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Performance Evaluation of Adaptive Traffic Control Algorithms with Real Diverse Traffic Data

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Abstract

Vehicle to infrastructure (V2I) communication may eliminate problems associated with traditional traffic control systems. With the SAE J2735 standard and IntelliDrive^{SM}, real time as well as vehicle specific information (such as vehicle occupancy or the engine capacity) is available to a traffic controller. This technology enables the controller to collect data from nearby vehicles periodically. Goal of designing adaptive traffic signal control that utilizes these data elements is to optimize appropriate metric at an intersection. This paper involves performance evaluation of adaptive traffic control algorithms with real and diverse traffic data. Such algorithms and results of their simulation with traffic data collected from a city junction are presented. Simulation reveals that adaptive algorithms perform better (more than 7%) than the normal algorithm in optimizing several metrics.

Keywords: Vehicle to Infrastructure (V2I), Adaptive Algorithms, Real Traffic Data.

1 Introduction

The signal scheduling on many of the traffic control systems works on a fixed-time basis, with signal timing plans based on the time of the day and day of the week are employed. Such fixed-time systems cannot cope-up with the modern day traffic conditions that varies. Furthermore, as traffic patterns change with the passage of time, fixed time plans become outdated as expected [1] and results in non-optimum performance. These problems make it clear that a more dynamic approach is needed for this changing traffic conditions. Adaptive traffic control technology holds potential to accomplish this task [2].

Vehicle-to-infrastructure communication (V2I) is the wireless exchange of operational data between vehicles and roadway infrastructure. Data can be used for safety, mobility, and environmental benefits [3][4][5][6][7].

Direct Short Range Communication (DSRC) Message Set Dictionary is part of Society of Automotive Engineers (SAE) standard J2735 [6][8]. Transit vehicles may transmit the relative occupancy of the vehicle under this standard [9]. Currently, most transit-signal priority systems give priority to buses regardless of the number of passengers [10]. With person delay information obtained from relative occupancy, a more accurate and effective transit-signal priority system can be designed.

It is difficult to develop algorithm based on emission information as it involves measurement of emission [9]. However, the engine details can be communicated to a controller with the existing J2735 standard. Information could include engine capacity, type of fuel used etc. It would be possible for the traffic signal controller to estimate the emission from a particular vehicle utilizing these data elements. Simulation of adaptive control algorithms involving synthesized traffic is reported in [11] [12]. This paper involves simulation of adaptive traffic control algorithms with real traffic data based on data elements of SAE J2735.

2 Algorithm Design and Implementation

The focus is to simulate the proposed adaptive algorithm with real traffic data in order to find the performance enhancements that can be achieved. The proposed adaptive traffic control algorithms are implemented in MatLab. Each algorithm minimizes one of the following metrics.

• Total Occupancy of a heading: sum of occupancy values of all the vehicles in a particular heading.
• Total Person delay of a heading: sum of person delay values of all the vehicles in a particular heading.
• Average Person delay of a heading: ratio of Total Person delay to the Total Occupancy of a heading.
• Total Emission of a heading: sum of emission values of all the vehicles in in a particular heading.
• Average Emission per Car of a heading: ratio of Total Emission to Total number of cars of that heading.

A comparative performance study of the algorithms is expected based on these different metrics as the criterion for traffic control. Eeach vehicle sends the data frames (conforming to SAE J2735 standard) to the traffic controller as shown in Figure 1. Details of calculating the metrics from these data set is included in [12].

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ID	Latitude	Longitude	Occupancy	Heading	Speed

Figure 1: Data Frame

Of interest is the waiting time of each vehicle calculated in the following manner. The traffic scenario at a particular instant of time is depicted in Figure 2. The numbers within the parenthesis indicate the waiting time of the vehicles represented by vehicle IDs (as alphabets) written adjacent to it. Four headings that are being considered is shown by the 4-way directional diagram to the right in Figure 2.

