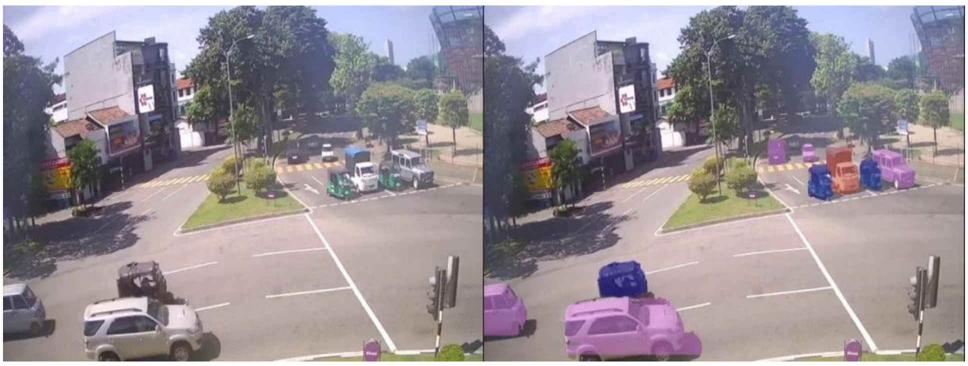

Fig. 4. Image labeling.

2) Traffic control: For traffic control, we used the Horton Place junction, Colombo, Sri Lanka (6.911472922759695, 79.87734081653434), as an experimental setup. A model of the Horton Place junction was built using the obtained, blueprints within SUMO and simulated the traffic using obtained vehicle counts and existing traffic light phase timings.

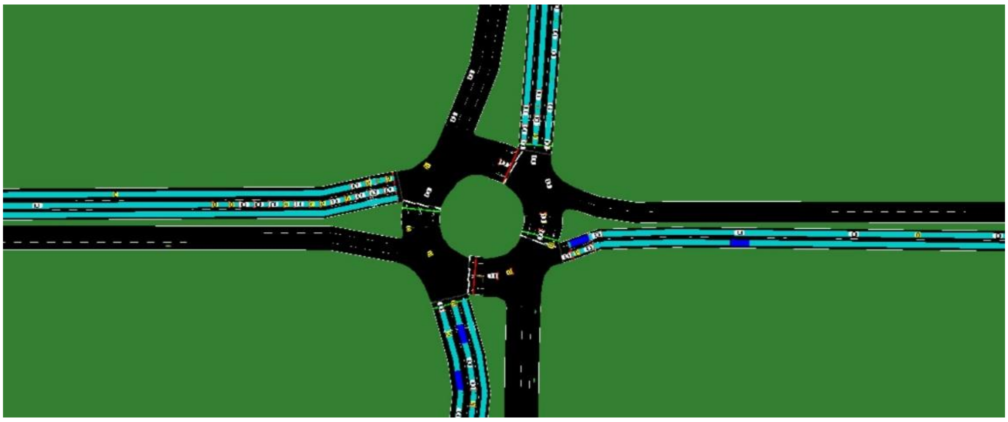

Fig. 5. Simulation of the Horton plains junction.

The traffic analysis model consists of two main parts. They are three Q-learning models and a phase separator. We were able to observe three distinct traffic patterns at three different ranges of traffic density, as in Table V.

TABLE V: TRAFFIC DENSITY LEVELS

Traffic Density Level	Average Traffic Density of Lanes in 30 s
High Level	29 +
Medium Level	14–29
Low Level	0–14

At each of the ranges of traffic density (0–14, 14 – 29, 29+), a distinct change in traffic flow was observed that needed separate traffic light patterns for each traffic density level. Therefore, each level needed a separate action space that became too complex for a single DQN. Therefore, we trained separate DQNs for each traffic level to simplify the process. The phase separator identifies the traffic patterns and allocates one of the three Q-learning models. Each Q learning model takes an input vector to consist of several parameters, including vehicle count, vehicle density, vehicle speed, vehicle queue length, vehicle delay times, and PCU values as the state of the environment. The Q-learning models were each trained using very high traffic densities, middle-level traffic densities, and low-level traffic densities. The phase separator model uses a buffer to collect traffic density counts and plots a graph of traffic density vs. time for low, medium, and high traffic scenarios, as depicted in Fig. 6. The graphs were collected and manually labeled as high density, medium density, or low density. Using a dataset of these graphs, a CNN classifier was trained to classify the graphs accordingly. When the model identifies the graph as one of the levels of densities, the scheme will choose the relevant Q-learning model to be deployed.

