Avrupa Bilim ve Teknoloji Dergisi
Sayı 20, S. 866-871, Aralık 2020
© Telif hakkı EJOSAT'a aittir
Araştırma Makalesi



www.ejosat.com ISSN:2148-2683

European Journal of Science and Technology
No 20, pp. 866-871, December 2020
Copyright © 2020 EJOSAT
Research Article

An Adaptive, Distributed and Intelligent Traffic Light System

Mehmet Dinçer Erbaş[1*]

[1] Bolu Abant İzzet Baysal University, Faculty of Engineering, Department of Computer Engineering, Bolu, Türkiye (ORCID: 0000-0003-1762-0428), dincer.erbas@ibu.edu.tr

(First received 1 November 2020 and in final form 12 December 2020)

(**DOI:** 10.31590/ejosat.831348)

ATIF/REFERENCE: Erbas, M. D. (2020). An Adaptive, Distributed and Intelligent Traffic Light System. *European Journal of Science and Technology*, (20), 866-871.

Abstract

In this study, it is aimed to create a low cost adaptive traffic light system. For this purpose, a probabilistic, discrete-time traffic simulator has been developed that can be used to model existing traffic networks. A unique adaptive traffic light system, which achieves higher service quality compared to a fixed time adjusted traffic light system, was developed and tested on the simulator. It has been shown that the developed system can manage the traffic flow in real time and is not affected by the information loss caused by the oversaturation of the modeled roads.

Keywords: intelligent transport system, multi-agent simulation, load balancing

Uyarlanabilir, Dağıtılmış ve Akıllı Trafik Işık Sistemi

Öz

Bu araştırmada, düşük maliyetli bir uyarlanabilir trafik ışığı sistemi oluşturulması hedeflenmiştir. Bu amaçla öncelikle mevcut trafik ağlarını modellemek için kullanılabilecek olasılıksal, ayrık zamanlı bir trafik simülatörü geliştirilmiştir. Geliştirilen simülatör üzerinde sabit zaman ayarlı bir trafik ışığı sistemi ile karşılaştırıldığında daha yüksek hizmet kalitesine erişen, özgün bir uyarlanabilir trafik ışığı sistemi geliştirilmiş ve test edilmiştir. Geliştirilen sistemin gerçek zamanlı olarak trafik akışını yönetebildiği ve modellenen yolların aşırı doygunluğundan kaynaklanan bilgi kaybından etkilenmediği gösterilmiştir.

Anahtar Kelimeler: akıllı ulaşım sistemi, çok-etmenli simülasyon, yük dengeleme.

[*] Corresponding Author: Bolu Abant İzzet Baysal Üniversitesi, Mühendislik Fakültesi, Bilgisayar Mühendisliği Bölümü, İstanbul, Türkiye, ORCID: 0000-0003-1762-0428, dincer.erbas@ibu.edu.tr

1. Introduction

Intelligent Transport Systems (ITS) aim to provide safer, smarter, more efficient and highly coordinated use of transport networks for vehicles and pedestrians (Dimitrakopoulos and Demestichas, 2010). Since 1970's, different types of ITS have been built as an alternative to preset, fixed-time traffic light systems in many cities all over the world. In addition to higher quality of service for the users of the transport networks, ITS aim to provide a considerable reduction in air pollution and fuel consumption. Recent studies inform that the economic gains that can be achieved by ITS are considerably high (Studer et al., 2015).

An ITS roughly contains 3 main components. First, it has a sensing module that collects real-time data about some specific properties of the on-going traffic. For this purpose, a number of different detector systems have been utilized, including video detectors (Chintalacheruvu and Muthukumar, 2012), inductive detectors (Gajda et al., 2001) or radar detectors (Garcia et al., 2012). Based on these sensory systems, a number of metrics, such as number of waiting or approaching vehicles or average waiting time for vehicles or pedestrians, are computed in order to build adaptive systems.