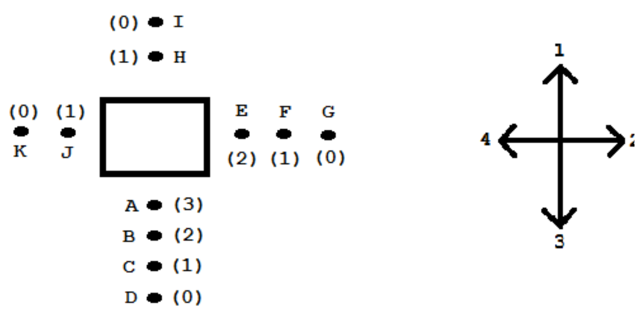

Figure 2: Initial State for Wait Time Calculation

Let heading 1 be given preference and that all the vehicles in heading 1 exit the network. Let the first vehicle take 3 units of time to exit the network and every other vehicle following that take 1 additional unit of time to exit the network. As such, 6 units of time is required in total. The traffic scenario after the vehicles of heading 1 have exited the network is depicted Figure 3.

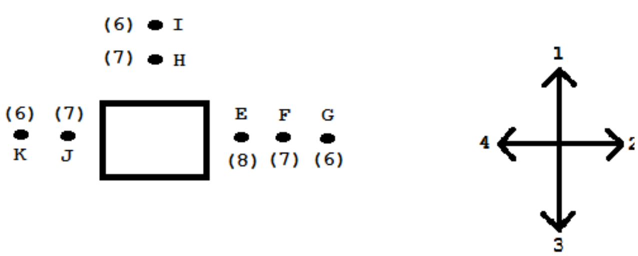

Figure 3: State after Vehicles Exit the Traffic System

An adaptive traffic control algorithm minimizes one of the above metrics. Algorithmic steps are depicted in Figure 4.

An implementation and simulation of the algorithms needs two major functionalities. They are traffic generation and traffic modulation discussed in next section.

3 Simulation

Traffic Generation

Simulation used a four-way intersection data obtained from Town of Cary, North Carolina. The real traffic data was collected between 6:00 AM and 10:00 PM at 15 minute intervals. This traffic junction consisted of four roads: Abberdyale Dr. (South), High House Rd. (West), Wood Hollow Dr. (North), and High House Rd. (East). There was a total of 21,567 cars. 283 cars were going south on Abberdyale Dr. 10,523 cars were going west on High House Rd. 231 cars were going north on Wood Hollow Dr. 10,530 cars were going west on High House Rd.

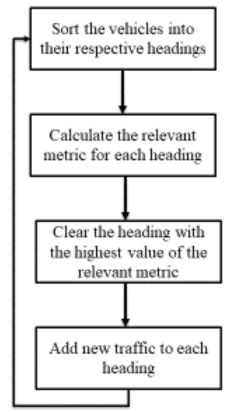

Figure 4: Algorithmic Steps for Adaptive Traffic Control

Case I: Four-way Intersection with Turning Lanes

Simulation starts with a fixed number of vehicles specified at 6:00 A.M. for the first iteration to verify the performance of the algorithm. In order to create a continuous traffic pattern, entries are generated from the second iteration onwards with traffic at 6:15 A.M., which gets added to the network. It is to be noted that the vehicles that have once exited the network will not enter the network again during the simulation.

Only two headings were chosen to represent the turning in this simulation, the High House Road West and the High House Road East. These two roads were chosen because they contain the biggest amount of cars in comparison with the other two roads. In addition, only the left turns and U-turns were counted as turning since these are the ones that need a green light to cross the road in contrast with right turn which does not need a light. Table 1 shows the traffic generated in different headings during the first trial.

Table 1: Traffic Generated During the First Four Iteration of First Trial

Time	**Abberdyale Dr. (South)**	**High House Rd. (West)**	**Wood Hollow Dr. (North)**	**High House Rd. (East)**
6:00 A.M.	2	27	2	35
6:15 A.M.	1	54	3	41
6:30 A.M.	7	90	6	65
6:45 A.M.	11	94	7	112
Hourly Total	21	265	18	253

In total, 277 cars are turning in East or West High House Road (from a total of 21,053 cars on that road). When compared to the total cars in the simulation (21,567), only 1.28% of the cars are turning.