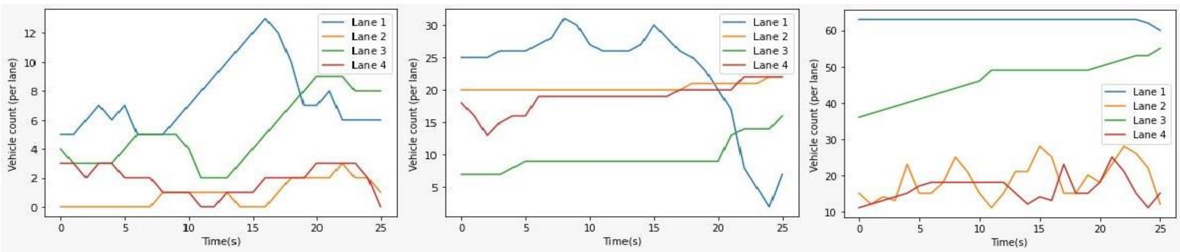

Fig. 6. Traffic density vs. time.

The agents were given a set of possible traffic light phase templates to choose as their actions. In the scheme, we trained the deep Q network with the data collected in SECTION III-A for 300 iterations, and the outcomes for low, medium, and high traffic scenarios are depicted in Fig. 7 below.

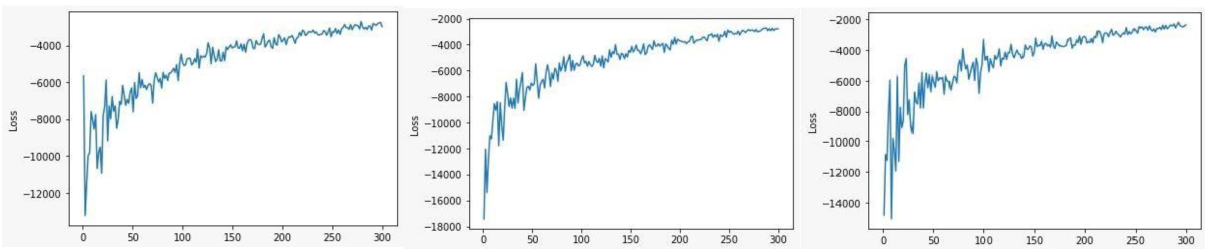

Fig. 7. Loss function response for 300 iterations.

The resultant trained model was connected with the vehicle detection module to create the overall scheme. The data obtained in the vehicle detection module were sent to the trained module, and the resultant traffic light phases generated by the model were fed to the traffic light scheme. The vehicle detection module observes the changes in the environment and sends the new vehicle traffic data to the trained model repeating the loop.

Here in this system, we separately trained three distinct models to compensate lack of information with regard to vehicle queues outside the range of CCTV observation.

In the low Traffic density scenario, only the observable vehicle count will be simulated to give an output. In the medium traffic density scenario, traffic is considered to be extended throughout the simulated lane length beyond the observational range. Finally, In the high traffic scenario, traffic beyond the observational range is considered to extend infinitely till the scenario changes.

3) System architecture: The system initially takes input from a CCTV feed and observes for 30 s. from the video feed, using a convolutional neural network (CNN), vehicles were identified and categorized *in*to various types. Each vehicle is assigned a PCU value according to its type, and a weighted count (PCU value x vehicle count) is taken as the vehicle density. By defining a region of space (RoS) for each lane and identifying vehicles at each end of the RoS and by calculating *the* average time taken to travel the RoS, a mean speed is obtained. By plotting Vehicle Count vs. Time graph for *the 30 s*. Traffic Level estimation can be obtained. A vehicle count graph will be sent to a CNN that will identify the traffic phase (Low, Medium, High) and assign a DQN that has the correct action space. The DQN will take vehicle density and mean speed as inputs. Each DQN consists of an agent, action space, and environment. The functionality of agents and environments are identical, while each DQN has a different action space. The DQN will choose a traffic signal pattern to be implemented in the next 30 s.

