

MODELLING OF AN INTELLIGENT TRAFFIC CONTROL SYSTEM

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Abstract: The rapidly increasing traffic congestion is affecting the population of the world in a variety of ways including personal (physical and mental health), family, social, environmental, accidents and passage of emergency and law and order vehicles. Out of the many varieties of approaches tested for solutions, the current research used roadside sensors to collect data and use them for simulations using PTV Vissim simulator with MS Excel algorithmic optimisation. The location of the test was which St Marks Road in the Merton region of the UK. This is indeed an inlet into a major road (A217). A subset of data from the Department of Transport (2019) [1] was chosen which had an AADT of less than 2,000. In 2018, it was an AADT of 1,086 for this location. Simulation results showed the superiority of adaptive green signal timing over fixed timing signals. The simulation results were applied to optimisation to specify the green light timing requirements. Accordingly, congestion can be prevented using adaptive green signal timings. The results were discussed within the scope of many approaches used by different researchers.

Keywords: Traffic Congestion, Adaptive Intelligent Traffic Control System, Traffic Sign Detection, Traffic Light Detection

1 Introduction

Traffic congestion has become a daily experience for commuters travelling to their educational institutions, offices or to buy things from shops. Traffic on the road consists of cars, public transport vehicles like buses and vans, office vans of specific firms, school vehicles, trucks etc. In addition, emergency vehicles of police, ambulance, fire service etc. are also on the road on many occasions. During peak hours, there is a ban on trucks on main roads in most cities. Traffic load on the road is maximum during peak hours when most people want to travel on the road at the same time, using a variety of vehicles.

To ensure reaching their workplace, commuters need to start much earlier and return home very late. This leaves practically no time to attend to children or other family matters. Such daily experiences lead to mental strain, frustration and psycho-social problems. An adjustment on food habits and absence of active life with no exercise leads to physical health problems too. Thus, the effects of traffic congestion on people are many and serious. Other problems include higher probability of traffic accidents, delayed emergency works and increased probability of traffic offenses.

The reports of Inrix, as cited in Korosec [2] and Tom Tom Index [3] listed Los Angeles, Moscow, San Francisco, Atlanta, Miami, Bangkok and Mexico City as the leading cities in traffic congestion and the order of ranking may be different in other different reports. At an annual rate of 102 hours spent on roads due to congestion, the driver cost is \$2828 and the total annual cost to the city of Los Angeles alone is about \$19.2 billion directly and indirectly. The corresponding global level impact will run into several billion USD. These data demonstrate the seriousness of the problem and the need to find a solution.

There have been many research studies to find solutions. The main technologies used for solutions include sensors, road infrastructures, intelligent vehicles, GPS, GPRS, RFID, communication technologies and applications, mobile devices and applications, internet of things and cloud computing. Some of them are add on to the current systems, while others incorporate adaptive intelligent traffic control systems.

In designing an adaptive intelligent traffic control system, three types of approaches are used: infrastructure based (Barba, Mateos, Soto, Mezher, & Igartua, 2012) [4], intelligent vehicle-based (Sandhu et al, 2015) [5] and combination of both (Khekare & Sakhare, 2013) [6] in an integrated manner. The technologies mentioned above are part of the three approaches. This paper

deals with a simulation research on the integrated use of both connected vehicles and roadside units.

2 Objective

The objective of the study was to model an intelligent traffic control system, which automatically adapts its traffic control system based on a dynamic analysis of traffic input data from sensors placed on the roadsides connected with green signal timing control.

3 Material and Methods

Traffic count data (hard numbers and estimates) were obtained from the Department of Transport [1] in the UK. The dataset included traffic data for more than 800,000 locations across the UK. Additionally, the data included the following attributes: major region associated with the data collection point, local authority name, road name, road category, road type, start junction name, end junction name, the coordinates of the location, the link length, direction of travel, and a total count (AADT) of all motor vehicles by the type of vehicle.

One of the major sources of congestion on motorways/freeways/major-roads is the point of infusion of vehicles into a motorway/freeway/major-road. A subset of data from the Department of Transport [1] was chosen which had an AADT of less than 2,000. This approach was a likely to exclude all data points attached to a motorway/freeway/major-road. From this subset, a data point was randomly selected for modelling. The data point so selected was the point at which St Marks Road in the Merton region of the UK (see Figure 1). A closer look at this data collection point confirmed that this is indeed an inlet into a major road (A217). The 2018 AADT traffic counts associated with the westbound inlet was 1086.



Figure 1: Selected data point for modelling

3.1 Simulation and Optimization

PTV Vissim and MS Excel software were used to model the scenario shown in Figure 2. PTV Vissim is an advanced traffic simulation proprietary software of PTV Group. Microscopic level vehicle interactions can be simulated using this software. However, one limitation is that it needs to be interfaced with some other applications like Vissim COM interface to process complex mathematical algorithms for customised applications [7]. The authors used Vissim-COM in an Indonesian traffic control case study with Vissim-Matlab interaction. Weyland, Buck, and Vortisch [8] used PTV Vissim for building and calibrating a dynamic traffic flow control to reduce emissions. Python was used as the control logic interfaced with COM for a German highway case. Shindgikar, Shahri, and Ghasemi [9] integrated PTV VISSIM and MATLAB Simulink to design and

analyse the flow of traffic in an urban traffic network using COM interface.

