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TRAFFIC MANAGEMENT USING IMAGE RECOGNITION AND MACHINE LEARNING

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ABSTRACT

Traffic lights, one of the methods of managing traffic, will greatly affect the waiting time of cars at junctions. This study aims to examine the performance of the intelligent traffic control system (ITCS) compared to the traditional and widely used fixed cycle traffic light (FCTL) control system in Malaysia. The object recognition model uses Tensorflow to identify the waiting cars at the junction. Simulation was done using Pygame with different car spawn rates at each junction during peak and non-peak hours. The simulation results show that the improvement in the average waiting time for cars is reduced when the spawn rate of cars increases. ITCS is capable of reducing the average waiting time of cars during non-peak hours by 25% or 3.6 seconds with a car spawn rate of 4 seconds at each junction. It has been identified that this ITCS design is capable of handling low traffic conditions very well. In peak hours, ITCS seems to struggle with the algorithm setting that was set during this study.

***Keywords**: Fixed cycle traffic light (FCTL), intelligent traffic control system (ITCS), object recognition, simulation, vehicle*

INTRODUCTION

Due to the increasing amount of total land transport in Malaysia, the breaking records of new car registration have posed a serious issue in traffic conditions [1]. Malaysians prefer using a car to travel instead of public transport [2], which means more cars are on the road and cause traffic congestion.

Traffic congestion often happens in specific, small critical areas, and there is poor traffic management [3]. Traffic lights serve as a tool to regulate traffic flow [4]. It often deals with the traffic that arrives from different areas. To manage the traffic flow more efficiently, this study aims to solve the difficulties faced by the traffic light system to manage the traffic flow. There are several difficulties with the traffic light in managing the traffic, which pose the problem statement of this study.

Problem Statement

The fixed cycle traffic light (FCTL) control system is a common use of the traffic light system in Malaysia. This system does not consider the real-time condition, making it unable to fit with the dynamics of the traffic volume [5]. The traffic volume may vary from time to time, causing different conditions and fixed duration cycles that are unable to manage the complicated traffic conditions. The peak hour in a junction differs from other junctions and may vary from time to time or day to day. A fixed duration cycle on the traffic light is unable to regulate the traffic efficiently. The traffic lights do not have enough flexibility to accommodate any unexpected conditions at the traffic junctions, such as road blocking, road accidents, road maintenance and many more. Therefore, this study aims to propose an intelligent traffic control system (ITCS). ITCS is a traffic control system that uses new technologies such as machine learning and artificial intelligence to provide flexibility in traffic management compared to traditional FCTL systems.

The objectives of this study are:

1. To study and evaluate the performance of the FCTL control system and the ITCS in managing the traffic flow using a dynamic duration cycle compared to a fixed duration cycle.
2. To identify the better parameter setting for the ITCS algorithm using simulation.

This study proposes an approach to traffic signal control. It addresses the limitations of the existing system and aims to improve traffic flow in response to real-time conditions and irregular events.

LITERATURE REVIEW

FCTL System

The FCTL system is commonly used in Malaysia. The cycle of the red and green light times has been set in the traffic control system; any changes in the design of the nearby road will impact the efficiency of the system in controlling the traffic conditions. Timmerman and Boon [6] identified the features of FCTL and listed them down, which are the consistent red and green light duration, arrival process, constant inter-departure times, and the fact that it does not turn red after the junction has cleared of cars. This method is not able to manage the dynamic traffic volume and the complicated traffic conditions.

Area Traffic Control (ATC) System

The ATC system is a system that monitors the number of vehicles and their respective speed using the detector loops installed on the vehicle lanes. This helps the traffic control system to determine the traffic flow using two techniques, named Split Cycle Offset Optimisation Technique (SCOOT) and Sydney Coordinated Adaptive Traffic System (SCATS) [6]. This method is not efficient enough, as the techniques do not provide rapid responses to any fluctuations in the traffic.

ITCS

An ITCS is a system that involves machine learning processes and artificial intelligence to enable object recognition, computer vision, and reinforcement learning [7]. Data collection devices such as sensors, detectors and cameras have been used to provide computer vision for object recognition. The algorithm used to control the traffic signals will be developed using these technologies to encounter the traffic flow dynamically.