Second, an ITS should have an analysis module, in which, the calculated metrics are matched with some environmental facts that explains the current situation of the transportation network. For instance, an increased waiting time for vehicles passing through a specific intersection is taken as a signal of high congestion. In some systems, these analysis are made in a completely automated fashion based on some predefined rules (Hunt et al., 1982). Other systems involve manual inspections by technicians (Slavin et al., 2013).

Third, based on the output of the analysis module, every ITS has a decision module that formulates necessary modifications on the parameters of the system so that the transportation network can adapt to the current traffic load. The electronic devices, whose parameters can be modified by the decision module, act as the actuators of the ITS. The main devices that are controlled by the system are traffic lights; almost all ITS attempt to compute the cycle time and specific green light intervals of traffic lights that are present on intersections. In addition to traffic lights, some systems make use of changeable message signs to inform drivers and pedestrians about some events on the transportation network.

Based on the specific properties of its main components, we can define some desirable characteristics of an ITS:

- The sensing module should be simple and cheap to implement and it should depend on the local information that can be captured in real-time. Furthermore, the information that is captured should be reliable enough to make adaptive decisions and it should not be affected by the environmental factors. Most systems make use of complex sensor technologies that attempt to capture the size, speed and direction of motorized vehicles and pedestrians that approach a specific intersection. Achieving such a complex task involves object detection, identification and tracking in real-time. It is reported that such systems are highly prone to errors especially on short roads that can get easily congested. In addition, these systems are highly expensive as they incorporate advanced video cameras or other type of sensors (Studer et al., 2015).

- The analysis module should be distributed over the transportation network. Some ITS have central controlling units (Hunt et al., 1982) that collect data from all intersections of the transportation network on which the systems have control on. As today's transportation networks tend to grow larger and complex in time, adding new nodes to such systems costs very high. In such systems, in order to include new nodes in the system, the operators have to manually modify some parameters of the system, and this process results with an additional maintenance and personal cost (Studer et al., 2015).

- The decision module of the ITS should be implemented in such a way that it is easy and cheap to upgrade the existing electronic infrastructure of the transportation network to include ITS related functionalities. Some ITS require large installation bases which result with a need for spaces on the current network and causes additional high costs (Studer et al., 2015).

The main objective of this study is to implement a distributed, low-cost, adaptive, intelligent traffic light system that can be implemented in any part of a transportation network. In order to do that, we first implement a probabilistic, discrete-time traffic simulator that can model traffic networks, that consist of a variable number of roads and intersections, with different traffic loads. On this simulation, we model a simple transportation network that consist of a single intersection which is present in a residential area in the Bolu province of Turkey. On this model, we implement and test a novel, adaptive traffic light algorithm that depends on the local information captured through simple sensors mounted on the existing traffic lights. It is shown that, compared with the fixed-time green light setting that is currently used on the modelled intersection, our adaptive algorithm achieves a higher service quality as we observe a decreased waiting time for vehicles that pass through the modelled intersection. Our algorithm works in real time and it is not affected by the information loss due to over saturation of the modelled roads.

The article proceeds as follows: in section 2, we present some well-known ITS that is widely used in many cities. Section 3 presents SimTraffic simulation software that we developed in order to test our adaptive algorithms. In section 4 we present our novel, adaptive traffic light control system. Section 5 shows some results about the adaptive control system. Finally, section 6 concludes the paper and mentions some further future work.

A number of ITS have been developed and effectively used in many cities since 1970's. One of the most well-known and widely-used ITS is SCATS (Sydney Coordinated Adaptive Traffic System) (Slavin et al., 2013). Originating from Sydney Australia, SCATS have been installed in approximately 55,000 intersections in 187 cities of 28 countries worldwide (Homepage | SCATS, 2020). The main idea behind SCATS is to have a distributed network of sensors that captures traffic related information, including number of vehicles waiting in each lane and pedestrians waiting to cross at all intersections. This information is then transferred to the central office in which an automated plan selection is made based on the acquired data. The system allows manual inspection and plan selection by the operators in the central office, therefore, the maintenance and management cost of the system is high. Furthermore, once the system is operational, adding new intersections to the system means modifications and re-planning in the central office. The selected plans include green light intervals and cycle lengths of traffic lights in the network. The system is mainly designed to cover a metropolitan area and reported cost of installation, excluding maintenance and

operational costs, is around 7,500 to 12,000 € per intersection (Studer et al, 2015). As the adaptive algorithm depends on the data that counts the number of waiting vehicles, it is reported that SCATS suffers from the ineffective capture of real-time traffic data when the transportation networks is over-saturated. It is especially a serious issue in short roads that can get easily congested.