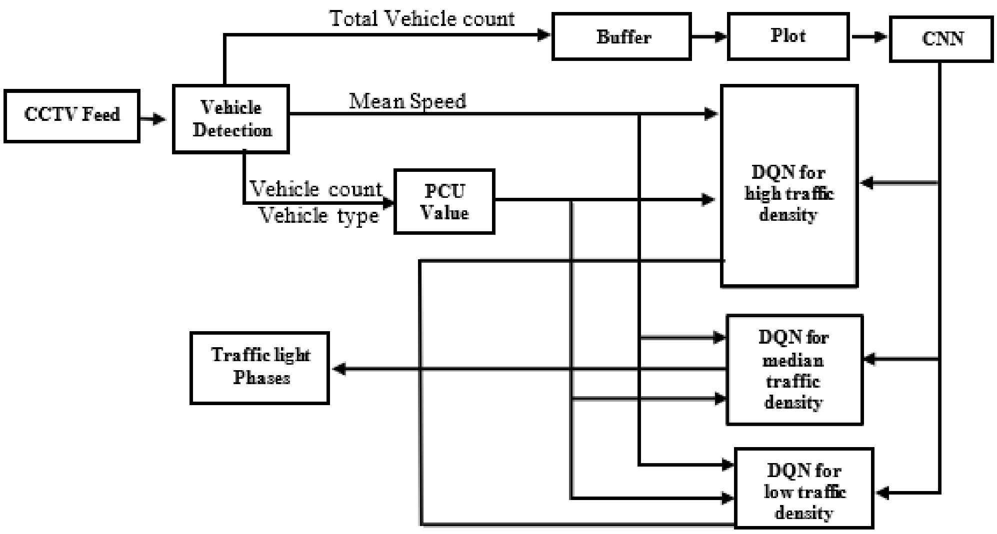

Fig. 8. System architecture.

IV. Results and Performance Analysis

A. Results

As discussed above, the proposed scheme is both adaptive and coordinated. Using the test data obtained in SECTION III-B, the simulation outcomes are as follows.

1) Comparison with existing static schemes: The proposed adaptive scheme showed enhancements in the following aspects, as presented in "Table VI."

a) Table VI shows that the average speed increased up to 5.597 km/h. The proposed scheme shows an average increment of 175.71% in average mean speed compared to the static schemes.

b) As shown in "Table VI," except for the high traffic scenario, for both mid traffic and low traffic scenarios, the proposed scheme shows a considerable improvement in both average densities and maximum densities.

In the mid-traffic scenario, the average mean speed shows an improvement of 3.85 km/h, while in the low-traffic scenario, the average mean speed shows an improvement of 7.96 km/h.

TABLE VI: Comparison between Previous Adaptive Scheme and New Scheme

		Average Mean Speed of a Lane (km/h)	**Average Density of a Lane (#Veh)**	**Average Max Density of a Lane (#Veh)**
Static Scheme		2.005	27.75	40
Previous Adaptive Scheme		3.79	22	38.75
Adaptive Scheme	High Traffic	0.98	29.3416	59
	Mid Traffic	5.85	14.61	37
	Low Traffic	9.96	1.19	6

2) Compared to the previously proposed scheme

a) The scheme was trained via 3 neural networks, each trained separately for different vehicle densities. Each traffic scenario, namely, high traffic density scenarios, mid traffic density scenarios, and low traffic density scenarios, was handled with uniquely optimized rules. Therefore, the overall results have been improved considerably.

b) In "Table VI," it is shown that the proposed scheme shows an improvement of 2.06 km/h. In the mid traffic scenario and a 6.17 km/h improvement in the low traffic scenario over the previous adaptive scheme [1].

In total, a 46.9% improvement in mean speed could be observed overall in the proposed scheme compared to the previously proposed adaptive scheme [1].

B. *Performance Analysis*

A comparison of traffic densities between the static scheme and the proposed scheme is plotted below.

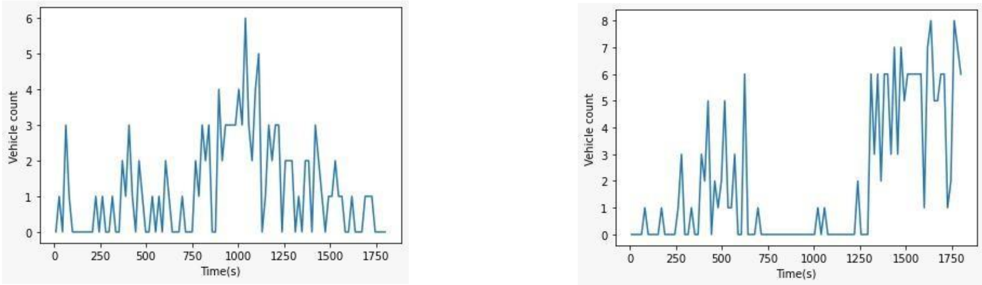

Fig. 9. Low traffic scenario with the proposed scheme and with the static scheme.

In the low traffic scenario, the average density of the static scheme shows a value of 1.89, while in the proposed scheme, the value has been improved up to 1.19.

For medium traffic scenarios,

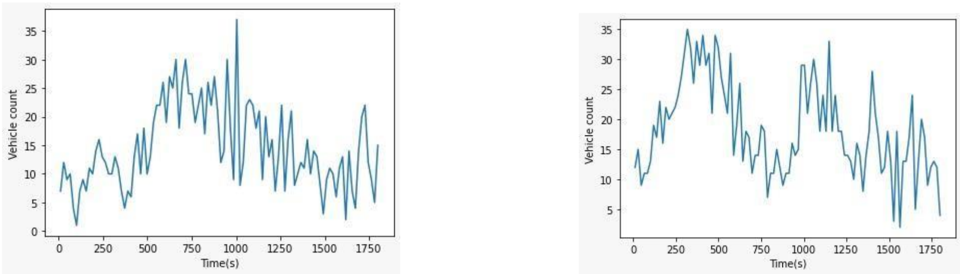

Fig. 10. Medium traffic scenario with the proposed scheme and with the static scheme.