Previous Work

Ng and Kwok [5] proposed an intelligent traffic light system (ITLS) in 2020 that identifies the vehicles in a real-life scenario and increases the efficiency of the traffic control system by around 50% for peak and non-peak hours compared to a fixed-cycle traffic light system. Uddin et al. [8] used an object detection method, such as real-time area-based traffic density estimation, to estimate the traffic density for a future traffic control system. Smith et al. [9] monitor the number of vehicles based on the detectors installed under every vehicle lane in the intersection, reducing the traffic waiting time by around 40% for different peak periods.

Wei et.al. [10] proposed a reinforcement learning approach by developing the model framework, agent design, network structure and memory palace to train the model. This brought an improvement of around 25% in efficiency compared to conventional methods.

Chavan et al. [11] designed a controller using an embedded system in 2009, using sensors mounted on roads to identify the length of the vehicles on each road. The waiting time of the vehicles has decreased by 3-5 seconds compared to the FCTL system [11], while Fahmy [12] used fibre optic traffic sensors to detect the traffic entering and leaving the section. The duration of the green light will be extended based on the traffic volume at each junction. Maged [12] and Yousef et al. [13] suggested a method for the traffic flow control system using wireless sensor networks. This results in a decrease of approximately 350 seconds of average waiting time on dynamic control for a 500-second simulation compared to a fixed cycle traffic control system.

Anirudh et.al. [14] use distributed reinforcement learning to regulate the traffic using an algorithm simulated in simulation of urban mobility (SUMO). Lane area detectors were being used to detect the amount of traffic waiting at the signals. The results show an improvement in waiting time [14].

Lin et.al. [15] proposed the concept of mobile intelligent traffic control system (MITCS) in 2009. It consists of an embedded system with a traffic control device, sensors, a camera and an embedded controller. This proposed concept shows the possibility of using cameras and vehicle detectors with a traffic control system to regulate the traffic flow.

Reza et al. [16] suggested another combination of deep learning and image processing approaches to develop ITCS. The article reviews the various techniques for predicting the traffic state and controlling the intersection traffic signal. It mentioned the rapid increase and decrease in traffic flow in the morning and evening due to society's behaviour. 42.9% out of 71 studied articles in [16], showing the popularity of using reinforcement learning on intersection traffic signal control between 2019 and 2021. Figure 1 shows the pie chart of the document published based on techniques between 2019 and 2021.

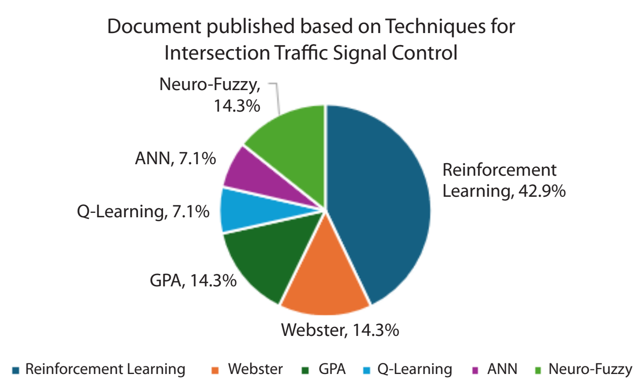

Figure 1 Pie chart of documents published based on techniques between 2019 and 2021

The previous work on the traffic control system can be summarised in Table 1.

Table 1 Summary of previous work

Source of Data	Technique used	Ref
Object Detection with video footage	Tensorflow Traffic control algorithm	[6]
Using a camera to capture images	Image processing or cleaning	[8]
Detectors under the vehicle lane in the stop zone and the exit lane	SURTRAC, Traffic signal controller	[9]
SUMO simulation Surveillance camera	Reinforcement learning, ITCS	[10]
Sensor mounted on the road	Embedded system	[11]
Fibre optic traffic sensor	Extend the green light based on traffic volume	[12]
Sensor nodes are placed on a road section	Wireless sensor network	[13]
Lane area detectors	Reinforcement learning using SUMO with a traffic control algorithm	[14]
Sensors and cameras	Embedded system (provide concept)	[15]
N/A	Image processing and deep learning	[16]

Table 1 shows that more researchers have used sensors and detectors on the vehicle lane. This ensures that the traffic control system has full control over the traffic conditions from entering the waiting zone to leaving the exit lane. There is less research regarding object detection with simpler algorithms [6]. It reduces the hardware and software requirements for the traffic control system setup, reducing maintenance costs.