Total Cars:	21567
East/West Cars:	21053
Turning Cars:	277
Percentage:	1.28%

The following chart (Figure 5) shows how the emission value is distributed. Each car is given an identification number. It can be observed that the distribution of the emission is random between 2.5 to 4.5 (in liters of engine size) for different cars.

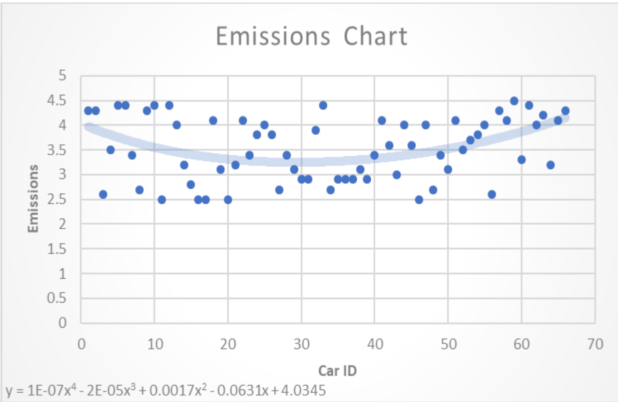

Figure 5: Emission Values for Different Cars

The following chart (Figure 6) shows how the occupancy is distributed. It can be observed that the occupancy is randomly distributed between 1 to 11 (in persons) for different cars. This randomness leads to meaningful and realistic simulation results.

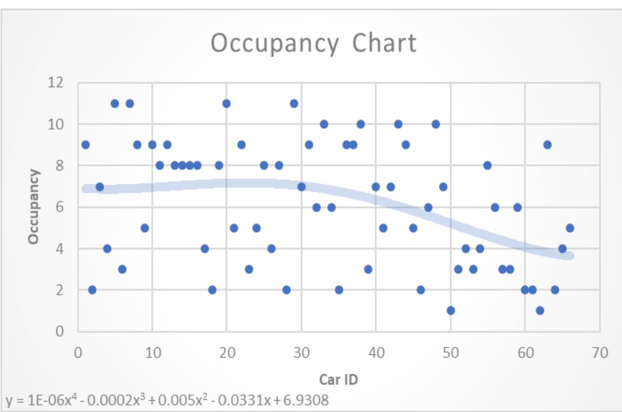

Figure 6: Occupancy Values for Different Cars

From such tables as Table 1 and the above charts, it is possible to calculate the total occupancy and total emission for each heading during each iterative step. Then the total metric values can be calculated and compared in order to make an adaptive decision.

Case II: Four-way Intersection with Public and Private Transportation

The next step was to add differentiation in public and private transportation (for example cars and buses). Traffic data was modified to randomly assign a number between 0 and 1 with the numbers below or equal to 0.05 being assigned as public transportation.

Once this was determined, the number of passengers assigned for public transportation was set between 1 and 31 (including 1 driver and up to 30 passengers) and the emissions between 6.7 and 9.0. Passengers for private transportation was set between 1 to 5 including the driver to reflect the maximum capacity of an average car with two front seats and a back seat. The size of the engine and emissions remained the same between 2.4 and 4.5. Furthermore, priority was given to any heading with public transportation over heading with only private transportation.

The following charts (Figure 7 and Figure 8) represent emission and occupancy of vehicles in the first iteration of the first trial of the real data with public vs private differentiation. It shows how the occupancy and the emission are distributed. The distribution of the emission and the occupancy are random between the limits with peaks corresponding to the public vehicles.

