Utilizing High Resolution Data to Identify Minimum Vehicle Emissions Cases Considering Platoons and EVP

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ABSTRACT

This paper describes efforts to optimize the parameters for a platoon identification and accommodation algorithm that minimizes vehicle emissions. The algorithm was developed and implemented in the AnyLogic framework, and was validated by comparing it to the results of prior research. A four-module flowchart was developed to analyze the traffic data and to identify platoons. The platoon end time was obtained from the simulation and used to calculate the offset of the downstream intersection. The simulation calculates vehicle emissions with the aid of the VT-Micro microscopic emission model. Optimization experiments were run to determine the relationship between platoon parameters and minimum- and maximum-emission scenarios. Optimal platoon identification parameters were found from these experiments, and the simulation was run with these parameters. The total time of all vehicles in the simulation was also found for minimum and maximum emissions scenarios. Time-space diagrams obtained from the simulations demonstrate that optimized parameters allow all cars to travel through the downstream intersection without waiting, and therefore cause a decrease in emissions by as much as 15.5%.

This paper also discusses the outcome of efforts to leverage high resolution data obtained from WV-705 corridor in Morgantown, WV. The proposed model was developed for that purpose and implemented in the AnyLogic framework to simulate this particular road network with four coordinated signal-controlled intersections. The simulation was also used to calculate vehicle CO, HC, NOx emissions with the aid of the VT-Micro microscopic emission model. Offset variation was run to determine the optimal offsets for this particular road network with traffic volume, signal phase diagram and vehicle characteristics. A classifier was developed by discriminant analysis based on significant attributes of HRD. Equation of this classifier was developed to distinguish between set of timing plans that produce maximum emission from set of timing plans that produce maximum emission. Also, current work investigates the potential use of the GPS-based and similar priority systems by giving preemption through signalized intersections. Two flowcharts are developed to consider presence of emergency vehicle (EV) in the system so called EV life cycle and EV preemption (EVP). Three scenarios are implemented, namely base case scenario when no EV is involved, EV scenario when EV gets EVP only, and EV scenario when EV gets preemption by signals and right-of-way by other vehicles. Research makes an attempt to compare emission results of these scenarios to find out whether EV effects vehicle emission in the road network and what is the level of this influence if any.

ABSTRACT

This thesis describes efforts to minimize vehicle emissions at signalized intersections. In the first section of the thesis, efforts are made to reduce emissions by adjusting times of the signals according to vehicles arriving. In second section of the thesis research targets intersections that already have problems with emissions so some actions can be made to bring down the emissions.
One way to reduce emissions is to identify several cars that are in close proximity and treat them as a single unit called a vehicle platoon. In this case start of green time and end of green time of the next/coming traffic light are flexible, in other words, green light depends on platoon arrival time. As a result, platoon does not wait at the intersections. Representation of the simple road network with two traffic lights was developed in simulation and optimization software. Optimization experiments were run to determine optimal platoon parameters and the simulation was run with these parameters. Results indicate a decrease in vehicle emissions by as much as 15.5%. Identifying platoons and handling them in a described way benefits the entire traffic since total delay of all cars is reduced by as much as 22.4%.
A second section of this thesis seeks methods to quantitatively evaluate the performance of intersections and thus identify which ones are most in need of improvements. This process is often done with field observations that are time consuming and costly. Many intersections store logs about traffic signal cycles and traffic patterns in a universal format called high resolution data (HRD). The information in these logs should be able to allow engineers to evaluate intersections, but no method currently exists to accomplish this task. Therefore, a virtual road network based on a real network in Morgantown WV was created. Simulations were run to simultaneously generate virtual HRD and independently evaluate intersection performance for three scenarios with different levels of emergency vehicle involvement. An equation was developed for each type of emission for each scenario to come up with a score for an intersection. This score indicates whether the current setting of a traffic light is efficient or some changes are required.

Dedication

I appreciate help and support of all of my family and friends, especially Olga Morozova, Michael Elufimov, Lucy Ulanova, Mani Venkat Ala, Josh Abelard, Apoorv Sharma, Scott Schreiber, Jane Kononova, and Valentine Zelenevsky. You filled me with notion that impossible is just a big word for little people to hide. Like lights you guided me home.

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Chapter 1: Introduction

1.0 Introduction

A major role of traffic engineers is to devise strategies for vehicles to reach their destinations as quickly as possible while maximizing safety and minimizing the impact on the environment. For passenger cars, busses, trucks, and other types of wheeled vehicles, this task is achieved by developing road networks that are appropriate for the type and volume of the expected traffic.

Intersections are an unavoidable component of road networks. Some form of control mechanism is necessary to direct vehicles through intersections without collisions. Throughout most of history, control mechanisms for intersections with high traffic volume have taken the form of traffic lights, which tell drivers whether they have right-of way or not. Although necessary for safety, signalized intersections have the unwanted effects of increased noise pollution, increased emissions, and an overall decrease in the rate of traffic flow because drivers who encounter a red light must come to a complete stop and then accelerate back to their previous speed. A well-designed intersection will minimize these detrimental effects to achieve the highest possible level of efficiency. Efficiency of an intersection can be estimated by evaluating traffic delay and calculating emissions.

1.1 Objectives

Researchers have sought a variety of methods to improve efficiency. One such method involves the use of connected or autonomous vehicles (CV/AV) to limit human interaction. This increases safety and reduces the headspace between cars, thus increasing the capacity of a road, by elimination of perception-reaction time. Moreover, CV/AV significantly reduces emissions because vehicle to vehicle communication (V2V) and vehicle to infrastructure communication (V2I) reduce the need for deceleration and acceleration. In fact, CV/AV may be able to eliminate the need for traffic lights. Another method to address the inefficiencies associated with traffic lights is to coordinate traffic movements better. For example, vehicles can be identified as platoons and accommodated through a chain of coordinated traffic lights in a corridor with the help of offsets so vehicles travel with as little stops as possible. Part of the work presented in this paper aims to develop an improved strategy to identify and accommodate platoons.

Traffic light delays are a particular problem for emergency vehicles. It is in the interest of public safety to give emergency vehicles (EVs) right of way over all other vehicles at intersections and thus allow them to reach their destination sooner. However, this process of interrupting the regular cycle in order to allocate a green light to an EVs disrupts the normal life of an intersection and might cause extra delays. It is important to minimize these disruptions thus adverse effect on the network. A careful choice of transition strategy from emergency vehicle preemption (EVP) back to the normal cycle operation is necessary to quickly restore traffic light coordination and prevent unnecessary delays.

Any method of improving the efficiency of intersections requires an efficient method to evaluate the performance of intersections. Some traffic controllers use sensors and loops to track signal and traffic event and save this information in the form of high resolution data (HRD). It is very useful for a Traffic Engineer to be able to estimate whether level of emission at the intersection is acceptable just by looking at HRD. One approach is to use a formula or algorithm to process outputs from HRD, such the number of vehicles that stopped at the intersection, and compare the results to a threshold condition in order to make a decision about whether to change timing plans for traffic lights or not. A portion of this paper describes research to develop such a formula and threshold condition.

The specific objectives in this thesis are as follows:

- To develop a method to connect vehicle emissions and platoon identification parameters.
- To identify which groups of vehicles form platoons with the help of a virtual traffic light and an identification algorithm that is based on changes in the traffic flow.
- To accommodate identified vehicle platoons through an intersection by optimizing offset, platoon identification parameters, and upper and lower bounds of traffic flow.
- To calculate emission based on VT-Micro with optimized platoon identification parameters and an optimized offset.
- To evaluate the potential use of the proposed algorithm by estimating maximum reduction in emissions and delay.
- Use discriminant analysis on the timing of traffic controller events, taken from HRD, and emissions data from VT-micro model to develop a formula and quantitative ranking system to predict emissions based on the number of stopped cars at an intersection.

1.2 Organization of thesis

This thesis is written in manuscript format incorporating one document that has been submitted and one that soon will be submitted to peer-reviewed journals. Both manuscripts are presented in the formatting of their respective journals. Summaries of each thesis chapter are provided below:

Chapter 1: This chapter provides a general introduction about the importance of this work, and describes the organization of the document.

Chapter 2: This chapter, co-authored by Dr. Montasir Abbas, was accepted for presentation at the 2016 TRB Annual Meeting as a poster. It describes efforts to optimize algorithm parameters used to identify platoons at intersections and accommodate them thereafter with the end goal of achieving an overall reduction in emissions and traffic delay.

Chapter 3: This chapter is co-authored by Dr. Montasir Abbas and will soon be submitted to a peer-reviewed journal, likely TRB, for publication. It describes research to develop a formula and quantitative score range to check if emissions at intersections is above acceptable levels. A secondary goal of this work was to test how the presence of EV in different scenarios at intersections affects emissions.

Chapter 4: This chapter summarizes how the combined research done in the previous two chapters furthers the field of Transportation Engineering.

Chapter 2: Optimizing Platoon Identification Algorithm Parameters for Minimum Vehicle Emissions

Nadezhda Morozova, Montasir Abbas

Abstract
This paper describes efforts to optimize the parameters for a platoon identification and accommodation algorithm that minimizes vehicle emissions. The algorithm was developed and implemented in the AnyLogic framework, and was validated by comparing it to the results of prior research. A four-module flowchart was developed to analyze the traffic data and to identify platoons. The platoon end time was obtained from the simulation and used to calculate the offset of the downstream intersection. The simulation calculates vehicle emissions with the aid of the VT-Micro microscopic emission model. Optimization experiments were run to determine the relationship between platoon parameters and minimum- and maximum-emission scenarios. Optimal platoon identification parameters were found from these experiments, and the simulation was run with these parameters. The total time of all vehicles in the simulation was also found for minimum and maximum emissions scenarios. Time-space diagrams obtained from the simulations demonstrate that optimized parameters allow all cars to travel through the downstream intersection without waiting, and therefore cause a decrease in emissions by as much as 15.5%.

2.0 Introduction

Cargo trucks and passenger cars both play a crucial role in our society, yet their engines produce emissions harmful to the ecology and human health. Traffic engineers have a responsibility to find ways to alleviate this problem. As it is impractical to significantly reduce the amount of traffic, efforts must be made to find other ways to reduce emissions. One approach that has been proven effective is to group vehicles into platoons, reducing both emissions and fuel consumption. In order to estimate the full benefit of platooning, vehicle platoons must be identified and effectively accommodated at traffic signals.
Two issues must be considered for successful platoon accommodation at intersections. First, the platoons must be identified properly. Figure 1A shows that decisions regarding how to parse traffic into platoons can be challenging, because vehicles can be grouped differently. Second, the time at which the downstream traffic signal turns green must be carefully selected in order to minimize the amount of time vehicles spend accelerating or idling, because both of these states decrease efficiency and increase emissions. As shown in Figure 1B, the traffic signal can be set to turn green before platoons, between them, or at some other time.

Much literature has been published on platoon identification and accommodation algorithms, and on emission models. However, limited research has been performed to find the optimal platoon identification parameters to minimize vehicle emissions. This paper discusses our efforts to optimize platoon identification parameters with a simulation-optimization model developed in AnyLogic software. The remainder of this paper is organized as follows. First the relevant literature is reviewed. Then our proposed model for platoon identification and accommodation is discussed with the aid of a flowchart. The network simulation in AnyLogic software is also described. The developed model is validated, and graphs that present data for vehicle movements and emissions are discussed. The results of experiments to find optimal platoon identification parameters to achieve minimum emission are provided. Finally we report our platoon identification parameters and conclude with applications and ideas for future research.