Object detection is becoming famous in the field of data science [17]. It is widely used as data input with machine learning techniques such as supervised, unsupervised, reinforcement, and artificial intelligence. TensorFlow has been used in object detection in [6] to detect vehicles in the waiting zone. This technique provides another option for collecting data regarding traffic conditions.

In contrast to the previous works, the proposed method in this research focuses on using a machine learning method with a camera to capture images to obtain the traffic condition data instead of devices that are placed on the road. The image will be processed through YOLOv8, which is trained using the synthetic and real-life datasets.

METHODOLOGY

Data Collection

The data collection for this object can be separated into two different datasets, one is the synthetic dataset, which can be used to train and test the object recognition model, while the real-life dataset can be used to test the model in real-life conditions.

Synthetic Dataset

This data was obtained from Soetanto [18], which also provided the images used to train the object recognition model. A total of 21723 images have been used to train the object recognition model. The dataset includes images of various types of vehicles. This dataset will be separated into two groups; 80% of the images will be used to train the object recognition model, while the other 20% will be used to validate the object recognition model. Figure 2 shows an example of images trained in the object recognition model.

Figure 2 Example of images trained on the object recognition model

Real-Life Dataset

This data was collected from traffic junctions in Malaysia. The image has been fed into the object recognition model to study the accuracy of the model for the traffic junction in Malaysia and count the number of vehicles in the specific traffic junction.

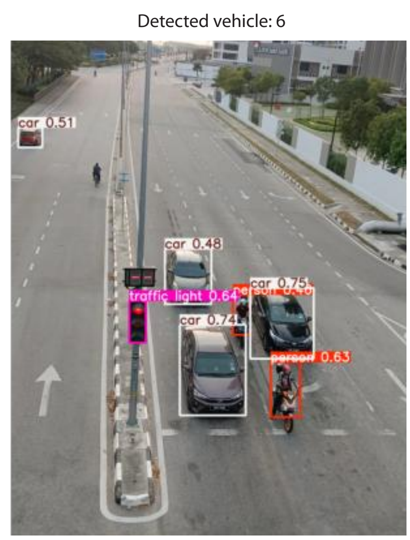

Figure 3 Output of the object recognition model under the sample image of the real-life dataset

Object Detection

The object detection model has been trained with YOLOv8 using TensorFlow. The images have been fed to the model. The trained model was able to identify the object that appears inside the image and provide the number of vehicles in the waiting zone. Figure 3 shows the output of the object recognition model under the sample image of the real-life dataset.

Simulation

The traffic conditions were simulated on a T-junction using Pygame. There are several restrictions and assumptions on this simulation:

1. T-junctions have been simulated with two junctions (Junction Left to Right and Junction Top to Bottom).
2. No pedestrians are involved in this simulation.
3. The traffic flow will be simulated in different conditions by using the spawn rate of cars.
4. FCTL and ITCS have been simulated.
5. In FCTL, the green light is fixed to 15 seconds while the yellow light is 5 seconds.
6. Only one car will start moving every second.
7. The waiting time will only be calculated after the second cycle of the traffic light.
8. The spawn rate is set to be fixed for every simulation for both FCTL and ICTS to ensure fair comparison.

9. For ICTS, the junction has been given 3 seconds of green light duration after there are no waiting cars.

Figure 4 shows the simulation program using the PyGame packages in PyCharm.