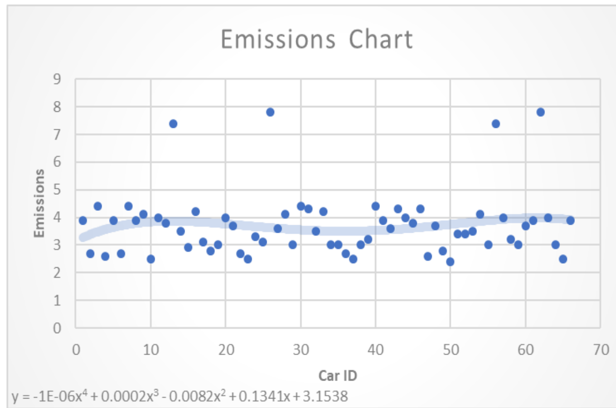

Figure 7: Emission Values for Different Private and Public Vehicles

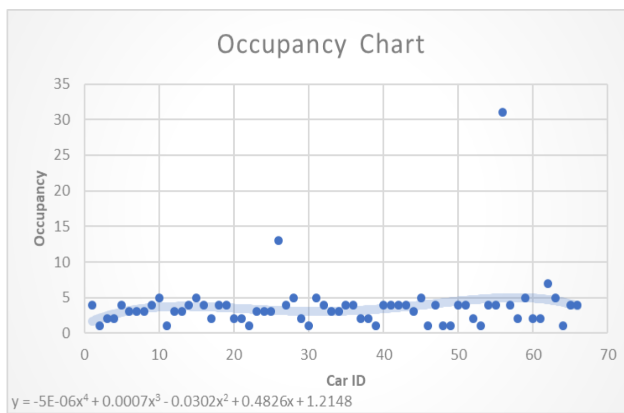

Figure 8: Occupancy Values for Different Private and Public Vehicles

Traffic Modulation

One of the five metrics (namely total occupancy of a heading, total person delay of a heading, average person delay of a heading, total emission of a heading, or average emission per person of a heading) is chosen for optimization in an algorithm and a decision is taken accordingly. Based on the decision taken, vehicles in a particular heading exit the network as shown previously in Figure 3. For example, under total occupancy algorithm, total occupancy of each heading is calculated. The heading having the highest value of total occupancy is cleared. This is called here as traffic modulation. Following this event, traffic gets added to the network to continue the next iteration of simulation i.e. a series of traffic generation cycles followed by traffic modulation cycles occur in a sequential fashion as depicted in Figure 9.

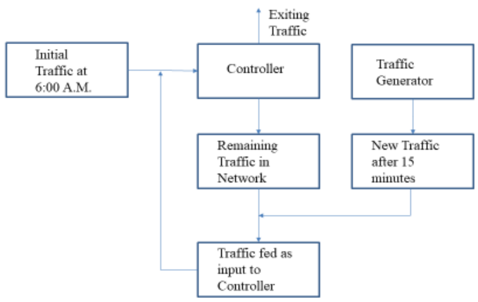

Figure 9: Overview of Traffic Generation and Modulation

4 Results and Analysis

Following description provides more details of simulation steps and the data collected after each step. Collected data lead to the comparison of all algorithms based on all the metrics. These data are obtained with the same traffic pattern for all algorithms.

Case I: Four-way Intersection with Turning Lanes

Let us first consider the occupancy algorithm which will clear headings based on the highest occupancy. Once the occupancy information is available for each car in each heading, the total occupancy for each heading is calculated accordingly. This is shown in the first row of Table 2.

In this first iteration of simulation, the total occupancies for the headings are 11, 28, 9, and 42, respectively. So, the East heading with maximum occupancy (42) will be cleared in the first iteration. All the metrics (average emissions per person, average person delay, occupancy, total emissions and average person delay) are determined under the occupancy algorithm for the first iteration. After the process is repeated for 15 iterations (one trial), cumulative value of the metric is calculated at the bottom right of each table.

Table 2: Occupancy after Each Iteration

	Heading			
Time	**Abbedyale Dr. (South)**	**High House Rd. (West)**	**Wood Hollow Dr. (North)**	**High House Rd. (East)**
6:00 A.M.	11	28	9	42
6:15 A.M.	4	60	11	46

Subsequently the whole process is repeated for all the 6 algorithms (namely total occupancy algorithm, total person delay algorithm, average person delay algorithm, total emission algorithm, or average emission per person algorithm, and the normal algorithm). Tables similar to Table 2 are created for each metric under each algorithm. Cumulative values of metrics for one trial with 6 to 7 iterations are also listed in each table. In normal algorithm, each heading is allowed to proceed for a fixed amount of time in a round-robin fashion. Table 3 shows the results of simulation.