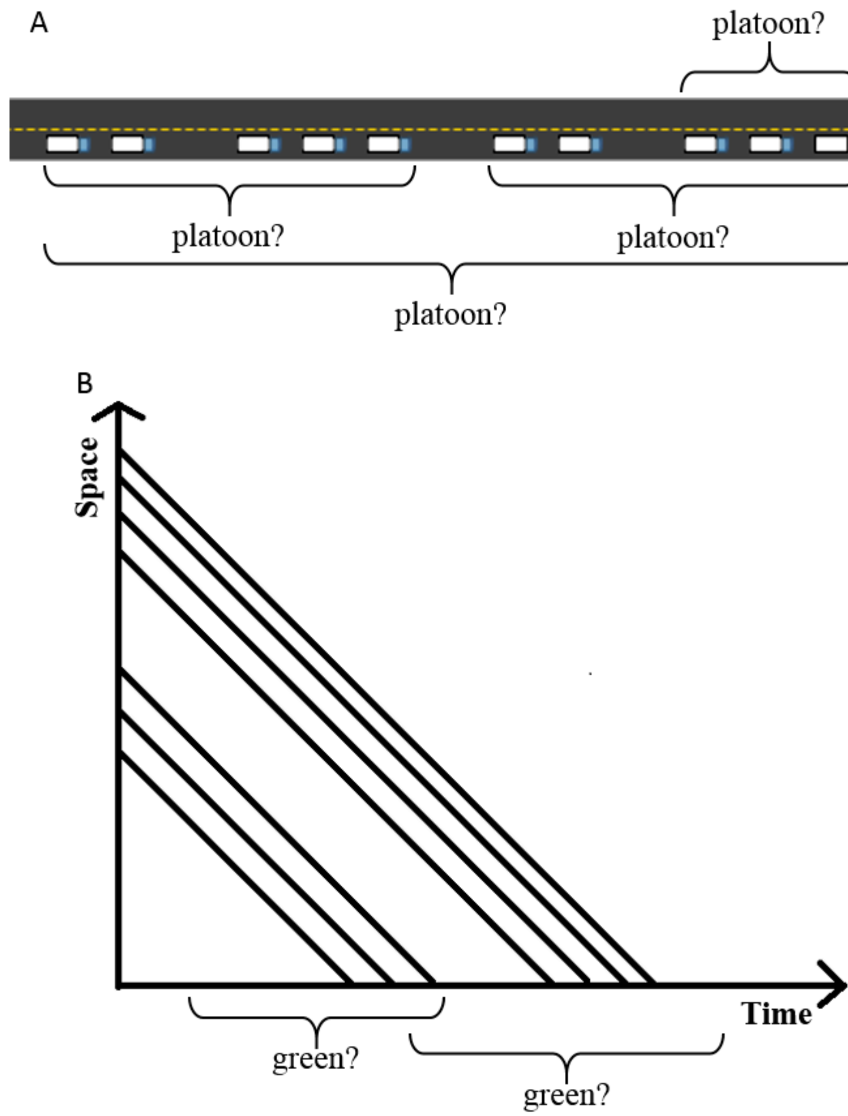

Figure 1: (A) Depiction of possible ways to identify a platoon; (B) decision when to turn on green traffic light

2.1 Literature Review

2.1.1 Platoon Identification Algorithms

A vehicle platoon is a group of vehicles travelling in physical or temporal proximity. Vehicle platoons are an essential part of transportation research, because they affect issues from traffic flow and signal control strategies, to fuel consumption and emission models. Previous research has addressed different aspects of platoon identification algorithms.

Some researchers focused on developing links between platoon identification software and traffic signal hardware at intersections and on the limitations of that technology. For example, Wasson et al. [1] addressed the problem of optimally allocating green light time at isolated intersections without coordinated traffic plans. They tried to eliminate the need for platoons on the major approach to stop for a few vehicles on the minor approach by issuing low-priority preemption. Chaudhary et al. [2] developed a platoon identification and accommodation system based on the cumulative headways of the vehicles. This system considered the speeds of individual vehicles and accommodated all vehicles in a platoon when they arrived at the next intersection along with any queues already present at the signal.

Other transportation research groups have addressed aspects of platoon management regarding traffic signal control in general, and future optimal signal plans in particular. For example, Jiang et al. [3] utilized the characteristics of vehicle platoons in signal timing to minimize traffic delays at intersections. A few key variables of platoon-based traffic flow were discussed, including the critical headway of vehicles within the platoon. These variables were utilized as a basis for the development of their own platoon-based signal control algorithm along with a simulation program. He et al. [4] tried to improve traffic signal control by developing a headway-based platoon recognition algorithm which identifies platoons based on online probe vehicles data. This algorithm was implemented in a unified platoon-based mathematical formulation called Platoon-based Arterial Multi-modal Signal Control with Online Data (PAMSCOD).

Several researchers have sought to identify platoons based on changes in link flow. For example, Mirchandani et al. [5] presented a real-time traffic-adaptive signal control system named RHODES. The system proposed in that work took input from the detectors, captured slow-varying characteristics of traffic, and calculated the approximate load on each link based on these characteristics. Dell'Olmo et al. [6] made efforts to predict vehicle movement based on measurements of traffic density, made in units of number of cars per unit time, and on the evaluation of various signal plans. This work resulted in the traffic model referred to as APRES-NET. The efforts of Gaur et al. [7] resulted in a method for real-time recognition of vehicle platoons based on the increase in link flow for specific time intervals. The algorithm developed in that work constantly calculated link flow within each rolling horizon, and took into account platoon identification parameters. Additionally, the link flow within each rolling horizon was compared to upper and lower bound parameters. The time horizon is a period of time that is long enough to represent stable measurements of the traffic state. The rolling horizon is a time during which the algorithm tries to determine whether there was a significant increase in traffic volume. The algorithm makes decisions about when platoons begin, how long they are sustained, and when they end.

2.1.2 Emission

Platoon identification and accommodation algorithms are also vital for fuel consumption and emission models [8]. Emission models can be classified as macroscopic, microscopic, and mesoscopic. Macroscopic models that are commonly used include the Elemental [9], Watson [10], MOBILE [11], and EMFAC models. Macroscopic models do not have strict resources requirements. However, their estimations are not precise, so they are typically used for rough project estimates for large road networks. Macroscopic models are outside the scope of this paper, since they do not suit our research purposes.
Microscopic models are mostly used in microscopic traffic simulation software when second-by-second vehicle characteristics of each vehicle are available. The most widespread microscopic models are VT-Micro [12] and CMEM [13]. Both models are acceptable to use in some cases. However, some research

shows that CMEM behaves abnormally in some scenarios, possibly due to its complexity [11].

Mesoscopic models require less data than microscopic models, and yield more accurate results than macroscopic models [14]. Therefore, they are desirable for situations that call for a balance between high accuracy and low computational cost. The commonly used mesoscopic models are Akcelik [15] and MEASURE [16].

Although the system developed in this paper is mesoscopic, a microscopic emission model is appropriate, because our simulation outputs speed, acceleration, and distance for every vehicle every second. Since our system provides sufficient data to use a microscopic model, the computational cost compared to a mesoscopic model is negligible. VT-Micro is a simple model that is effective for this purpose. Previous work demonstrates that it can provide estimates of vehicle fuel consumption to within 2.5 percent of actual measured field values [17]. Thus we choose to use the VT-Micro model in AnyLogic [18].

Although much progress has been made in the related topics of platoon accommodation and emission models, very little research has been done to determine the optimal platoon identification parameters for minimizing vehicle emission. The primary objective of the work presented here was to use optimization experiments to find parameters for minimum and maximum emission scenarios. Secondary objectives were to find the upper and lower bound parameters of a traffic flow, to find travel times for both scenarios, and to find the offset of a second traffic light for a minimum emission scenario. To this end, a model was developed in AnyLogic simulation software with an extensive flowchart for platoon identification. The VT-Micro emission model was implemented in AnyLogic to find vehicle emission. The highest and lowest emission values were compared to highlight the effect parameters have on the efficiency of traffic flow. The longest and shortest travel times were also compared to provide further evidence regarding differences in efficiency. Results of our work are summarized here, including time-space diagrams for optimized identification parameters for both scenarios.

2.2 Methodology

2.2.1 Proposed Model

In this section we describe a generalized platoon recognition model with various embedded parameters to be optimized. Two intersections are simulated in this model. One of them is a virtual intersection that we use to generate platoons. The other is a subject intersection at which we vary the timing of the traffic signal. Simulated traffic on the two-lane one-way road is shown in Figure 2A. AnyLogic requires the definition of two components for every road segment. The first component is a physical layer (e.g., a line, an arc or a curve), which defines the physical characteristics of a road. The second part is a functional layer e. g. a “CarMoveTo” block. This block is used to define how vehicles interact or move on a physical layer. CarMoveTo essentially represents the road segment. Figure 2B shows a physical layer on top and a functional layer on the bottom. CarSource is the block at the beginning of the road that produces cars. CarDispose is the block at the end of the road where cars exit the simulation. The numbers below the road segments represent cars in different states associated with this segment. For example, on carMoveTo2 602 vehicles entered this segment, 8 are moving, and 594 exited, as shown on Figure 2B. A detector is located at the beginning of the carMoveTo2 block. A detector is triggered when a new car passes over it.

Traffic lights are best represented in AnyLogic using statecharts. A statechart shows the different states that the traffic light is at every point in time, e.g., “green” and “red.” The statechart also defines how a state is transferred from green to red as shown in Figure 2C. To fully represent the traffic lights, combinations queue+hold on a functional layer (Figure 2B), along with the statechart (Figure 2C), are used. There are two traffic lights in our system. The length of a platoon, or the number of vehicles in the platoon, is limited by the duration of a traffic light’s green phase. Thus, the first (virtual) traffic light is used to form the platoons of cars. This traffic light is shown in Figure 2A in the shape of a circle. The state of this traffic light is green at the time of the screenshot. A second traffic light 1010.1 m away is responsible for platoon accommodation. The flowchart shown in Figure 3, the essence of our algorithm, was developed in AnyLogic to fit our needs. The algorithm is triggered by vehicles passing over the detector.

Before the algorithm begins running, the overall link flow is calculated as the average number of vehicles that pass over the detector within the time horizon. Also, the upper bound parameter and the lower bound parameter are defined before the algorithm begins. These parameters are used in some phases of the algorithm to make a decision about a platoon lifecycle. The upper bound and the lower bound parameters are calculated by multiplying the overall link flow by the upper and lower bounds. These parameters will be optimized below.