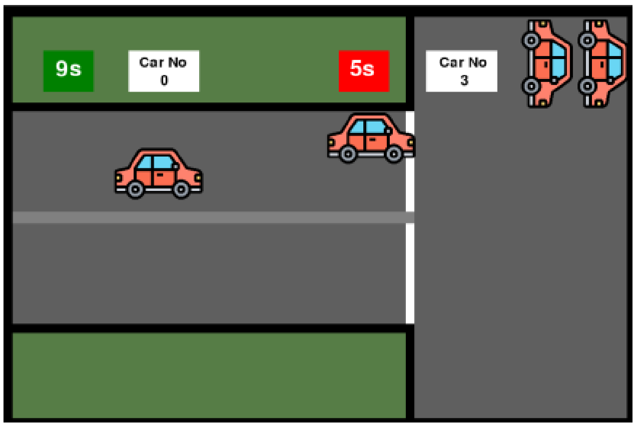

Figure 4 Simulation program using Pygame packages in PyCharm

The simulation program shows the number of cars waiting at the junction as well as the traffic light condition and duration. Two lanes of cars will be simulated, from left to right (LR) and from top to bottom (TB). The number of cars that are waiting for a green light will be shown in the simulation program. The waiting time for the car was collected after the car reached the stop position.

Table 2 shows the changes of spawn rate on FCTL. The condition A1, A2 and A3 will be simulating the peak condition whereby the spawn rate of cars is shorter with 1 to 3 seconds per car spawning out from each direction. Condition B1 and B2 shows a lower spawn rate of 4 and 5 seconds per car to spawn in each direction. This simulation is to create a baseline to compare the performance of FCTL with the performance of ICTS in the same condition.

Table 2 Changes in the spawn rate on FCTL

Condition	Peak/ Non-Peak	Spawn Rate (Left to Right)	Spawn Rate (Top to Bottom)
A1	Peak	1 seconds /car	1 seconds /car
A2	Peak	2 seconds /car	2 seconds /car
A3	Peak	3 seconds /car	3 seconds /car
B1	Non-Peak	4 seconds /car	4 seconds /car
B2	Non-Peak	5 seconds /car	5 seconds /car

Traffic Control Algorithm

Several conditions need to be satisfied to allow traffic control on the green light and red-light duration. The parameters will be identified as the condition that needs to be satisfied by the traffic control system to alter the duration of the green light. The critical parameters and their purposes are listed in Table 3.

Table 3 Parameters of the intelligent traffic control algorithm

Parameter	Purposes
Number of cars at the junction	Baseline on the number of cars in the waiting zone
Maximum number of cars at the junction	Record the maximum number of cars in the system during the cycle
Total number of cars at the junction	To calculate the green light duration given to the specific junction
Minimum green light duration	Ensure that the green light duration allows the cars to pass the junction
Maximum green light duration	Ensure that the busiest vehicle lane can have the longest green light duration
Yellow light duration	Fixed to 5 seconds to ensure the car can pass through the junction fully

These parameters act as a threshold or a condition for the traffic control algorithm. The design of the algorithm of FCTL and ITCS can be illustrated as Figures 5 and 6.

In Figure 6, the durations of the red light, green light, and yellow light for the fixed cycle traffic light control