SCOOT (Split Cycle Offset Optimization Technique) (Bretherton et al., 2006) is another type of ITS that originated from United Kingdom during 1970's. Nowadays, it is installed 350 cities worldwide (SCOOT™ – TRL Software, 2020). Similar to SCATS, SCOOT has a network of sensors that are installed on every intersection. These sensors collect information about approaching vehicles by using a set of inductive loops or other types of detectors. It has been reported that the correct location, continuous calibration and maintenance of these sensors are crucial for the success of the SCOOT system (Robertson and Bretherton, 1991). The perceived information about the real-time traffic is sent to the central computer which submits necessary adjustments on the cycle time and green light intervals to the intersections. Its installation cost is between 15,000 to 19,000 € per intersection and it is reported that it may achieve a low performance on over saturated short roads (Studer et al., 2015).

COMPASS (also known as Freeway Traffic Management System) is an ITS that depends on the real-time traffic data by operators at a central office (Hellinga and Van Aerde, 1994). The system make use of pairs of in-road sensors to capture the density of the traffic. Operators of the system can also view the current situation by using cameras placed on the intersections. COMPASS uses changeable message signs to inform drivers about high congestion, closures or accidents.

There are also some proprietary ITS that have been successfully installed in a number of cities, including INSYNC (Stevanovic et al., 2016), SURTRAC (Smith et al., 2013), and STREAMS (Nowacki, 2012).

2. Material and Method

2.1. Simulation

As stated above, in order to test our novel intelligent traffic light algorithm, we build a probabilistic, discrete-time traffic simulator that is called *TrafficSim*. A *TrafficSim* model can both run in real-time mode for visualization purposes and in fast-time mode. Figure 1 shows a model that includes 7 roads and 2 intersections. A *TrafficSim* model M = {*R,I,L,V,P*} consists of 5 components. These components can be defined as follows:

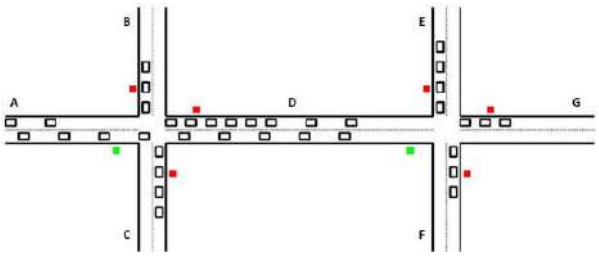


Figure 1. A sample model that consist of 7 roads and 2 intersections. Roads ***A, B, C, E, F*** and ***G*** are defined as external roads while road ***D*** is an internal road. The small rectangles on the roads represent generated vehicles.

R is the set of roads that are part of the model. Each road has parameters of roadLength and numberOfLanes, that represent the length of road in meters and number of lanes that the road possesses, respectively. Each road, otherwise stated, can have traffic heading towards both directions. Based on the type of endpoints of a road, the model can have two types of roads. If both endpoints of the road are intersections that are part of the model, then it is called an internal road. The traffic in both directions on internal roads are result of vehicles passing through the intersections at the endpoints of these roads. Alternatively, if one endpoint of the road goes out of the model, then the road is called an external road. As it will be explained below, new vehicles enter the model through external roads.

I is the set of intersections that connect roads of the model. When a vehicle passes through a traffic light, it enters an intersection and then pass to another road that is connected at the intersection. The default setting is that vehicles randomly pass to the next road with equal probability. However, it is possible to match distinct probabilities to each road. Furthermore, every intersection has a control tool that sets the cycle length and green light intervals of the traffic lights that are present on the intersection.