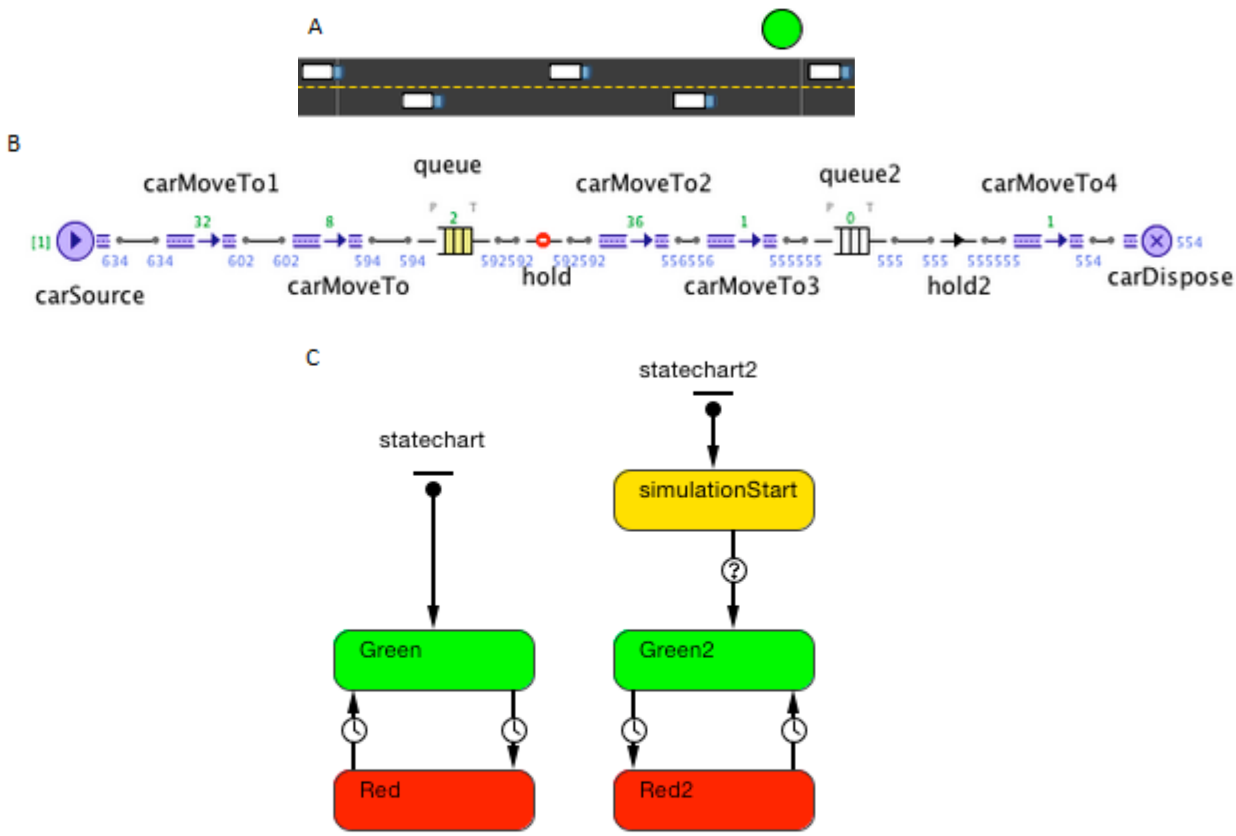

Figure 2: (A) Simulated traffic on a physical layer of the road in AnyLogic; (B) the functional layer of the road in AnyLogic; (C) statecharts for the first (statechart) and second (statechart2) traffic lights.

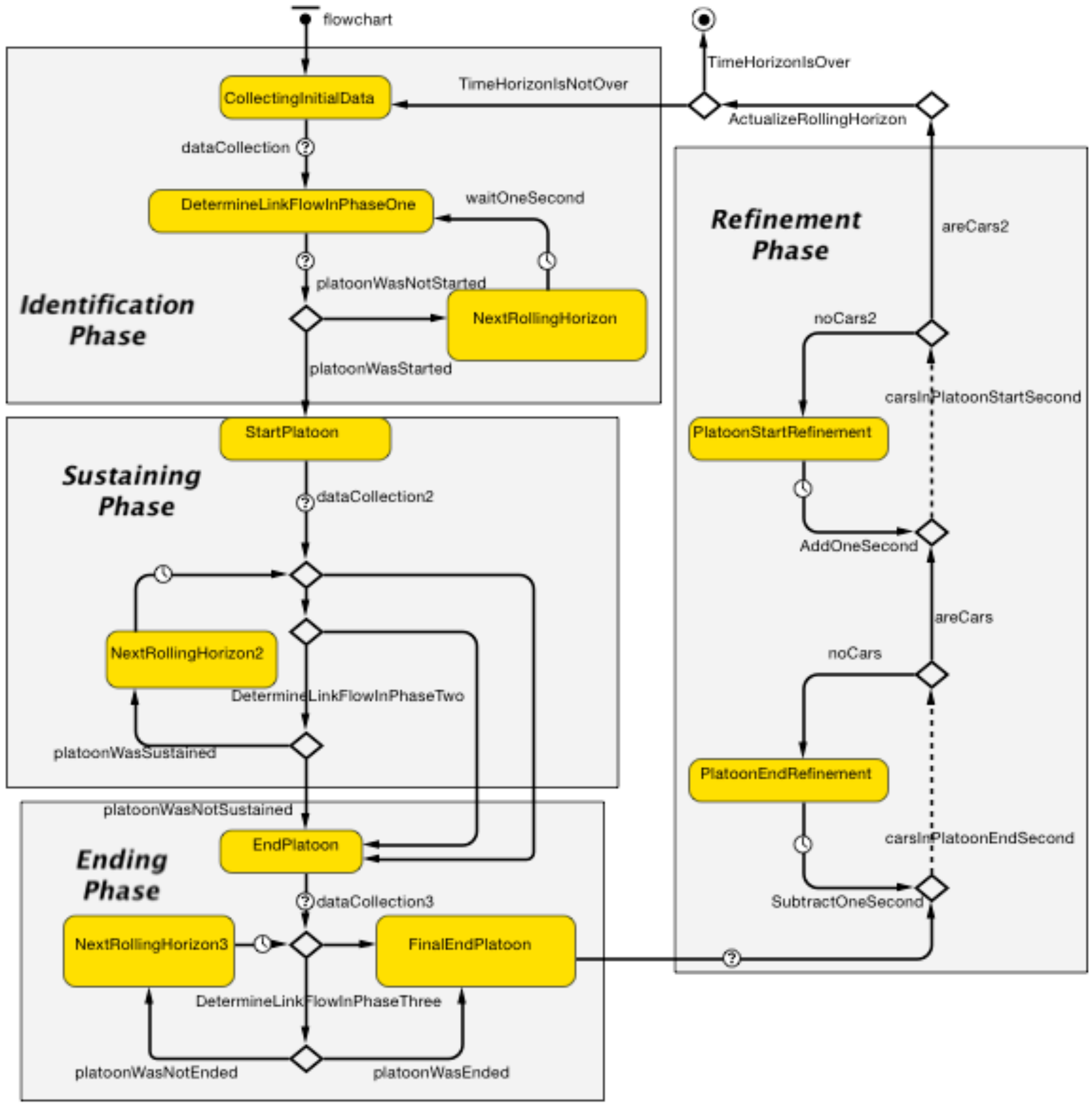

Figure 3: Flowchart of platoon identification.

The platoon identification and accommodation algorithm is divided into four phases:

1. Start a platoon
2. Sustain a platoon
3. End a platoon
4. Refine start time and end time of a platoon

The details of our algorithm are as follows. The first module is called the platoon identification phase. It depends heavily on the first platoon identification parameter (the identification interval). If the traffic volume during the identification interval exceeds the average traffic volume by a predefined threshold, the vehicle stream is identified as a platoon. The threshold added to the average traffic volume is defined in this phase as the upper bound of normal traffic flow. The upper bound of normal traffic flow can be related to a significance level based on the statistical distribution from which the traffic flow is drawn. The same concept also applies to the lower bound of traffic flow (indicating the end of the platoon) as will be described later.

If the traffic flow within this interval is less than the upper bound, the current time (t) is incremented by 1 and the traffic flow for next identification interval starting time (t+1) is calculated. Otherwise, the platoon is considered to be started and the second module, the platoon sustaining phase, begins.

The second module is similar to the first, except that the relevant platoon identification parameter is called the sustainability interval, and traffic flow is compared to normal traffic flow instead of the upper bound of traffic flow. The normal traffic flow is a threshold value of the platoon sustaining phase. If the traffic flow within the sustainability interval is greater than or equal to the normal traffic flow, then the platoon is extended, the evaluation time is incremented by 1, and steps of the platoon sustaining phase repeat. Otherwise, the third module, called the platoon ending phase, begins.

The platoon ending phase is similar to the identification and sustaining phases. The traffic flow is calculated within the ending time interval, which is the third platoon identification parameter. The traffic flow is compared to the lower bound of traffic flow. The lower bound is a threshold value of the platoon ending phase. If the traffic flow within ending interval is greater than the lower bound of traffic flow, the platoon is extended, evaluation time is incremented by the length of ending interval, and steps of this module repeat. Otherwise, the platoon is considered to have ended, and the forth module, the platoon refinement phase, begins. This final module cleans up the platoon start and end times by ensuring that the platoon interval starts and ends with a vehicle.

In previous work, the platoon identification, platoon sustainability, and platoon ending intervals were reported as 7, 10 and 5 s respectively [7]. No explanation was provided to justify these values. Our work here seeks the optimal platoon identification parameters by conducting two experiments. In our experiments we optimized platoon identification parameters, with the objective function set to minimize or maximize vehicle emissions.
The provided algorithm processes platoon data from the detector and finds the optimal offset for the second traffic light. Cycle lengths for both traffic lights do not change (40 s of green and 60 s of red for first traffic light, 50 s of green and 50 s of red for second traffic light). Protected left turns are not presented in the simulation, but their durations are included in the red phases. The platoon end time, calculated based on formulas (1), (2) and (3) in the last module of the algorithm, affects the offset between the two signals:

$$EGr2 = PlEnd + mod\left(\frac{d}{v}, cycle\right) \tag{1}$$

$$BGr2 = EGr2 - GrDur \tag{2}$$

$$Offset = BGr2 - BGr1 \tag{3}$$

Where:
PlEnd = Platoon end time,
d = Distance between intersections that equals to 1010.1 meters,

v = Average speed of vehicles in traffic flow (note: differs from the Maximum speed of 20.12 meters/seconds of vehicles specified in AnyLogic settings). The average speed equals to 15.42 meters/seconds,
cycle = cycle length (100 seconds),
BGr2 = Beginning of green for the second traffic light,
EGr2 = end of green for the second traffic light,
GrDur = duration of green at the second traffic light,
BGr1 = Beginning of green for the first traffic light.

2.3 Analysis

2.3.1 Simulation

Our model for vehicle platoon recognition was developed with AnyLogic 7.1.2 software with the Road Traffic, Analysis, Presentation, Agent, Process modeling, and Statechart libraries. The simulation performed in this paper considered a period of 3600 s. In one of our simulations we used 2446 vehicles per hour. Vehicles were generated based on the rate of vehicles per unit time. Thus, flow calculations can be made with the following equation (4):

$$F = \frac{Ncars}{tsim} = \frac{2446}{3600} = 0.68 \quad (4)$$

Where:
F = traffic flow (vehicle/s),
Ncars = number of vehicles, and
tsim = seconds of simulation.

Two important criteria for platoon-recognition algorithm are upper bound and lower bound of traffic flow (4, 5). These values are calculated as follows based on equations (5), (6):

$$Fupr = upperBound \times F \quad (5)$$

$$Flw = lowerBound \times F \quad (6)$$

Where:
Fupr = upper bound of traffic flow (vehicle/s),
Flw = lower bound of traffic flow (vehicle/s),
upperBound = upper bound parameter, and
lowerBound = lower bound parameter.

In previous work the upper bound and lower bound parameters were reported as 1.3 and 0.7 respectively [7]. However, no explanation was provided to justify such a choice. In this research we sought the optimal upper bound and lower bound parameters by conducting an experiment. In our experiment we optimized upper and lower bounds and the objective function was set to minimize vehicle emissions.