Use of MS Excel was reported by Nikolaev, Sapego, Jakubovich, Berner, and Ivakhnenko [10]. The procedure used was that sensors were installed on the roadway to provide the data for algorithm of incident detection. After the incident was detected, the algorithm of defining its priorities was started. The traffic flow for research was modelled in the PTV Vissim, after all receives information were uploaded to excel for further processing. A similar procedure was also described by Narasip [11] to optimise vehicle movements in mixed traffic junctions in Singapore, where heavy goods vehicles predominate slowing the traffic and by Park and Qi [12] to calibrate of simulation models. Thus, the method adopted here is a very widely used one.



Figure 2: Modelling scenario

The above figure shows an inlet into a major highway. There is a sensor installed at point A as shown in the figure which will capture the traffic flow rate (i.e., vehicles per second). The data from point A will be transmitted to the traffic signal at point B and this will inform the adaptive traffic control optimisation.

The following assumptions were made before running the simulation and optimisation:

1. The traffic flow rate is between 0 to 5 vehicles per second. This assumption is inspired from Roupail, Tarko, and Li [13] who suggested that the average traffic flow rate per second at signalised intersections is between 2-4 vehicles seconds. The traffic flow rate of 0 to 5 vehicles per second was used by taking into account and potential interruptions and changed traffic conditions between when that study was done and now.
2. The fixed green signal duration is 2 seconds and the lag between the pair of fixed green signals is a variable n seconds.
3. One vehicle can pass a green signal in 1 second.

The traffic flow rate was simulated 3 times for a period of 100 seconds each. The values simulated were between 0 to 5 vehicles per second. The results of the simulation are reported in the subsequent section.

Congestion has been computed as the cumulative difference between the vehicles per second and the duration of the fixed or adaptive traffic signal in seconds.

$$\text{Congestion} = \sum n1 (\text{TrafficFlowRate} - \text{DurationTrafficSignal})$$

Where, n ranges from 1 to n seconds.

The Generalized Reduced Gradient (GRG) Nonlinear optimisation function has been used to minimise congestion. Therefore, the objective function is:

- minimise (Congestion)

The changeable variable is the duration of the adaptive traffic signal. The constraints used are:

- Congestion ≥ 0
- $0 < \text{SignalDuration} < 5$
- SignalDuration is an integer

The results obtained from the optimisation for the three simulation scenarios are presented in the following section.

4 Results

The results of the simulation of traffic flow rate are shown in Table 1 and Figure 3 below.

Table 1: Traffic flow rate simulations

Second	Traffic Flow Rate 1	Traffic Flow Rate 2	Traffic Flow Rate 3
1	3	0	2
2	2	4	0
3	5	3	1
4	4	1	2
5	2	4	0
6	5	2	4
7	0	0	2
8	5	4	2
9	2	0	1
10	0	1	3
11	1	3	2
12	1	3	0
13	5	1	4
14	0	4	1
15	1	4	4
16	3	0	2
17	2	1	5
18	2	2	1
19	2	4	0
20	4	4	0
21	1	0	0
22	1	3	0
23	3	3	0
24	4	4	3
25	1	3	5
26	0	0	1
27	4	0	1
28	2	5	5
29	1	2	0
30	0	2	2
31	5	5	5
32	2	1	1
33	2	2	0
34	2	2	4
35	5	0	2
36	3	2	1
37	1	3	3
38	4	5	4
39	3	3	0
40	5	0	4
41	2	1	0
42	2	2	5
43	2	5	5
44	5	5	2
45	4	4	3
46	4	1	4
47	4	4	5
48	5	0	1
49	0	4	1
50	4	5	2
51	4	5	4
52	1	3	0
53	1	4	0
54	0	0	0
55	3	0	3
56	0	1	2
57	3	5	5
58	1	3	4
59	5	3	2
60	1	3	4
61	0	0	2
62	4	5	5
63	3	0	5
64	0	0	1
65	4	4	5

The above results clearly show that congestion is frequent with fixed green signal simulation and adaptive green signal leads almost to a no congestion situation.

4.2 Fixed Signal Duration of 2 Seconds

Table 3 below shows the results of the optimisation for the three scenarios for a period of 100 seconds. For each simulation, the table shows the simulated traffic flow rate per second, the duration of the fixed green signal (2 seconds), the amount of cumulative congestion for each second in the fixed green signal scenario, the adaptive green signal duration (i.e., the result of optimisation), and the amount of cumulative congestion for each second in the adaptive green signal scenario. The simulation results led to the optimisation results given in Table 3.