In the medium traffic scenario, the average density of the static scheme shows a value of 18.35, while in the proposed scheme, the value has been improved up to 14.61.

For high traffic scenarios,

Fig. 11. High traffic scenario with the proposed scheme and with the static scheme.

In the high traffic scenario, the average density of the static scheme shows a value of 44.99, while in the proposed scheme, the value has been improved up to 29.34.

When comparing the theoretical output of our proposed system with established systems such as INSYNC (where fuel consumption has been reduced up to 33% [34]), our proposed system shows a 3.68% greater fuel consumption reduction. Compared to SCOOT (where fuel consumption has been reduced up to 5.7% [34]), our proposed system shows an approximately 31% greater fuel consumption reduction.

V. Conclusion

In this research, we introduced an adaptive traffic signaling scheme based on road traffic density to facilitate optimal traffic signal control as well as effective traffic management. We also proposed effective coordination of the traffic. The proposed scheme used live video as an input provided to a deep Q network to give adaptive phase timings as the output. Compared to the existing works, we introduced per car unit (PCU) as a novel input to represent the effect of each vehicle type on the traffic condition. Extensive tests on real-time data amply prove that the proposed scheme enhances the average speed of traffic up to 5.597 km/h. The proposed scheme shows an average increment of 175.71% in average mean speed compared to the existing static schemes. Except for the high traffic scenario, for both mid traffic and low traffic scenarios, the proposed scheme shows a considerable improvement in both average densities and maximum densities. In the mid-traffic scenario, the average mean speed shows an improvement of 3.85 km/h, while in the low-traffic scenario, the average mean speed shows an improvement of 7.96 km/h. The test results also indicate that our proposed solution, compared to the previously proposed scheme [1], provides a 46.9% improvement. From the calculations performed according to the AASHTO guidelines [48], daily fuel loss in the junction was reduced by 36.38%, and the average delay was reduced by 36.71%. Thus, the outcome of our research duly fulfills the objective of Transport 4.0, being more efficient and greener while optimizing the travel timings and minimizing costs for passengers overall.

CONFLICTS OF INTEREST

The authors hereby declare that there is no conflict of interest.

AUTHORS CONTRIBUTION

U.D.: Initial Conceptualization. U.D, and W.A.G.: Experimental setup. W.A.G., D.P.D, T.D.M., and. W.D.K.: Field testing; U.D., W.A.G., D.P.D, T.D.M., and. W.D.K.—Wrote the main manuscript text. W.A.G., D.P.D, T.D.M., and. W.D.K.: Prepared Figs. U.D., W.A.G., and D.P.D.—wrote the analysis section. U.D.: Reviewed the final manuscript.

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Gayashan Weerasundara is with Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka.
Orcid: https://orcid.org/0000-0003-1419-8938

He completed BSc honors in electronics & telecommunication engineering from the Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka and currently he is pursuing his post-graduate studies. His current research interests include agriculture 4.0 and artificial intelligence.

Pasindu Udugahapattuwa is with Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka.
Orcid: https://orcid.org/0000-0001-6318-7392

He completed BSc honors in electronics & telecommunication engineering from the Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka and currently he is pursuing his post-graduate studies. His current research interests include optimization and transport 4.0.

Thamali Munasingha is with Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka.
Orcid: https://orcid.org/0000-0002-2319-4130

Thamali Munasingha completed BSc honors in electronics & telecommunication engineering from the Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka and currently pursuing her post-graduate studies. Her current research interests include NextGen networks and transport 4.0.

W. D. K. Gunathilake is with Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka.
Orcid: https://orcid.org/0000-0002-6706-4151 W. D. K. Gunathilake completed BSc Honors in electronics & telecommunication engineering from the Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka and currently pursuing his post-graduate studies. His current research interests include transport 4.0.

Udaya Dampage (Senior Member, IEEE; Fellow, Institution of Engineers, Sri Lanka) is an Engineering Consultant, a Platinum Grade Inventor and currently working as a Senior Lecturer at Faculty of Engineering, General Sir John Kotelawala Defence University, Sri Lanka. He was conferred with Presidential Awards for his inventions in 2016. His research interests include NextGen networks, agriculture 4.0, smart grid integration, transport 4.0, society 5.0.
Orcid: https://orcid.org/0000-0003-0151-8218.