L is the set of traffic lights that control the entrance to intersections. All traffic lights that belongs to the same intersection share the same green light cycles, which is determined by the control tool of the intersection. Each traffic light has a *FIFO* (First-In-First-Out) queue that stores the vehicles that are stopped at the traffic light. A vehicle can pass through a traffic light at a constant speed if it approaches the light during the green light interval. However, if the vehicle approaches the traffic light during the red light interval, the vehicle is added to the *FIFO* queue of the traffic light. When the green light gets on, the vehicles that are in the queue can pass the traffic light at a rate that is equal to one vehicle per 2 seconds.

V is the set of vehicles that become part of the model. Each vehicle can move on a road, pass through an intersection or wait at a traffic light. At each time unit, new position of the vehicle is determined by adding its displacement to its previous position. Furthermore, at the open endpoint of every external road, a new vehicle may enter the model with a probability equal to $P_{newVehicle}$. By setting different vales to $P_{newVehicle}$, we can simulate traffic at different instensity levels. A high probability results with a high density traffic while low $P_{newVehicle}$ value means a sparse traffic entering the model. At current implementation, each external road can have different $P_{newVehicle}$ values.

Finally, ***P*** is the set of pedestrians that can come to intersections. With probability equal to $P_{newPedestrian}$, new pedestrians may arrive at intersections. Once the green light interval for the pedestrians starts, all pedestrians waiting at the intersections are set to leave the intersection. In current implementation, all intersections have the same $P_{newPedestrian}$ value.

Table 1 sumarizes the components of a *TrafficSim* model and gives a list of parameters of each of the components

.

Table 1. Simulation parameters

Component name	Parameter Name	Explanation
R (Roads)	roadLength	Length of the road (m)
	numberOfLanes	# of lanes
	type	Internal or external
	$P_{newVehicle}$	If external, new vehicle probability
I (Intersections)	roadList	List of roads that are connected
	roadPassProb	Array of probabilities of passing to next road
	lightList	List of traffic lights
	controlModule	Module that controls traffic lights
	$P_{newPedestrian}$	New pedestrian probability
L (Lights)	waitingVehicles	FIFO queue for waiting vehicles
	curLight	Green or red
V (Vehicles)	curRoad	Current road
	curSpeed	Current speed
	curDirection	Current direction
	curPosition	Current position
P (Pedestrians)	CurIntersection	Current intersection

2.2. Adaptive Traffic Light System

The adaptive traffic light system is implemented and tested on *TrafficSim* simulation platform. The system works in a fully distributed manner and depends on the information that is received from video cameras that are mounted on the existing traffic lights. The controller, based on a load balancing technique, basically counts the number of vehicles that pass the traffic lights during the green light interval. This task involves object detection and we argue that, with a simple video camera detection system, the task can be achieved with a high success rate in real time. The video detection system needs to capture baseline background image of passing line of the traffic light and compare it with the consecutive captured image frames to detect the existence of passing vehicles. Based on this information, at the end of every green light cycle, the effective usage of a specific light ***l*** at tine ***t***, ***Effective(l,t)*** can be defined as:

$$Effective_{(l,t)} = \frac{\#\ of\ vehicles\ passed\ at\ cycle\ t}{Green\ light\ duration\ of\ cycle\ t} \quad (1)$$

Based on this observation the estimated load on the road that ends with traffic light ***l***, ***EstimatedLoad(l,t)*** is calculated as follows:

$$EstimatedLoad_{(l,t)} = \alpha Effective_{(l,t)} + (1-\alpha)EstimatedLoad_{(l,t-1)} \quad (2)$$

When the system starts, all lights that are on a specific intersection have the same share of green light cycle, so the green light intervals for each of them are equal. At the end of each green light cycle, the adaptive system updates the green light intervals in the following way:

- If the traffic light ***l*** has higher estimated load than the average estimated load plus a threshold value, γ, it is assigned one more unit of share of the green light interval in the next cycle.
- If the traffic light ***l*** has lower estimated load than the average estimated load minus a threshold value, γ, it is assigned one less unit of share of the green light interval in the next cycle.