After all experiments and simulations are conducted, it was critical to verify that the results compare well with real-world values. During simulations, microscopic parameters of vehicles such as speed, acceleration, distance are stored every second. These data are used for producing the graphs and for emission calculation based on (7):

$$\begin{aligned} MOE = \exp(& C_{11} + C_{12}V + C_{13}V^2 + C_{14}V^3 + \\ & C_{21}A + C_{22}AV + C_{23}V^2 + C_{24}AV^3 + \\ & C_{31}A^2 + C_{32}A^2V + C_{33}A^2V^2 + C_{34}A^2V^3 + \\ & C_{41}A^3 + C_{42}A^3V + C_{43}A^3V^2 + C_{44}A^3V^3) \end{aligned} \quad (7)$$

Where,
MOE is the calculated measure of effectiveness (fuel, HC, CO, NOx) per second,
V is Speed (km/h),
A is Acceleration (m/s2), and
Cxy are the coefficients provided in Table 1 [19]

Table 1: Coefficients of VT-Micro Emission Model

Coefficients	Fuel	HC	CO	NOx
C_{11}	-7.533E+00	-7.280E-01	8.874E-01	-1.068E+00
C_{12}	3.255E-02	2.738E-02	7.790E-02	5.094E-02
C_{13}	-3.323E-04	-2.468E-04	-9.464E-04	-2.083E-04
C_{14}	1.965E-06	2.575E-06	6.099E-06	7.518E-07
C_{21}	1.484E-01	0.000E+00	1.633E-01	2.791E-01
C_{22}	5.789E-03	1.222E-02	4.660E-03	1.864E-02
C_{23}	-2.713E-05	-1.361E-04	1.232E-04	-1.731E-04
C_{24}	8.032E-08	8.959E-07	-1.024E-06	4.755E-07
C_{31}	1.920E-02	2.814E-02	3.678E-02	1.068E-02
C_{32}	1.101E-04	-7.253E-04	-1.223E-03	3.800E-03
C_{33}	1.358E-06	5.450E-05	7.130E-05	-8.504E-05
C_{34}	-3.945E-08	-3.388E-07	-4.995E-07	3.818E-07
C_{41}	-1.571E-03	-1.232E-04	-1.781E-03	-1.256E-03
C_{42}	-8.890E-05	-1.638E-04	0.000E+00	-4.654E-04
C_{43}	4.836E-07	5.266E-06	-2.243E-06	3.091E-06
C_{44}	-7.803E-09	-3.037E-08	0.000E+00	-2.199E-08

2.4 Experiments

Previous research did not fully consider the effects of platoon identification parameters on emissions. In this paper, we propose a new schema to link emissions to platoon identification parameters and determine optimum values for these parameters. Figure 4 shows how emission depends on intervals for platoon identification along with the parameter cycle length and platoon end time.
In order to minimize the vehicles' emissions with respect to the platoon identification parameters, the experiment was developed and run (Figure 5A). Platoon identification, platoon sustainability, and platoon ending intervals, along with upper bound and lower bound parameters, were set as parameters. The objective function was used to minimize the total emission of all vehicles. The experiment was run for 500 iterations. The lowest emissions obtained were approximately 410 g for the total hydrocarbon (HC), carbon monoxide (CO), and oxides of nitrogen (NOx) for all vehicles. Optimal values of platoon identification, platoon sustainability, and platoon ending parameters are presented in Table 2. The location of the detector, immediately after the first traffic light, is a main reason for why the identification interval is not larger than 1. A large volume of cars is released when the first traffic light turns green. This volume does not change significantly within the first few seconds. Thus one second is sufficient to start a platoon. It should be noted that optimal platoon identification values will be

different with different rates of cars per unit time, because parameters are volume sensitive. The model is not sensitive to slight variations of upper and lower bounds, so the experiment found that upper and lower bounds do not affect emission. The model is only sensitive to the time when cars held up at first traffic light get released. That is why any rough estimate for upper and lower bounds resulted in low emissions. For this work, values of 1.3 and 0.7 were used based on previously-reported values [7].

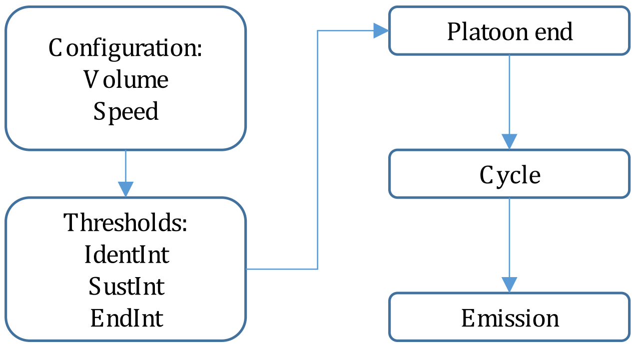

Figure 4: Flowchart depicting the relationship between emission and other parameters.

Table 2: Platoon identification parameters for different scenarios

Platoon parameters	Best values	Worst values
Identification (s)	1	1
Sustainability (s)	16	15
Ending (s)	10	1
Total Emission (g)	410	485

After the experiment was conducted, the simulation was run with optimal platoon identification parameters set to produce the best possible scenario. For 500 iterations, AnyLogic looks for the minimum value of the objective function, and constantly compares the current value with the best value found among prior iterations. It happened that it found the minimum value on one of few first iterations, which is why the orange line for the best feasible value becomes horizontal after several iterations. AnyLogic chooses parameter values in random order. Therefore, if the same experiment is run multiple times with identical objective functions, the resulting plots will have different shapes. A few plots were generated during the simulation runs. The time-space diagram in Figure 5C shows that no cars in the platoons had to wait for the second traffic light to turn green. This means the optimal offset was calculated by the system for the second traffic light, allowing all cars to arrive during the green phase. The offset in our system is 24 s when the optimal platoon identification parameters (1, 16, and 10 s) for minimum emission were used. Thus, the presented situation is optimal. The total travel time of the vehicles was calculated to be 263,325 s. Graphs of acceleration, smoothed speed, CO, and fuel consumption for one of the simulated vehicles are provided in Figure 6. Graphs of two other outcomes from the VT-Micro model (HC and NOx) were obtained. However, they were not presented here since they were very similar to the CO graph.

Another experiment to find maximum emissions was conducted to compare its results to the those of the minimum emission experiment. Platoon identification, platoon sustainability, and platoon ending intervals, along with upper bound and lower bound parameters, were set as parameters. The objective function was set to maximize the total emission of all vehicles. The experiment was run for 500 iterations. The function reached its maximum at approximately 485 g for total emissions. Optimal values of platoon identification, platoon sustainability, and platoon ending parameters were found to be 1, 15 and 1 s respectively (also listed in Table 2). Again, platoon identification parameters are volume sensitive.

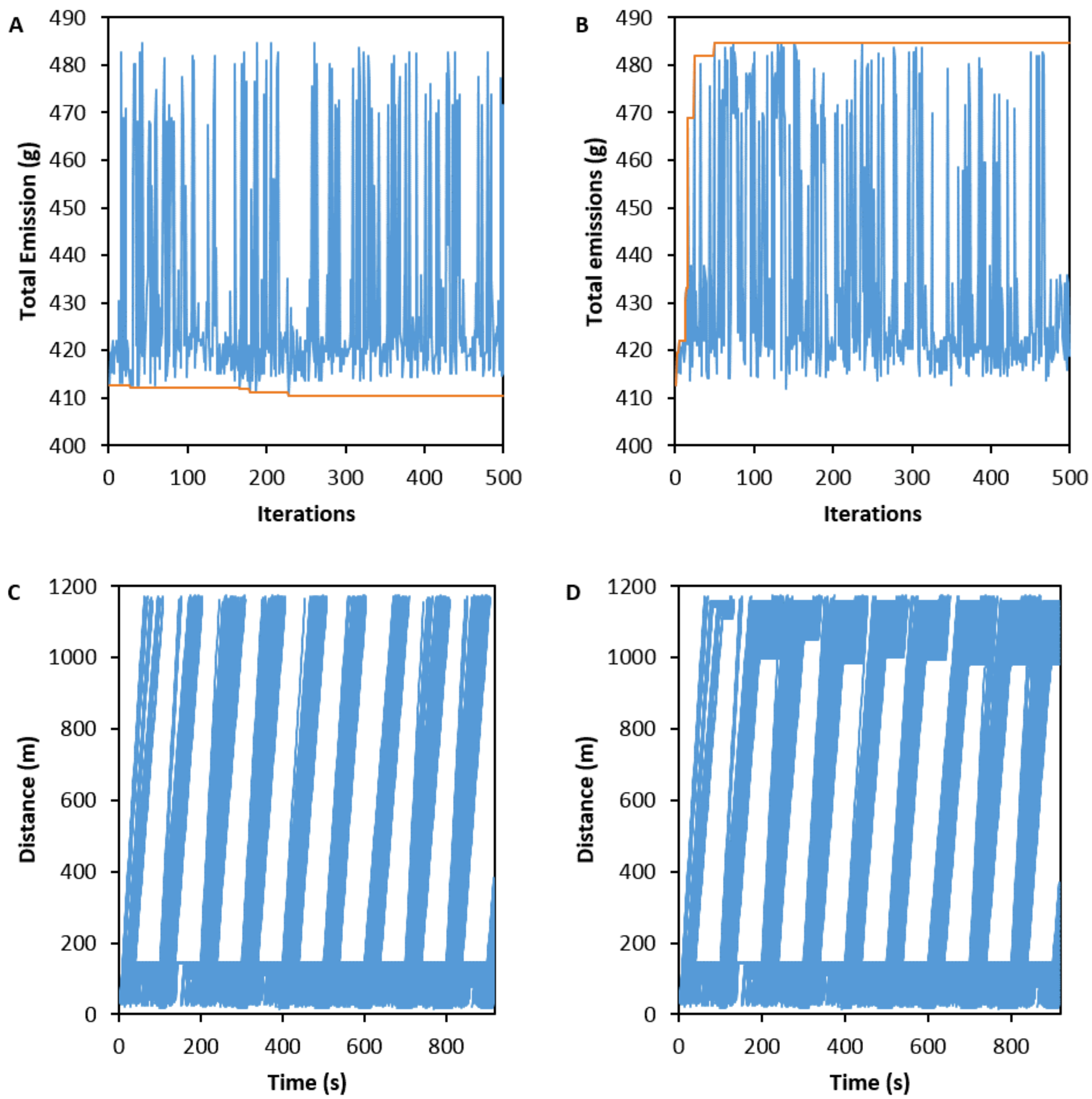

Figure 5: (A) Total minimum emission for different iterations depending on platoon identification parameters (blue line) with best feasible solution (red line); (B) total maximum emission for different iterations; (C) time-space diagram for best case scenario; (D) time-space diagram for worst case scenario

After the second experiment was conducted (Figure 5B), a simulation was run with platoon identification parameters of 1, 15, 1 s as a representation of worst case scenario. The time-space diagram in Figure 5D displays that almost every vehicle of the platoon had to wait for the second traffic light to turn green. The total travel time of vehicles was calculated to be 339,130 s.