Table 3: Optimisation results

Table with 100 rows and 13 columns. Columns include Traffic Flow Rate 1, Fixed Green Signal Duration (Sec.), Congestion - Fixed Green Signal Scenario, Adaptive Green Signal Duration (Sec.), Congestion - Adaptive Green Signal Scenario, Traffic Flow Rate 2, Fixed Green Signal Duration (Sec.), Congestion - Fixed Green Signal Scenario, Adaptive Green Signal Duration (Sec.), Congestion - Adaptive Green Signal Scenario, Traffic Flow Rate 3, Fixed Green Signal Duration (Sec.), Congestion - Fixed Green Signal Scenario, Adaptive Green Signal Duration (Sec.), Congestion - Adaptive Green Signal Scenario.

Table with 100 rows and 13 columns. Columns include Traffic Flow Rate 1, Fixed Green Signal Duration (Sec.), Congestion - Fixed Green Signal Scenario, Adaptive Green Signal Duration (Sec.), Congestion - Adaptive Green Signal Scenario, Traffic Flow Rate 2, Fixed Green Signal Duration (Sec.), Congestion - Fixed Green Signal Scenario, Adaptive Green Signal Duration (Sec.), Congestion - Adaptive Green Signal Scenario, Traffic Flow Rate 3, Fixed Green Signal Duration (Sec.), Congestion - Fixed Green Signal Scenario, Adaptive Green Signal Duration (Sec.), Congestion - Adaptive Green Signal Scenario.

5 Conclusion

A summary of the findings is provided in the Table 4 below.

The results show that the amount of congestion when the fixed green signal duration is 1 second for simulation 1 was 133 vehicles, for simulation 2 it was 138 vehicles and for signal 3 it was 152 vehicles. The amount of congestion for the adaptive green signal approach was 0 vehicles for all the simulations.

The results show that the amount of congestion when the fixed green signal duration is 2 seconds for simulation 1 was 34 vehicles, for simulation 2 it was 39 vehicles and for signal 3 it was 62 vehicles. The amount of congestion for the adaptive green signal approach was 0 vehicles for all the simulations.

This indicates that adaptive green signals or intelligent traffic control out performs fixed green signal approach in all instances. Given the low traffic flow rate of 1,086 AADT on St Marks Road in Merton, it is safe to claim that replacing fixed green signals by adaptive green signals would eliminate any potential congestion at that point.

Table 4: Optimisation results summary

Summary table with 4 columns: Scenario, Simulation 1, Simulation 2, Simulation 3. Rows include Fixed Green Signal Duration of 1 Second and Congestion - Fixed Green Signal Scenario (133, 138, 152), Congestion - Adaptive Green Signal Scenario (0, 0, 0), Fixed Green Signal Duration of 2 Seconds and Congestion - Fixed Green Signal Scenario (34, 39, 62), Congestion - Adaptive Green Signal Scenario (0, 0, 0).

6 Discussion

Usefulness of adaptive signals with neural networks and genetic algorithm to reduce congestion was demonstrated by Kaur and Agrawal [14]. In this work, only roadside sensors were used to transmit traffic data to the signalling system at the junction and optimisation algorithm was used for applying the data for reducing congestion. A wide range of approaches which basically uses automatic signalling system for congestion control have been proposed by various researchers. Some of the more recent ones are cited here. These works largely support the findings of this research at the same time provides other types of solutions which can be researched in future in continuity with this work. For example, Gao, Shen, Liu, Ito, and Shiratori [15] proved the value of the precise algorithms in such contexts. Such adaptive signalling for traffic control can be extended to through a unity parameter to serially integrate signal timings in multiple intersections [16]. Use of reinforcement learning has become an integral part of roadside sensor based adaptive signal control to reduce congestion as reviewed by Mannion, Duggan, and Howley [17]. A tree-like configuration of a decision-making model was suggested by Sadollah, Gao, Zhang, Zhang, and Su [18] to reduce traffic congestion at intersections using adaptive traffic signals. Different traffic networks with different sizes, varying from nine to 400 intersections were tested to validate the model. Multi-agent reinforcement learning (MARL) approach has also been used with automatic signalling systems for effective traffic control [19]. The availability of a variety of methods to acquire traffic data for use in intelligent traffic signal control systems was highlighted in a recent review by Wang, Yang, Liang, and Liu [20]. These methods include information technologies on computing science, autonomous driving, vehicle-to-vehicle, and mobile Internet. Since these were not used in this study, more works related to them are not considered to support the findings here. Future research may be on self-adaptive systems using integrated systems of vehicle-based and infrastructure-based technologies.

7 Limitations of This Research

The results may be very specifically applicable to intersections of a by-lane entering a main road. More work needs to be done to extend this to real time situations and to multiple intersections. No attempt was made for modelling and prediction although long term data were available. Other aspects like emission control were not included in the variables. Integrating roadside sensors with sensors in vehicles was not attempted but can be considered in future research when extending to multiple intersections.

8 Future Research and Proof of Concept

Future research can look into extending the simulations to a more complex scenario, for example, the effect of implementing adaptive traffic control signals on all inlets of a major road. Such an exercise can help with macro level transport planning for a city or a region within a city.

Also, the results from this analysis can be tested by a real life implementation of an adaptive traffic control signal through a pilot project.

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