In this way, the controller attempts to balance the load on each traffic light by assigning more green light interval to the traffic lights with higher relative load.

3. Results and Discussion

In order to test the utility of the adaptive traffic light system, we created a *TrafficSim* model of a simple transportation network which is present in a residential area in the Bolu province of Turkey (figure 2). The model incorporates an intersection that connects 4 external roads. The traffic lights on these roads share the same green light cycle. In the current fixed-time system, the green light cycle is 75 seconds in which 11 seconds are set as the green light for pedestrians (during which all traffic lights for vehicles are set to red) and 16 seconds are set as the green light interval for each of the traffic lights. The adaptive system similarly assigns 11 seconds of every cycle as green light for pedestrians, however, it dynamically assigns remaining green light interval to traffic lights based on the load metric. To quantitatively compare the performance of the adaptive system with the fixed-time system at different traffic densities, we calculated average waiting time at the intersection.

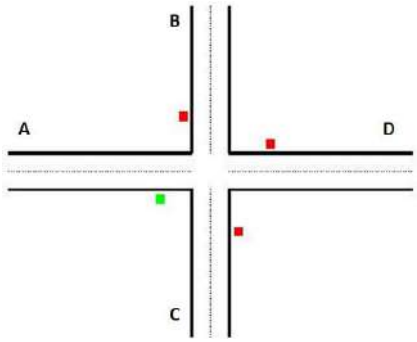


Figure 2. *TrafficSim* model of an intersection that is present in a residential area of Bolu, Turkey. The exact coordinates of the intersection is 40°44'23.5"N 31°35'55.1"E

In order to test the utility of the adaptive system, we simulate variable traffic loads in different sets of experiments. For this purpose, an external road with a normal load is set to have $P_{newVehicle}$ = 0.05, while an external road with a high load is set to have $P_{newVehicle}$ = 0.1. As it will be explained below, the external roads in each experimental setting set to have a different combination of normal or heavy loads.

In the first set of experiments, all four external roads are set to have normal load. Figure 3 shows results for the first set of experiments. In this setting, the adaptive system, after a minimal increase in the average waiting time at the beginning of the experiment run, achieves a similar performance with the fixed-time system. When we compare the average waiting time metric for two settings at the end of the experiments, a pair-wise t-test reveals that there is no statistically significant difference between two systems. The average waiting time for the adaptive system is 27.63 seconds (*std* 0.63) and the average waiting time for the fixed-time system is calculated as 27.48 seconds (*std* 0.61). In fact, at the end of the first hour of the simulation time, the difference in the performance of the two systems becomes statistically insignificant. Therefore, we can deduce that the adaptive system is able to detect that the load on all roads are same and it assigns the same amount of green light interval to all traffic lights, achieving the same performance with the fixed-time system.

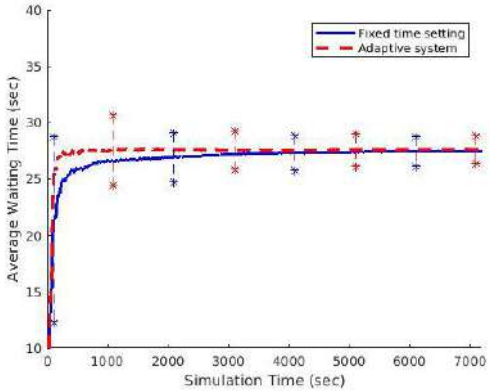


Figure 3. Results for the first set of experiments. The figure shows the average waiting time for 100 experiment runs. At specific points, 95% confidence intervals are shown for both of the systems. α is set to 0.25 and γ is set to 0.1 for the adaptive system

In the second set of experiments, we assign different loads to different roads. In this setting, Road ***A*** and road ***C*** are set to have normal load while road ***B*** and road ***D*** are set to have heavy load. Figure 4 shows the results for the second set of experiments. As can be seen, the adaptive system achieves a lower waiting time for vehicles. A pair-wise t-test reveals that the difference between the two systems is statistically significant. At the end of the experiment runs, we observe a 38% decrease in average waiting time for vehicles for the adaptive system, as the average waiting time for the adaptive system is 35.04 seconds (*std* 2.22) and the average waiting time for the fixed-time system is 56.86 seconds (*std* 11.39). This result shows that the adaptive system is able to detect the roads with higher congestion and then assign these roads longer green light intervals, which results with a lower average waiting time at the intersection. Furthermore, as can be seen in figure 4, the confidence intervals for fixed-time system is much wider than of the confidence intervals of the adaptive system. This means that, in comparison with the fixed-time system, the adaptive system is more robust to random fluctuations in the traffic load.