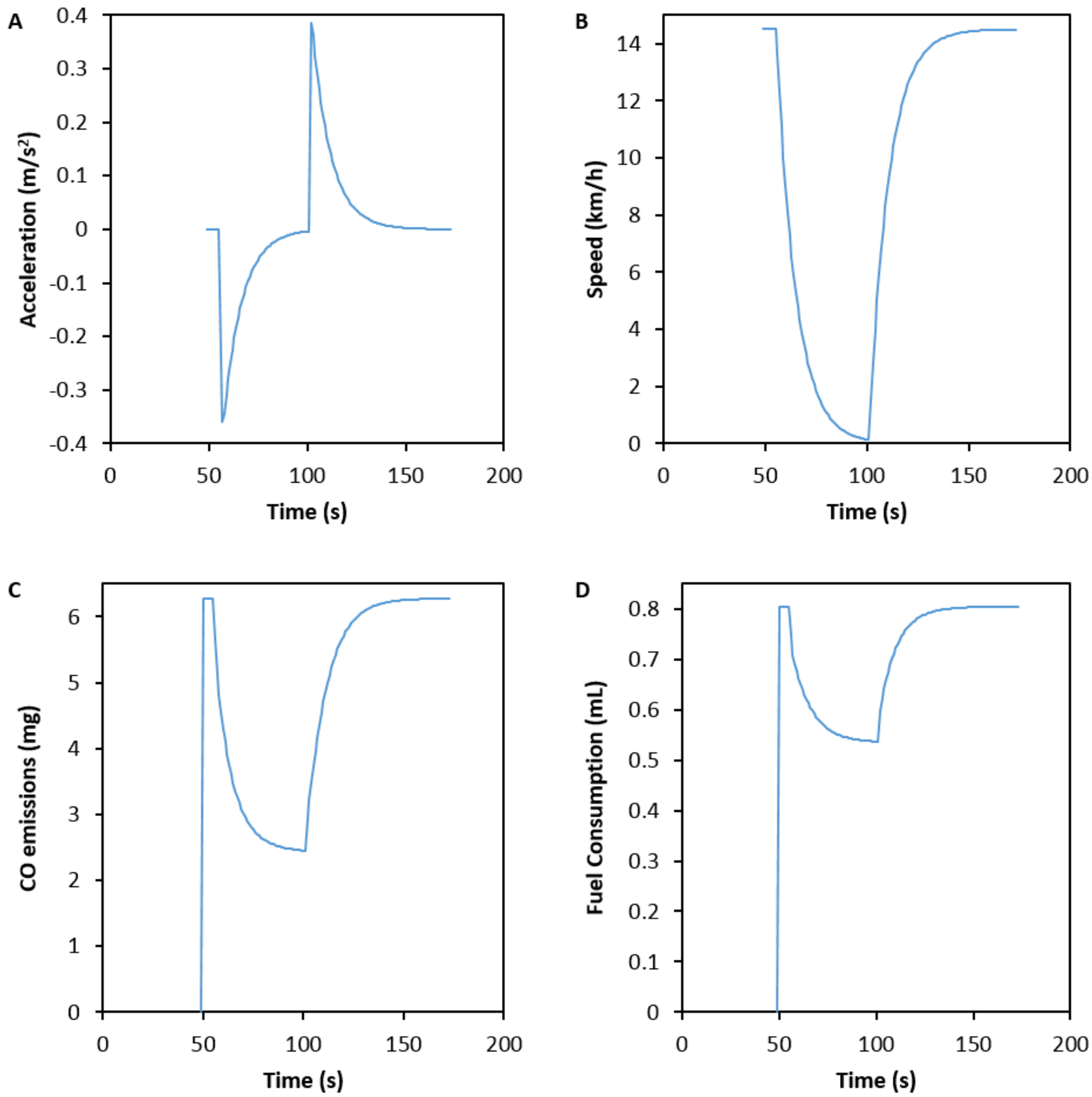

Figure 6: (A) Acceleration diagram of one of the simulated vehicles; (B) smoothed speed diagram of one of the simulated vehicles; (C) CO emission diagram of one of the simulated vehicles; (D) fuel consumption diagram of one of the simulated vehicles.

2.4.1 Model Validation

To validate the developed model, the simulation conditions were changed to make it more comparable to previous work. Specifically, the first traffic light was temporarily eliminated from the model. This had the effect of allowing the simulation to identify platoons, which was the objective of the previous work, instead of making platoons, the main objective of the present work. The modified simulation was run six times for one hour each time with the traffic volumes as provided by Gaur et al. (7) (1,035, 1,079, 1,087, 1,170, 1,210, 2,446 vehicles per hour). On average, 90.57 percent and 64.63 percent of the vehicles were captured in platoons for simulations with the optimal platoon identification intervals for minimum and maximum emissions, respectively. Running the simulation with the platoon identification intervals provided by Gaur et al. found that 87.35 percent of vehicles were captured in platoons, compared to 88 percent reported by Gaur et al.

Our model was also validated against Jiang et al. [3]. The simulation was run for 1 hr with the same traffic volume values used by Jiang et al. (ADT 40,000 or 1,667 vehicles per hour). In our simulation with the optimal platoon identification intervals for minimum emission (1, 16, 10 s), 92.62 percent of vehicles were captured in platoons on average. When optimal platoon identification intervals were set for maximum emission (1, 15, 1 s), 62.69 percent of vehicles were captured in platoons on average. The value reported by Jiang et al. (70 percent) falls in between our results of 62.69 percent and 92.62 percent. Thus, the model developed in this paper is consistent with previous models.

2.5 Results and Discussion

A new method to connect vehicle emission and platoon identification parameters through cycle length and platoon end time was presented in this work. Two problems were addressed. First, a platoon identification algorithm was developed and used to identify platoons in AnyLogic simulations. Second, the simulations were used to find the time at which the downstream traffic light should turn green to accommodate platoons and resulting in the lowest emissions.

To fulfill our purposes, an experiment was developed to optimize platoon identification parameters by minimizing total emission from the vehicles. The minimized emission value of approximately 410 g was found when these parameters were 1, 16 and 10 s. The simulation was run with optimal parameters, and a time-space diagram was made that showed the vehicles went through the second traffic light without having to stop when the algorithm was run. The total travel time of vehicles was 263,325 s. The offset value for the second traffic light in the minimum emission scenario was 24 s.

A second experiment was conducted to find the maximum vehicle emissions value, approximately 485 g. The parameters associated with maximum emission were 1, 15 and 1 s. The second simulation was run with these maximum-emission platoon identification parameters. The time-space diagram showed that almost all the vehicles were waiting at the second traffic light. The total travel time of vehicles was 339,130 s. The difference between the best scenario and the worse scenario is significant. The comparison between scenarios indicated that a careful choice of algorithm can reduce emissions by as much as 15.5 percent compared to the worst case scenario of maximum emissions. The difference between total travel times of vehicles shows that our algorithm can reduce total delay by as much as 22.4 percent when compared to the worst case scenario. This work also shows that the platoon identification parameters from our algorithm are sensitive to traffic volume. However, our experiment indicates that there is little correlation between upper/lower bound parameters and emissions. Therefore, the effect of parameter variations can be ignored.

Our research is significant due to its potential to traffic flow and to minimize vehicle emissions. Implementation of our platoon identification algorithm would cause more accurate estimates in platoon start and end times, and thus more accurate offsets for downstream traffic lights. Our algorithm would work on all links of a road network, producing optimized platoon identification parameters for emission and delay management in each link. Overall, improvements in traffic operation throughout the entire road network would cause a considerable decrease in the total travel times of vehicles and a large reduction in vehicle emissions. Reduced emissions and delays would lead to healthier transportation in general.

2.6 Conclusion and Future Research

The platoon recognition model was developed in AnyLogic 7.1.2 software. The model was carefully validated by running it with different volumes and with simulation conditions taken from the literature. Validation results demonstrate that our model agrees well with previous work. Plots of microscopic vehicle characteristics along with vehicle emission were generated and described. The VT-Micro emission model was implemented in AnyLogic to calculate emission from the vehicles involved in the simulation and considered collected speeds, distances, and accelerations.

Future research consists of, but would not be not limited to, further platoon dispersion considerations in traffic signal optimization. Future research could also handle the situation when multiple platoons in close temporal proximity are accommodated within a single cycle. In addition, car input can follow any probability distribution instead of the rate of vehicles per unit time.

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Chapter 3: Finding a Classifier to Distinguish Between Minimum and Maximum Vehicle Emissions Considering EVP Using High Resolution Data

Nadezhda Morozova, Montasir Abbas

Abstract

This paper discusses the outcome of efforts to leverage high resolution data obtained from WV-705 corridor in Morgantown, WV. The proposed model was developed for that purpose and implemented in the AnyLogic framework to simulate this particular road network with four coordinated signal-controlled intersections. The simulation was also used to calculate vehicle CO, HC, NOx emissions with the aid of the VT-Micro microscopic emission model. Offset variation was run to determine the optimal offsets for this particular road network with traffic volume, signal phase diagram and vehicle characteristics. Significant combination of attributes of HRD called classifier was found by regression. Equation of this classifier was developed to distinguish between set of timing plans that produce maximum emission from set of timing plans that produce maximum emission. Also, current work investigates the potential use of the GPS-based and similar priority systems by giving preemption through signalized intersections. Two flowcharts are developed to consider presence of EV in the system so called EV life cycle and EVP. Three scenarios are implemented, namely No-EV, EVP, EVP with right-of-way scenarios. Research makes an attempt to compare emission results of these scenarios to find out whether EV effects vehicle emission in the road network and what is the level of this influence if any.

Keywords: High resolution data; Emission; CO; HC; NOx; Classifier; Regression; Discriminant analysis; VT-Micro; AnyLogic; Flowchart; Traffic flow; Simulation; Cycle length; Offset; Acceleration; Speed.

3.0 Introduction

Traffic controllers have certain outputs that can be logged and stored. Researchers can then use this data to analyzed when specific detectors were triggered. Although detector logs were initially stored in a multitude of different formats, a universal format for representing events of controllers using High Resolution Data (HRD) is now widely in use.

Much literature has been published on how to best apply HRD to evaluate intersection performance measures, emergency vehicle preemption (EVP), and emission models. However, limited research has been performed to predict vehicle emissions at intersections based on HRD. The work presented herein strives to use HRD and come up with something useful with it for Traffic Engineers in terms of emission.

As known, emission from vehicles is influenced by timing plan, traffic volume, and characteristics of the traffic. The question that we seek to answer here is how to distinguish between a set of timing plans that produces maximum emissions and a set of timing plans that produces minimum emissions just by looking at the HRD. As a result of research efforts a Traffic Engineer will be equipped with the classifier threshold to identify if any changes to existing timing plans are required. A secondary objective of this paper is to compare effect of EV presence (so, EVP is given to it by traffic lights and right of-way is given by other vehicles) on the road network in terms of emission with base case scenario without EV.

This paper discusses efforts to come up with a classifier to distinguish between maximum and minimum emission cases with a model developed in the simulation-optimization software AnyLogic. The remainder of this paper is organized as follows. First the relevant literature is reviewed. Then our proposed model is discussed with the aid of an EV life cycle flowchart and EVP flowchart. The network simulation in AnyLogic and offset variation are also described. A classifier to distinguish between max and min emission cases along with its threshold and equation is developed and discussed. Cases including and excluding EV were compared in terms of emission values. The work is concluded with applications and ideas for future research.

3.1 Literature review

3.1.1 Emergency vehicle preemption

Preemption of emergency vehicle (EVP) concept was around probably as long as signalized intersections themselves. One of the earliest mentions about EVP was in 1929 in the publication “Street Traffic Signs, Signals, and Markings” of American Engineering Council [1]. Since then the topic of EVP was widely explored by researchers in their previous publications.

Part of the previous research concentrated on decision making process of EVP and on cost-benefit ratio of preemption implementation. For example, research of Paniati et al. identified available technology options for preemption and agencies

that should be involved in decision making process [1]. Paniati et al. also performed a site study at Fairfax county, VA, Plano, TX and St Paul, MN. These researchers discussed the costs of EVP implementation and benefits from this system in place at each particular site.
Some studies made an attempt to address deficiencies of available EVP methodologies. For instance, Louisell et al. presented proposed earlier method that decides which intersections or which corridors should use EVP [2]. Safety, delay, distance to origin/destination of EV and intersection index in regional emergency response plan are criteria for this method suggested by researchers.
Other group of researchers are focused on developing and deploying different control strategies for EVP. Qin et al. came up with signal sequences-based control strategies: one that transitions from normal traffic operation to EVP mode and another that brings traffic back to normal operation [3]. It was claimed that these strategies work better than existing approaches even when over-saturated traffic conditions are involved. Nelson et al. provided results of a case study performed in a four-intersection corridor in Lafayette, IN [4]. Researchers estimated the impact of EVP on general traffic considering different preemption paths, transition algorithms, and frequency of preemption events. Jordan et al. developed three preemption strategies based on vehicle-to-infrastructure communication and assessed them using EV travel time and overall network delay as guidelines [5]. These researchers tried to clear the queue at the intersections prior to EV arrival and thus allow the EV to proceed unimpeded. All proposed strategies aimed to estimate, find, or calculate the appropriate start time of preemption. Simulation runs showed that the queue length-based strategy provided the best performance.
Some researchers considered how preemption delays traffic. Chou et al. used preemption duration and transition duration to quantify the effect of EVP on overall traffic flow. Researchers defined preemption duration as time between the states of trigger ON and OFF of a controller. Similarly, they defined transition duration as time that takes for the controller to return to its normal operation (time between states OFF and IN STEP). Chou et al. concluded that Smooth transition provides the shortest duration to return to normal traffic and Dwell the longest duration. The research presented in this paper expands EVP and utilizes Dwell as the most appropriate for our purposes transition strategy.