Table 3: Cumulative Values of Metrics for One Trial with 7 Iterations

ALGORITHM ↓METRICS →	AVG_EMISSIONS	AVG_PERSON_DELAY	OCCUPANCY	TOTAL_EMISSIONS	TOTAL_PERSON_DELAY
AVG_EMISSIONS	139.78	267197.38	452121.00	256980.40	1869285618.00
AVG_PERSON_DELAY	147.24	45790.96	127220.00	73480.70	34896025.00
OCCUPANCY	146.43	306720.75	196397.00	114080.20	341186126.00
TOTAL EMISSIONS	146.43	306720.75	196397.00	114080.20	341186126.00
TOTAL_PERSON_DELAY	151.52	77064.92	134074.00	77965.70	51715808.00
NORMAL	148.28	69213.52	258285.00	149688.00	225816790.00

By looking at each column of Table 3, we can find the minimum value (highlighted) of a particular metric and its associated algorithm. The Average Emissions algorithm gives the best result for the average emissions metric. In the rest of the metrics, the Average Person delay performs better than the rest of the algorithms. However, these conclusions from one trial of simulation are premature. As such, we decided to extend the simulation for ten trials with different traffic patterns at different time of the day. Once all the simulations completed for ten trials, then metrics are added for each algorithm and an average is found. Then the algorithms are compared based on these average values of metrics. The results are shown in Table 4 with minimum values highlighted.

Table 4 shows that the Average Person Delay algorithm outperforms the Occupancy, Total Emissions, and Total Person Delay algorithms in their respective metrics. Meanwhile, the Average Emissions algorithms is best suited for the Average Emissions metric.

Table 4: Average Values of Metrics for Ten Trials

ALGORITHM ↓METRICS →	AVG_EMISSIONS	AVG_PERSON_DELAY	OCCUPANCY	TOTAL_EMISSIONS	TOTAL_PERSON_DELAY
AVG_EMISSIONS	276.38	748270.14	982085.20	553001.38	5710720614.20
AVG_PERSON_DELAY	296.89	90307.30	255496.40	146579.44	69712160.60
OCCUPANCY	295.80	371864.52	456163.60	262615.88	564639056.80
TOTAL EMISSIONS	294.26	602125.24	393358.80	226187.74	672296227.00
TOTAL_PERSON_DELAY	297.33	382751.86	333595.40	191559.92	395650132.80
NORMAL	297.21	147623.01	395280.40	227580.56	280159425.40

Table 5 shows the minimum value of each metric, the algorithm that provides the minimum, and the improvement in comparison to the normal algorithm.

As seen from Table 5 that adaptive algorithms perform better than the normal algorithm in minimizing all the above- mentioned metrics in real traffic. The percent improvement varies from 7 % to 75%. The percent improvement of the metric in real traffic is higher than that reported in random traffic (2% to 5%) [12]. Also, the simulation shows that two algorithms (Average Emission and Average Person delay) are sufficient to minimize all the above metrics in this real traffic obtained from a particular junction.

Case II: Four-way Intersection with Public and Private Transportation

For simulation with public and private transportation, five trials were carried out with the following characteristics in Table 6.

Table 5: Improvements in the Metrics with Turning Lanes

Metric	The Minimum Value	Algorithm Providing the Minimum	Percent Improvement (Compared to Normal Algorithm)
Average Emission	276.38	*Average Emission*	7.00
Average Person delay	90307.30	*Average Person delay*	38.82
Occupancy	255496.40	*Average Person delay*	35.36
Total Emission	146579.44	*Average Person delay*	35.59
Total Person delay	69712160.60	*Average Person delay*	75.11

Table 6: Distribution of Public Vehicles in various Trials

	Total Vehicles	Public Vehicles	Percentage
Trial 1	21,567	1,079	5.00%
Trial 2	21,567	1,137	5.27%
Trial 3	21,567	1,032	4.79%
Trial 4	21,567	1,058	4.91%
Trial 5	21,567	1,066	4.94%

Cumulative values of metrics for each trial with several iterations are listed in tables similar to Table 3 above. Table 7 shows the results of simulation after one trial.