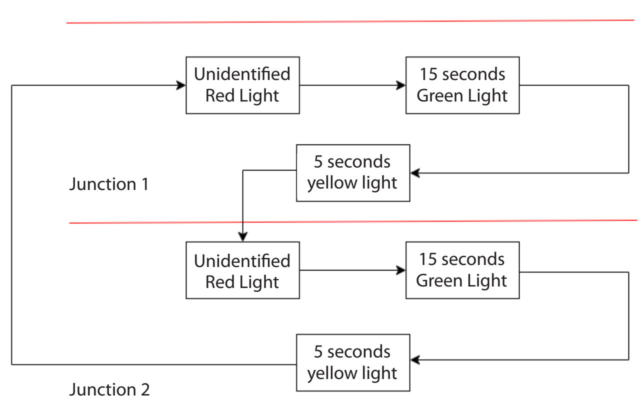

Figure 5 Proposed flow diagram of FCTL control system

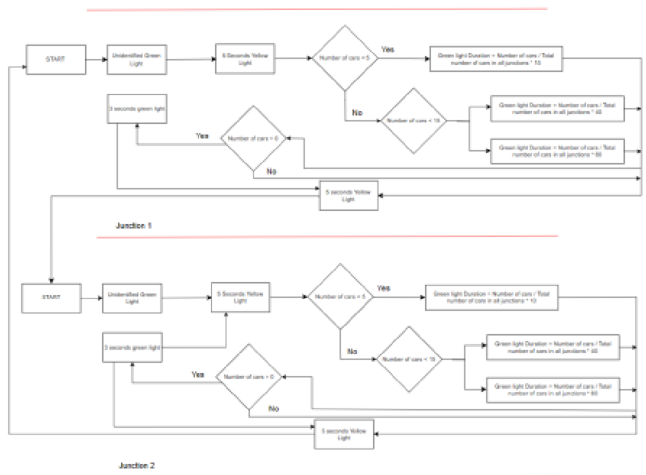

Figure 6 Proposed flow diagram of an intelligent traffic control system

system are the same throughout the three junctions. For intelligent traffic control systems, use conditions that identify the duration of the red light and green light. The condition will be based on the parameter stated in Table 3.

The algorithm set for the ITCS starts with a red light. The object detection model developed using datasets will identify the number of cars waiting in the waiting zone before the red light ends. The number of cars provided will calculate the duration of the green light once the red light ends. No car in the waiting zone will set the green light duration to the minimum green light duration. The number of cars in the waiting zone will be based on the formula to calculate the duration of the green light. After the green light ends, it will have 5 seconds of yellow light.

To further understand the best algorithm setting, the simulation program able to calculate and show the graphical results of the average waiting time of cars. By changing the simulation, the best parameter setting and the efficiency of the algorithm to the traffic condition can be identified. The change of traffic condition to test the modified simulation has been shown in Tables 4 and 5. Table 4 shows the changing on spawn rate while Table 5 shows the changing on algorithm setting.

The default value of the total green light duration when the total number of cars for both junctions is less than 5 is 10 seconds, for a total number of cars less than 15 is 40 seconds, while for a total number of cars less than 30 is 60 seconds.

Table 4 Changing on spawn rate

Cycle	Peak/ Non-Peak	Spawn Rate per car (Left to Right) (seconds)	Spawn Rate per car (Top to Bottom) (seconds)
1	Peak	1	1
2	Peak	2	2
3	Peak	3	3
4	Non-Peak	4	4
5	Non-Peak	5	5

Table 5 Changing on the algorithm

Cycle	S Spawn rate (seconds /car)	Total green light duration for the total number of cars less than		
		5	15	30
1	3	5s	40s	60s
2	3	30s	40s	60s
3	3	10s	20s	60s
4	3	10s	50s	60s
5	3	10s	40s	80s

Model Evaluation

To identify the performance of the developed algorithm on the intelligent traffic control system and fixed cycle traffic light control system, the average waiting time of the cars has been calculated. The differences in the average waiting time during peak hours and non-peak hours for both FCTL and ITCS have been calculated. The maximum number of cars waiting at the traffic junction has been observed to identify the traffic conditions.

RESULTS AND DISCUSSIONS

The waiting time and the maximum number of cars waiting at the junction for each condition have been observed and calculated. The results have been discussed and summarised into a graph using simulation software.

FCTL

Figure 7 shows the FCTL results generated by the software. The results have been simulated with 15 seconds of green light duration for both junctions, LR and TB.

Figure 7 shows the average waiting time data for junctions LR and TB. It shows that the first cycle has the highest average waiting time of 34.8 seconds for junction LR and 36.6 seconds for junction TB. According to Table 2, the spawn rate for both junctions is 1 second/car, which is a peak traffic condition for both junctions. During the simulation, it shows that the car starts to age after a few cycles and eventually causes a traffic jam with the slow cycle of FCTL. This can be seen in the results of Cycles 2,3,4, and 5. Cycles 2, 3,4 and 5 have almost the same value on the average waiting time. This shows that the simulation has the capability to simulate the junctions realistically according to the algorithm provided to the simulation. The graph also shows the equation for both junctions. Junction LR has the equation of:

$$y = -5.16x + 29.72 \tag{1}$$

while junction TB has the equation of:

$$y = -7.12x + 34.36 \tag{2}$$

Equation 1 shows that the junction LR has a steep decrease in the relationship between the spawn rate of cars and the average waiting time. When cars are being spawned continuously in the simulated junction, there will be a waiting time of 29.72 seconds in junction LR. Junction TB has a steeper gradient, greatly decreasing when the spawn rate decreases. The waiting time in junction TB is 34.36 seconds when cars are spawning continuously in junction TB. This shows the weakness of the algorithm set in the ITCS of this experiment, as the system is unable to handle an extremely large amount of traffic flow at one time. Equation 1 also shows that when the cycle increases by 1, which leads to a spawn rate increase by 1 second/car, the average waiting time of the car reduces by 5.16 seconds, while junction TB has a reduction of 7.12 seconds for every second reduction of the spawn rate.

ITCS

Figure 8 shows the results of the Intelligent Traffic Control System generated by the software. The results have been simulated with 15 seconds of green light duration for both junctions.

Figure 8 shows a similar result to the FCTL system, that when the spawn rate of the car decreases, the average waiting time of each car decreases. The graph shows the equation for both junctions. Junction LR has the equation of:

$$y = -8.12x + 38.64 \tag{3}$$

while junction TB has the equation of:

$$y = -7.04x + 33.28 \tag{4}$$

Equation 3 shows that the junction LR has the highest value of 43.60 seconds of average waiting time, and junction TB has 35.60 seconds when the spawn rate of cars is 1 second/car. This causes car ageing and shows the capability and limitations of the ITCS in handling traffic. Equations 3 and 4 show a steeper gradient, showing the advantages of the ITCS in handling a lower spawn rate that would not cause traffic congestion.

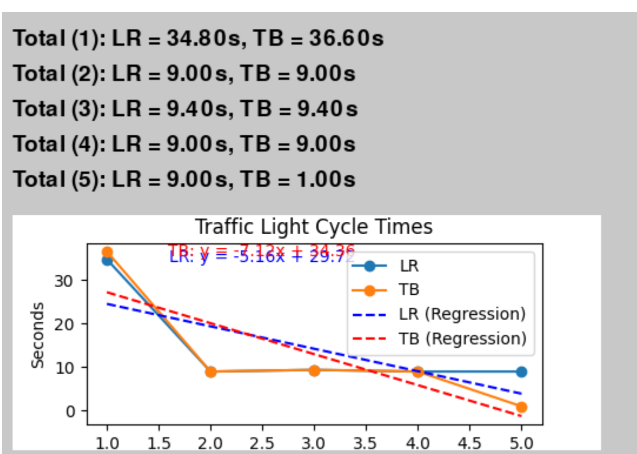

Figure 7 FCTL results generated by simulation

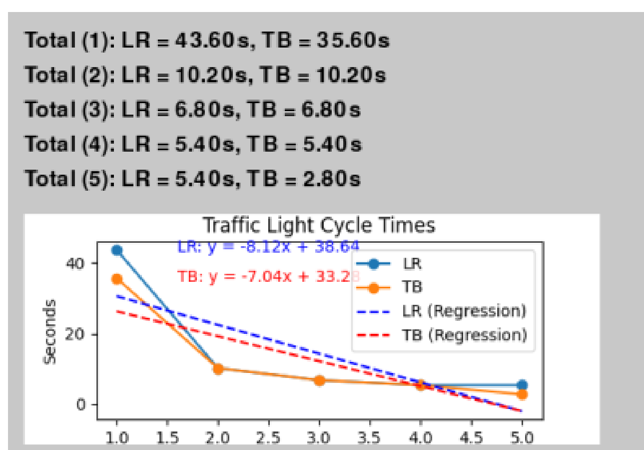

Figure 8 FCTL results generated by simulation with a change of car spawn rate

To identify the best setting for the ITCS algorithm, the simulation has been done based on Table 5. The results have been shown in Figure 9.