3.1.2 Emission

It is an important task for Traffic Engineers to use appropriate emission models [6] and to estimate emissions from HRD. Emission models can be classified as macroscopic, microscopic and mesoscopic. Macroscopic models that are commonly used include the Elemental [7], Watson [8], MOBILE [9], and EMFAC models. Macroscopic models do not have strict resources requirements. However, their estimations are not precise, so they are typically used for rough project estimates for big road networks. Macroscopic models are outside the scope of this paper since they do not suit our research purposes.
Microscopic models are mostly used in microscopic traffic simulation software when second-by-second vehicle characteristics of each vehicle are available.

The most wide-spread microscopic models are VT-Micro [10] and CMEM [11]. Both models are acceptable to use in some cases. However, some research shows that CMEM behaves abnormally in some scenarios, possibly due to model complexity [9].
Mesoscopic models require less data than microscopic models and yield more accurate results than macroscopic models [12]. Therefore, they are desirable for situations that call for a balance between high accuracy and low computational cost. The commonly used mesoscopic models are Akcelik [13] model and MEASURE model [14].
Although the system developed in this paper is mesoscopic, a microscopic emission model is appropriate because based on output of loop detectors individual speed of a vehicle, its acceleration can be calculated. Since we have sufficient data to use a microscopic model, the computational cost compared to a mesoscopic model is negligible. VT-Micro is a simple model that is effective for this purpose. Previous work demonstrates that it can provide estimates of vehicle fuel consumption to within 2.5 percent of actual measured field values [15]. Thus we choose to use the VT-Micro model in AnyLogic [16].

3.1.3 High Resolution Data

HRD is provided by the traffic controllers in commonly agreed format and contains traffic info and signal phase info [17]. HRD is generated by controller 10 times per second. If two loop detectors are installed in one lane, then HRD is a great tool for measuring the characteristics of vehicle arrival such speeds and accelerations. This significant tool has attracted much attention from researchers recently.

Some research groups wanted to get away from the conventional way of measuring performance of signalized intersection based on calculating average vehicle delay and total approach delay and made an attempt to calculate something more vehicle-specific. For example, group of Lavrenz et al. used HRD to estimate the upper threshold of delay of the particular vehicle based on time interval between first detection event on an approach and start of green time of this approach [18].

Other group of researchers utilized HRD for studies on diamond interchanges. For example, Hainen et al made efforts to optimize offsets while keeping the existing sequence of signal phases [19]. In later work, the same researchers also included left turns in different sequences in addition to offset optimization [20].

Some research was done on measuring performance of system-in-the-loop simulations [21], [22], [23]. For example, Day et al. estimated delay as a traditional measure of simulation performance and arrivals on green along with traffic volume to lane capacity ratios as operational measures of simulation performance [21]. Researchers compared a few strategies for intersection network under heavy traffic.
Other groups of researchers tried to visualize HRD and facilitate analysis of this

data [24], [25]. For example, Chou et al. developed an improved format to present performance measures and coordination events with the use of signal phase spectrum plots [25].

To the best knowledge of the authors of this paper, no previously published research has found a classifier that can help estimate emissions just based on looking at HRD. The current work uses HRD obtained from a real corridor in WV-705 in Morgantown, WV to estimate vehicle emissions.
Although much progress has been made in the related topics of EVP, HRD and emission models, very limited research has been done to determine a classifier to distinguish between optimal and not optimal vehicle emissions cases based on HRD and considering EVP. The primary objective of the work presented here is to find the combination of traffic flow characteristics that affect emission the most and to come up with equation for this classifier. A secondary objective is to evaluate if and to what degree the presence of EVs affect network emissions. To this end, a model was developed in AnyLogic simulation software with flowcharts for all four traffic lights of the road network, for EV life cycle, and for EVP. The VT-Micro emission model was implemented in AnyLogic as a tool for finding vehicle emission to analyze it later on.

3.2 Methodology

3.2.1 Proposed Model

This section describes the way the real road network was created in simulation and optimization software AnyLogic. The signal phase diagram for all intersections coordinated with each other along with offsets are presented. Turning volumes for all approached within the road network is introduced. The section also gives an overview of proposed EVP mechanism along with EV life cycle. VT-Micro model is presented in the end.

Road Network (The physical layer):

The road network is the representation of the WV-705 traffic corridor in Morgantown, West Virginia. A Google Earth satellite view of this corridor is presented in Figure 7.

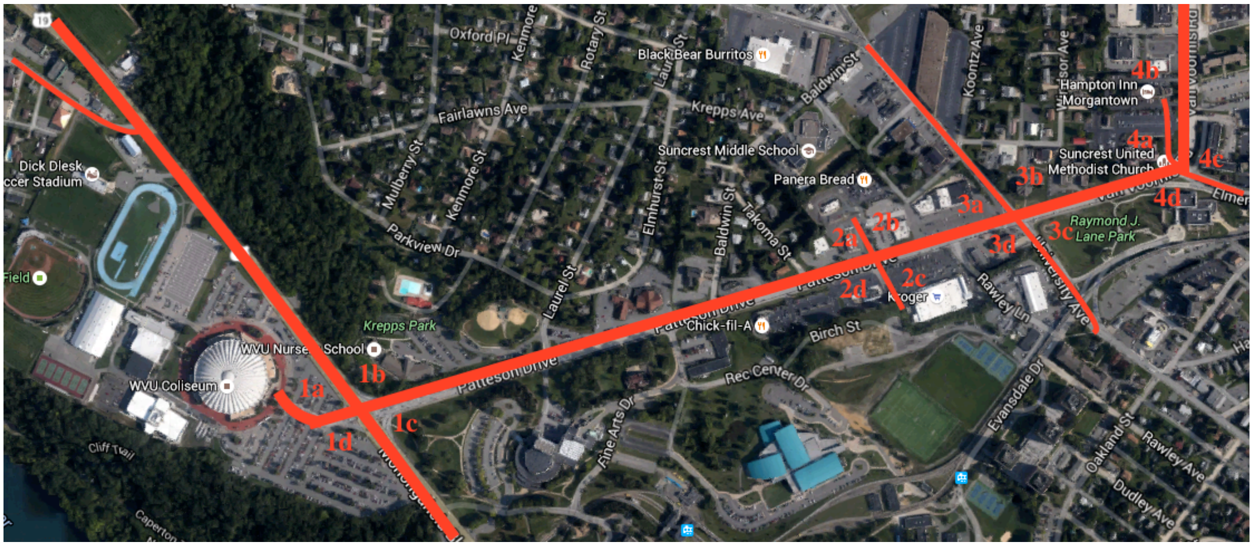

Figure 7 Google maps Earth view of the route WV-705

The flow (the geometry) of the corridor, the distances between intersections, number of intersections, number of lanes in each direction, and the lengths of the turning lanes are accurately modeled to match their real-world dimensions. The distance between intersection 1 and intersection 2 is 2792 ft (851.0 m), between 2 and 3 is 774 ft (236.0 m), between 3 and 4 is 868 ft (264.4 m). However, lane assignments are handled in a way that deviates from the real intersection. All modeled lanes allow traffic to proceed in a single direction even if the corresponding real lane is designed to allow traffic to proceed in two directions. For example, if a real lane allows traffic to go straight or turn right, then the modeled lane only allows traffic to turn right and a separate lane is used for vehicles going straight through the intersection.
The simulation and optimization package AnyLogic is used for current research. Two different layers, one physical and one functional, should be created for every road segment to run a model in AnyLogic. Figure 8 represents a physical layer of the road in terms of lines and arcs. Arcs are always used for turning lanes as well as for making curved road sections. The circle near each traffic light of the intersection represents the overall state of the traffic light. Only one signal color is shown for simplicity. Green circle of the traffic signal represents that green light is given at least to one of the approaches (either through, left or right). Yellow light turns on after green light, warns drivers that light is about to turn red and stops vehicles on every lane from moving. Red circle of the traffic signal turns on after yellow light and prevents vehicles on every lane from moving.

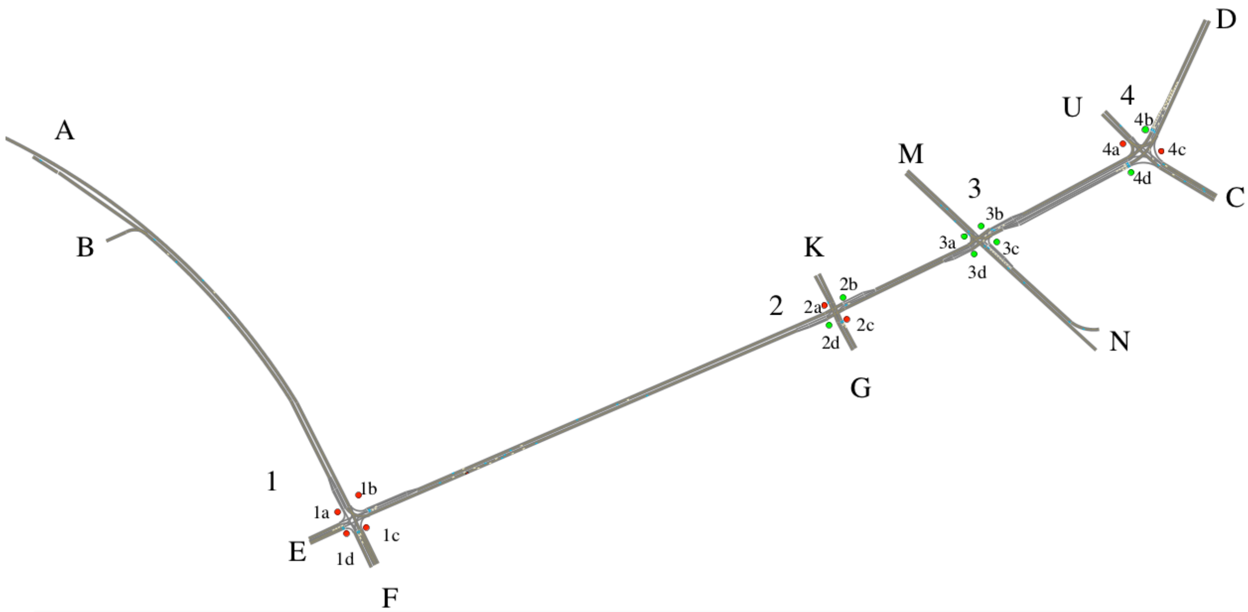

Figure 8 The physical layer of the road in AnyLogic

3.2.2 Logic of the model (the functional layer):

Vehicle interactions on a physical layer mostly depend on the logic inside of the functional layer. Thus, the functional layer is one of the responsible players for controlling vehicle movements. The functional layer consists of few blocks, which are arranged in a specific order as shown in Figure 9. CarSource is the block at the beginning of the road that produces vehicles. It also generates infusion of vehicles in the road network. There are eleven CarSources for normal vehicles and one for EV. CarMoveTo blocks are responsible for one of the road segments/road stretches. There are 201 CarMoveTo blocks. CarDispose blocks represent the end of the road where vehicles get extracted/removed from the simulation. There are 11 CarDispose blocks in the model. SelectOutput(5) blocks are responsible for dividing lanes and reassigning the vehicle flow. To facilitate programming, lanes are handled as separate roads at intersections with each road allowing traffic to proceed in a single direction (either through, right, or left).