Table 7: Cumulative Values of Metrics for One Trial with Public and Private Transportation

ALGORITHM ↓METRICS →	AVG_EMISSIONS	AVG_PERSON_DELAY	OCCUPANCY	TOTAL_EMISSIONS	TOTAL_PERSON_DELAY
AVG_EMISSIONS	232.17	328975.47	344240.00	333676.20	1655349017.00
AVG_PERSON_DELAY	263.72	44314.94	78321.00	78101.40	21635897.00
OCCUPANCY	257.23	307245.79	121344.00	120820.80	210101785.00
TOTAL EMISSIONS	257.23	307245.79	121344.00	120820.80	210101785.00
TOTAL_PERSON_DELAY	267.55	78298.60	82646.00	83116.80	31885547.00
NORMAL	264.99	69152.98	159883.00	158871.10	139815741.00

Once all the simulations completed for ten trials, then metrics are added for each algorithm and the total is found. Then the algorithms are compared based on these total values of metrics. The results are shown in Table 8 with minimum values highlighted.

Table 8: Total Values of Metrics for Five Trials with Public and Private Transportation

ALGORITHM ↓METRICS →	AVG_EMISSIONS	AVG_PERSON_DELAY	OCCUPANCY	TOTAL_EMISSIONS	TOTAL_PERSON_DELAY
AVG_EMISSIONS	1171.33	1893511.73	1635661.00	1592789.70	10543806529.00
AVG_PERSON_DELAY	1318.18	222607.52	388873.00	389334.10	106357218.00
OCCUPANCY	1306.04	1520079.01	601000.00	599581.00	1038265101.00
TOTAL EMISSIONS	1306.48	1513743.77	602476.00	601049.00	1034758383.00
TOTAL_PERSON_DELAY	1335.95	389447.94	413942.00	415098.90	161653705.00
NORMAL	1343.25	345508.86	790106.00	794186.80	690596808.00

Table 8 shows that the Average Person Delay algorithm once again outperforms the Occupancy, Total Emissions, and Total Person Delay algorithms in reducing their respective metrics. Also, the Average Emissions algorithms is best suited for the Average Emissions metric.

The following table (Table 9) shows the minimum value of each metric, the algorithm that provides the minimum, and the improvement in comparison to the normal algorithm.

Table 9: Improvements in the Metrics with Public and Private Transportation

Metric	The Minimum Value	Algorithm Providing the Minimum	Percent Improvement (Compared to Normal Algorithm)
Average Emission	1171.33	*Average Emission*	12.79
Average Person delay	222607.52	*Average Person delay*	35.57
Occupancy	388873.00	*Average Person delay*	50.78
Total Emission	389334.10	*Average Person delay*	50.97

Total Person delay	106357218.00	*Average Person delay*	84.59

As seen from Table 9 that the adaptive algorithms perform better than the normal algorithm in minimizing all the above- mentioned metrics in real traffic even with public and private vehicles. The percent improvement varies from 12 % to 84%. Results are very similar to the results obtained without the public and private vehicles enlisted in Table 5.

5 Conclusion and Future Work

This paper presents different adaptive traffic control algorithms using V2I communication and their performance under real traffic obtained from a particular junction in North Carolina. Five traffic control metrics were defined for traffic regulation. Simulation results with real traffic (collected from a junction over a period of 16 hours) reveal that adaptive algorithms indeed minimize the specified metrics (Measure of Effectiveness). That means that these algorithms (for optimizing metric) results in the metric value that is less than the value produced by normal algorithm. It exhibits improvement of about 7% to 75% over the normal algorithm. Improvement figures are between 12% and 84% considering public and private vehicles. It supports our expectation well. Overall, the simulation was able to prove that the adaptive algorithms are better choices for future Measure of Effectiveness (MOE) even with real and diverse traffic. However, the algorithms should be chosen wisely to control traffic as some algorithms perform better than the other in a specific situation. As such, the controller's response would be adaptive and more effective in real time.

For further studies, more trials are needed taking into account more junctions from urban and suburban areas. In addition, the combination of multiple adaptive algorithms will be investigated as possible solution to further optimize traffic control.

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