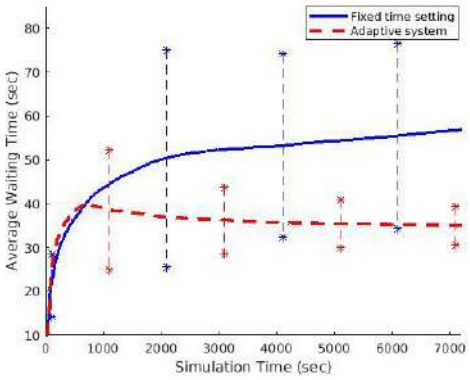


Figure 4. Results for the second set of experiments. The figure shows the average waiting time for 100 experiment runs. At specific points, 95% confidence intervals are shown for both of the systems. α is set to 0.25 and γ is set to 0.1 for the adaptive system

Finally, in the third set of experiments, we check the utility of the adaptive system on changing conditions. To simulate such an environment, we alternate the load of the roads in the following way: we have a two-hour simulation in which during the first hour, road ***A*** and road **C** are set to have normal load while road ***B*** and road ***D*** are set to have heavy load. In the second hour, road ***A*** and road ***C*** are set to have heavy load while road ***B*** and road ***D*** are set to have normal load. Figure 5 shows results for these experiments. As can be seen, the adaptive system achieves a higher performance compared to a fixed-time system in terms of decreased waiting time at the intersection. As the traffic loads on different roads are altered at the halfway through the simulation, we observe a small performance loss of performance for the adaptive system. However, it quickly adapts itself to the new conditions and achieves a high performance. The performance gain manifests itself in terms of decreased waiting time for vehicles. At the end of the experiment runs, we observe a 29% decrease in average waiting time for vehicles for the adaptive system, as the average waiting time for the adaptive system is 39.19 seconds (*std* 3.42) and the average waiting time for the fixed-time system is 55.41 seconds (*std* 9.63).

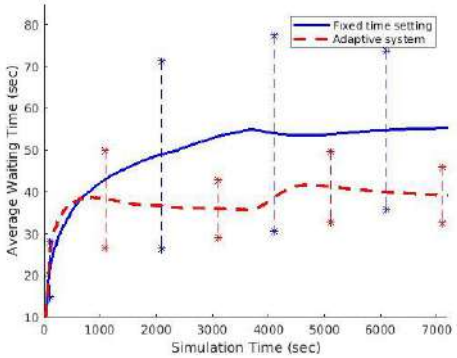


Figure 5. Results for the third set of experiments. The figure shows the average waiting time for 100 experiment runs. At specific points, 95% confidence intervals are shown for both of the systems. α is set to 0.25 and γ is set to 0.1 for the adaptive system

4. Conclusions and Recommendations

In this study, we implemented a probabilistic, discrete-time traffis imulator that can be used to model traffic networks. Based on this simulator, we were able to create models of existing traffic networks with different levels of real-time traffic density. Furthermore, we made a first attempt in building a novel adaptive traffic light system that estimates and then balances the load on a set of traffic lights that are present on a specific intersection. As stated in section II, most of the well-known adaptive traffic light systems depend on the information of waiting or approaching vehicles at an intersection. Capturing such an information is a complex task that involves real-time object detection and tracking. However, our system involves only object detection procedures that are necessary to determine number of vehicles that pass through a specific traffic light during the green light interval. By having a simpler task, our system possesses a number of a benefit:

- Our system can be built on and integrated with existing hardware with relatively low cost.
- The performance of our system does not suffer from over saturation. As stated in section II, over saturation, especially on short roads, is a serios problem that affects the performance of many ITS. However, as our system only depends on the information about number of passing vehicles, it would work exactly same on any type of road or intersection.