For example, on Figure 3 the two lane road represented by carMoveTo15 is divided to three 1-lane roads (carMoveTo132, carMoveTo122, carMoveTo112) with the help of SelectOutput(5)8. Hold blocks is needed to stop the first vehicle of the vehicle queue of the particular lane at the red traffic light. A Queue block is placed before a Hold block and is needed to store the second vehicle of the vehicle queue of the particular lane. Queue and Hold blocks are present in each lane to account for lane assignment in each lane separately. Hold blocks for center, right-turn, and left-turn lanes are designated as C, R, L respectively. SelectOutput(5), hold and queue blocks along with lines, arcs, and statecharts participate in the traffic light creation and operation. Connectors on the right from carMoveTo16 and carMoveTo47 connect current route with other routes. After traffic light queue22+hold3cL car turns left, gets on the road segment carMoveTo47 and merges into another route with the help of the connector.

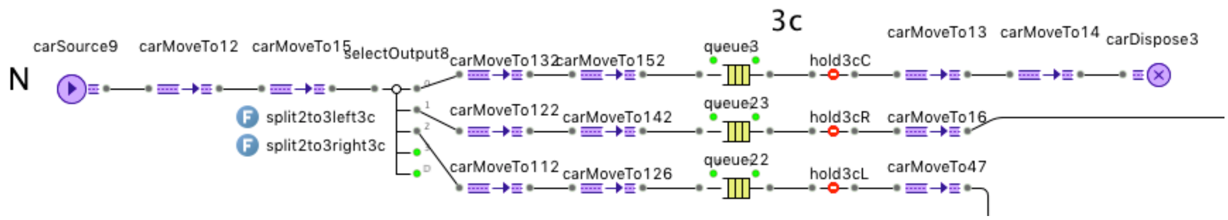

Figure 9 A sample of the functional layer of the roads in AnyLogic

The scheme of the whole road network is too large to include in a single figure. Only part of it is shown in Figure 9. That is why names (lettering) of intersections, approaches and CarSources are important. There are four intersections numbered from 1 to 4. There are four approaches at each intersection like 1a, 1b, 1c and 1d. Letters a, b, c, and d represent southbound, westbound, northbound, and eastbound respectively (Figure 8). CarSources are named alphabetically as A, B, C etc. The lettering of the intersections, approaches, and CarSources are the same on the physical layer of the roads (Figure 8) and on the functional layer of the roads (Figure 8).

3.2.3 Signalized intersections (statechart of the intersection, signal phase diagram/ring barrier diagram, offsets):

The Road Traffic Library of the current version of AnyLogic lacks native support to implement signalized intersections [26]. To circumvent this limitation, intersections were built from combinations of existing blocks of AnyLogic including custom classes and functions. Besides combinations of SelectOutput(5)+hold+queue blocks on the functional layer, statecharts are used to manipulate hold blocks and signal timings. There is a separate statechart for each of the four intersections of the model. Figure 10 displays the statechart of one of the traffic lights in the model. In a statechart, the first state in yellow on the left is an initialization state that is responsible for a traffic light to start operating. Signal phases in real life can go parallel (start in the same time) or sequentially (start one after another). Signal phases are represented in AnyLogic as the sequence of different states (events) on the timeline. Each state describes the lane assignments of all four approaches of the particular intersection. Each phase contains two states: one for green signal, one for red signal. There are two modes of traffic light operation: normal and after EVP (to restore cycle to its original timings). Normal mode is displayed on
Figure 10 by arrow from one state to another with watch in between. After EVP mode is displayed by arrow from one state to another with the question mark in between.
For example, the statechart of intersection 2 is displayed on
Figure 10. Signal phases 1, 2, 3 are presented at the top and phases 5, 6, 7 are presented at the bottom. Since green light of the phases 1 and 5 start in the same time, there is only 1 state that represents both of them. Red light of phases 1 and 5 also starts in the same time, so similarly there is only 1 state for both of them. The same is applied for green and red of states 2 and 6, 3 and 7. For visual purposes a state is allocated on green background if it represents green state of the traffic light and on a red background if it represents a red state. The dimensions of the sections are to scale with respect to their durations. In Figure

4, green light of phases 1 and 5 continues for 7.1 seconds and red light of these phases for 4.9 seconds. Green light of phases 2 and 6 continues for 72.7 seconds and red light of these phases for 5.3 seconds. Green light of phases 3 and 7 continues for 25.1 seconds and red light of these phases for 4.9 seconds. The red and green bars are sized proportionally based on these durations.

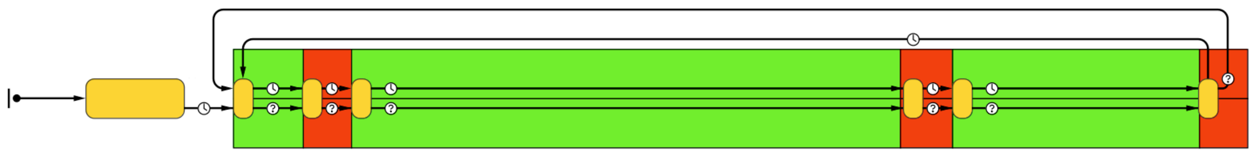

Figure 10 Statecharts of second intersection

The ring diagram and signal phase diagram display traffic assignment on each lane. The diagrams on Figure 11 and Figure 12 represent real vehicle assignment in traffic corridor WV-705 in Morgantown, WV along with the duration of each phase [21].