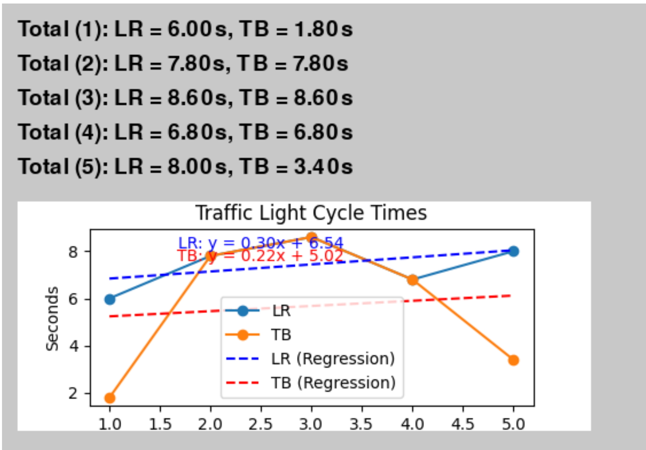

Figure 9 ITCS generated by simulation with a change in the ITCS algorithm

According to Table 5, it shows that cycle 1 and cycle 2 identify the change of the algorithm when total number of cars for both junction is less than 5, by changing the value, it shows that when increasing the green light duration, the average waiting time for each car increases, encouraging lower green light duration.

Cycles 3 and 4 show the change of the algorithm when the total number of cars in both junctions is less than 15. It shows a decrease in the average waiting time when the green light duration increases from 20 to 50, according to Table 5. This shows that the simulation encourages higher green light duration.

Cycle 5 shows the change of the algorithm when the total number of cars in both junctions is less than 30. It shows a decrease in average waiting time when the green light duration increases from 60 to 80 seconds compared to the average waiting time with Cycle 3 in Figure 8. The average waiting time for both junctions has reduced by 1.1 seconds. This shows that the green light duration when the total number of cars in both junctions is less than 30 should increase to reduce the average waiting time of each car.

Comparison of FCTL and ITCS Performance Across Varying Spawn Rates

Table 6 shows the differences between FCTL and ITCS in terms of improvement. It shows that when the spawn rate increases, the ITCS has a better advantage compared to FCTL. When the spawn rate is at 1 second, the FCTL is better in terms of waiting time by 5.18% compared to ITCS. This is because ITCS uses the extra waiting time when there are no cars in the junction to release the car at the other junction. However, according to the simulation, the number of cars waiting to be released from the junction is smaller. When no extra waiting time is available, the ITCS algorithm takes 60 seconds to the maximum green light duration, which is unable to release all the cars at the junction, causing traffic congestion. The maximum green light duration can be discussed in a future study to further understand the optimal algorithm for handling extremely high traffic volume. When the spawn rate is more than or equal to 3 seconds, ITCS has better advantages in handling the extra waiting time to release the car from another junction. It hits the maximum improvement of 25% when the spawn rate of cars is every 4 seconds. The advantage decreases when the spawn rate is 5 seconds/car. This is due to FCTL handling the traffic condition well, showing that ITCS loses its advantage when there is plenty of extra time to release the car at both junctions.

Table 6 Average waiting time for simulation on FCTL and ITCS

Spawn Rate (second/car)	FCTL (Avg)		ITCS (Avg)		Average (FCTL)	Average (ITCS)	Differences (%)
	LR (s)	TB (s)	LR (s)	TB (s)			
1	34.8	36.6	43.6	35.6	35.7	39.6	-5.18
2	9.0	9.0	10.2	10.2	9.0	10.2	-6.25
3	9.4	9.4	6.8	6.8	9.4	6.8	16.05
4	9.0	9.0	5.4	5.4	9.0	5.4	25.00
5	9.0	1.0	5.4	2.8	5.0	4.1	9.89

CONCLUSION

In conclusion, the performance of the FCTL and ITCS system have been studied. The performance of ITCS is better compared to FCTL system with a shorter average waiting time for each car for at least 25% in non-peak hours for one car enters the junction every 4 seconds. For future work recommendations, it will be focus on object detection model and the simulation. Image quality and quantity can help improve the object detection model in counting the number of vehicles by providing more images taken from the top of the car to simulate the position of the traffic light. YOLOv8 also provides tuning capability to the user to adjust the parameter to further improve the accuracy of the model. For simulation, the parameter of the algorithm can be studied to obtain better performance of ITCS. More junctions can be simulated as well to mimic the real-life situations.

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