We tested the utility of our system on the model of a simple transport network that consists of a single intersection that connects four roads. It was shown that the system was able to estimate the traffic load on specific roads. Based on this information, the system was able to dynamically assign green light intervals to traffic lights so that, compared to a fixed-time system, it could achieve a higher quality of service in terms of reduced vehicle waiting time at the intersection.

Obviously, there is still much to be discussed and improved about our adaptive system. First, we compared it with a fixed-time system that has a specific cycle length. It should be possible and testable to modify the length of the cycles to achieve a higher quality of service. Second, we tested the system on a simple model with only one intersection. Using the simulator, it should be possible to check the utility of our system on complex traffic networks that include many intersections. As the adaptive system works based on the local information that can be captured on each intersection separately, we may be able to quantitatively measure the cumulative increase in the quality of service in a larger network. Finally, the performance of our system should be compared with other ITS in terms of increase in quality of service and cost of implementation.

References

Bretherton, D., Bodger, M., and Cowling, J. (2006). SCOOT-Managing congestion, communications and control. Traffic Engineering and Control, 47(3), 88-92.

Chintalacheruvu, N., and Muthukumar, V. (2012). Video based vehicle detection and its application in intelligent transportation systems. Journal of transportation technologies, 2(4), 305-314.

Dimitrakopoulos, G., and Demestichas, P. (2010). Intelligent transportation systems. IEEE Vehicular Technology Magazine, 5(1), 77-84.

Gajda, J., Sroka, R., Stencel, M., Wajda, A., and Zeglen, T. (2001). A vehicle classification based on inductive loop detectors. Proceedings of the 18th IEEE Instrumentation and Measurement Technology Conference, 460-464.

Garcia, F., Cerri, P., Broggi, A., de la Escalera, A., and Armingol, J. M. (2012). Data fusion for overtaking vehicle detection based on radar and optical flow. In IEEE Intelligent Vehicles Symposium, 494-499.

Hellinga, B., and Van Aerde, M. (1994). An overview of a simulation study of the Highway 401 freeway traffic management system. Canadian Journal of Civil Engineering, 21(3), 439-454.

Homepage | SCATS. (2020). Available at: https://www.scats.nsw.gov.au/. Retrieved September 25, 2020.

Hunt, P. B., Robertson, D. I., Bretherton, R. D., and Royle, M. C. (1982). The SCOOT on-line traffic signal optimisation technique. Traffic Engineering & Control, 23(4), 190-192.

Nowacki, G. (2012). Development andStandardization of Intelligent Transport Systems. TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation, 6(4), 403-412.

Robertson, D. I., and Bretherton, R. D. (1991). Optimizing networks of traffic signals in real time-the SCOOT method. IEEE Transactions on vehicular technology, 40(1), 11-15.

SCOOT™ – TRL Software. (2020). Available at: https://trlsoftware.com/products/traffic-control/scoot/. Retrieved September 25, 2020.

Slavin, C., Feng, W., Figliozzi, M., and Koonce, P. (2013). Statistical study of the impact of adaptive traffic signal control on traffic and transit performance. Transportation Research Record, 2356(1), 117-126.

Smith, S. F., G. J. Barlow, X. F. Xie, and Z. B. Rubinstein. (2013). Smart urban signal networks: initial application of the SURTRAC adaptive traffic signal control system. Proceedings of the Twenty-Third International Conference on Automated Planning and Scheduling, Rome, Italy, 1-9.

Stevanovic, A., Dakic, I., and Zlatkovic, M. (2016). Comparison of adaptive traffic control benefits for recurring and non-recurring traffic conditions. IET Intelligent Transport Systems, 11(3), 142-151.

Studer, L., Ketabdari, M., and Marchionni, G. (2015). Analysis of adaptive traffic control systems design of a decision support system for better choices. Journal of Civil and Environmental Engineering, 5(6), 1-10.