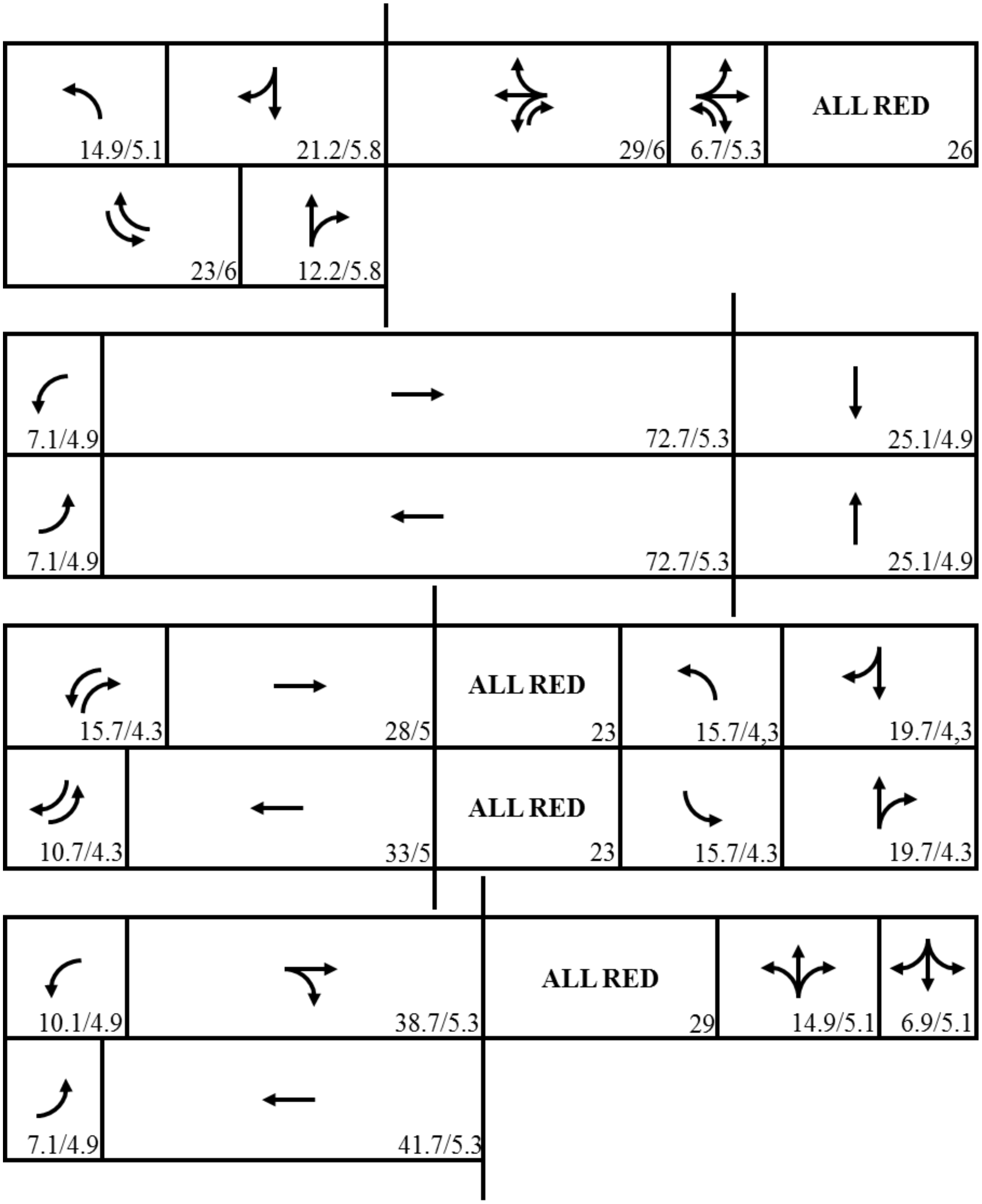

Figure 11 The ring barrier diagram for four intersections

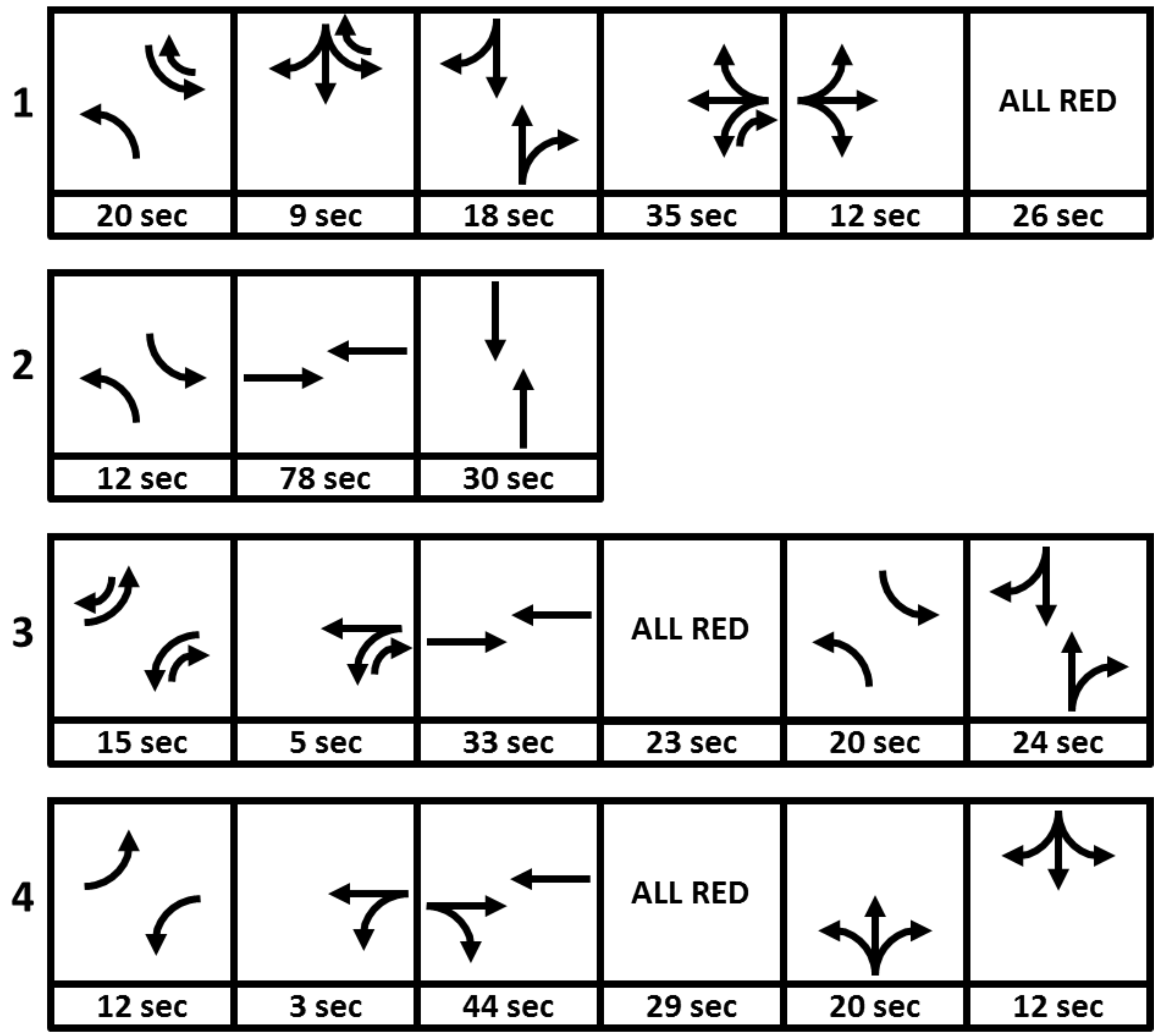

Figure 12 The signal phase diagram for four intersections

The offsets of downstream traffic lights are important for traffic coordination. The offsets in the developed model on Figure 13 represent real offsets in the coordinated traffic corridor WV-705 in Morgantown, WV [21]. Offsets values of 110 sec, 26 sec and 28 sec were provided from a case study on WV-705. These are in agreement with the output values 110, 20, 20 sec from offset variation with step equal to 20 sec in the current work.

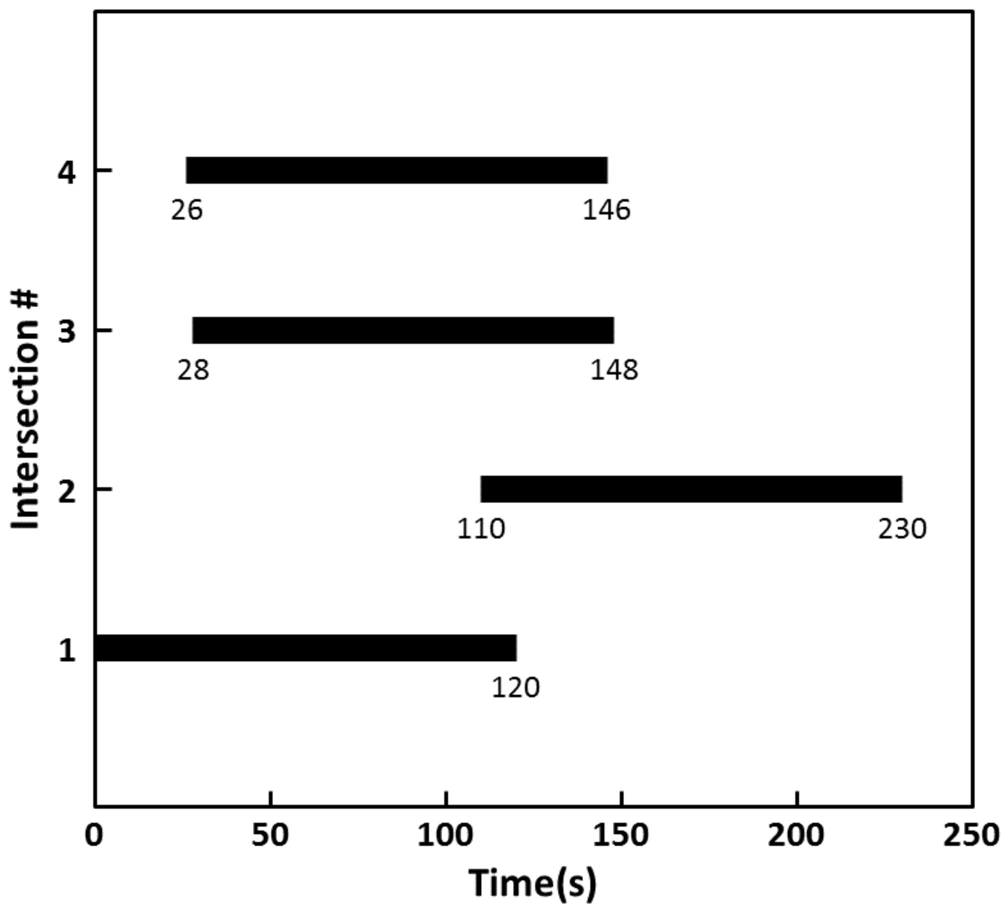

Figure 13 Offsets of four coordinated intersections

3.2.4 Turning volumes:

The turning volumes in the developed model on Figure 14 represent real traffic flow going through, left and right in the Morgantown WV-705 corridor [21]. The morning peak-hour data (5:30-9:30 am) are used as an input parameter to represent the maximum load on the road network and to test the robustness of our model. The frequency of u-turns is negligibly small even at peak traffic volume, thus they are omitted from the model.

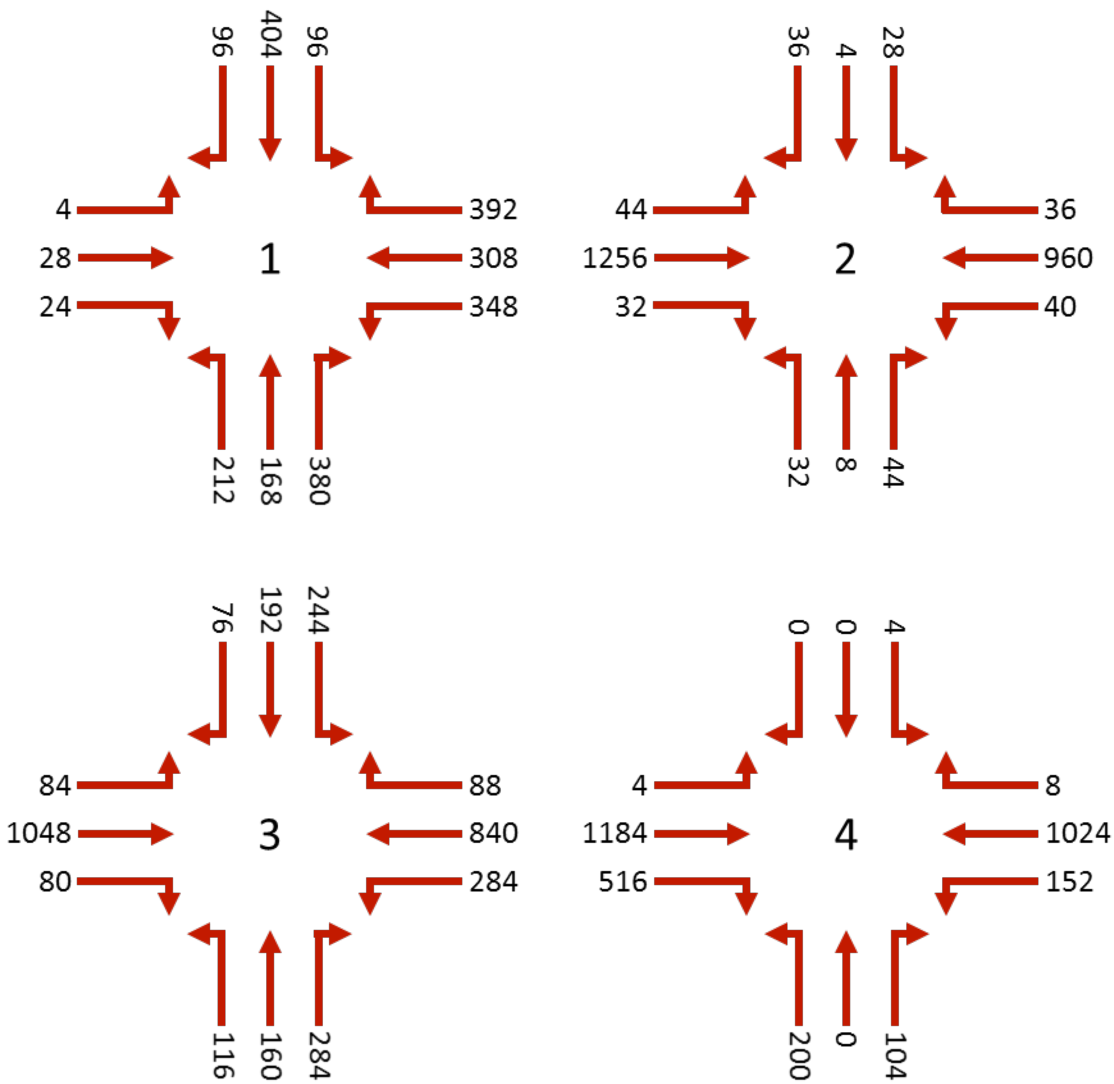

Figure 14 Turning volumes for morning peak-hour 5:30-9:00am

3.2.5 EV life cycle

When a simulation starts, vehicles are constantly produced by all carSources blocks based on the corresponding rates/minute assigned there. EV in the proposed model runs every 15 minutes on major westbound approach. It starts from D and is disposed at A. An EV can potentially effect emission since other cars have to give it right-of-way and stop for a few seconds. Therefore, it makes more sense to put EVs on the approach with more vehicles, the westbound approach in this case. A flowchart is developed to display life cycle of each EV.
The life cycle of an EV starts from production by its own EVcarSource block that is located near carSource D (Figure 15). The next step is to check whether the EV is in the road network or not. If the EV is not in the road network, it means that the EV has already made it through all 4 intersections and has already been disposed by carDispose block at A. If the EV is still in the road network, then we

check if the next road segments that the EV is about to enter are included in "intersection set". This check is done as follows: we determine which road segment the front of the car is on (we specify front because the front and back of a car can be on different segments if the car in is transition between them) and consider the upcoming road segments. We iterate through the next segments to check if one of them is included in one of our four intersections. For that we look inside IntersectionCollection in AnyLogic and call the getTrafficLightByLaneName() method of every intersection with «segment name» as a parameter. This method returns the particular traffic light that the EV is approaching. Thus, we can determine whether this next segment belongs to any of the traffic lights and if it does belong, to which one exactly so we can give EVP to the specific intersection. If no traffic light is determined, the simulation goes back to check whether EV is in the road network. If a traffic light was found, we check the distance to this traffic light by calling the getOffset() method. This method returns distance that car already passed along current road segment. The distance to intersection is stored in the variable offsetToIntersection and is calculated by subtracting the distance that the car already passed along the current road segment from the segment length. If the distance to the intersection is bigger than the preemption distance of 200 meters, then it is too early to give EVP. In this case, the flowchart checks whether EV is still in the road network. If the distance to the intersection is smaller or equal to the preemption distance, we turn on EVP on the relevant traffic light by calling the method preemptionOn() with the traffic light as a parameter. As a next step, the simulation checks whether the EV entered an intersection. If the EV did not enter an intersection yet, it is probably got hold/stuck in the traffic jam, so we turn EVP ON again. If the EV already entered an intersection, the next step of the simulation is to check whether the EV left an intersection. If the EV did not leave an intersection yet, the simulation continues to check every second until the EV leaves this intersection. If the EV already left an intersection, the simulation checks again if the EV is still in the road network.

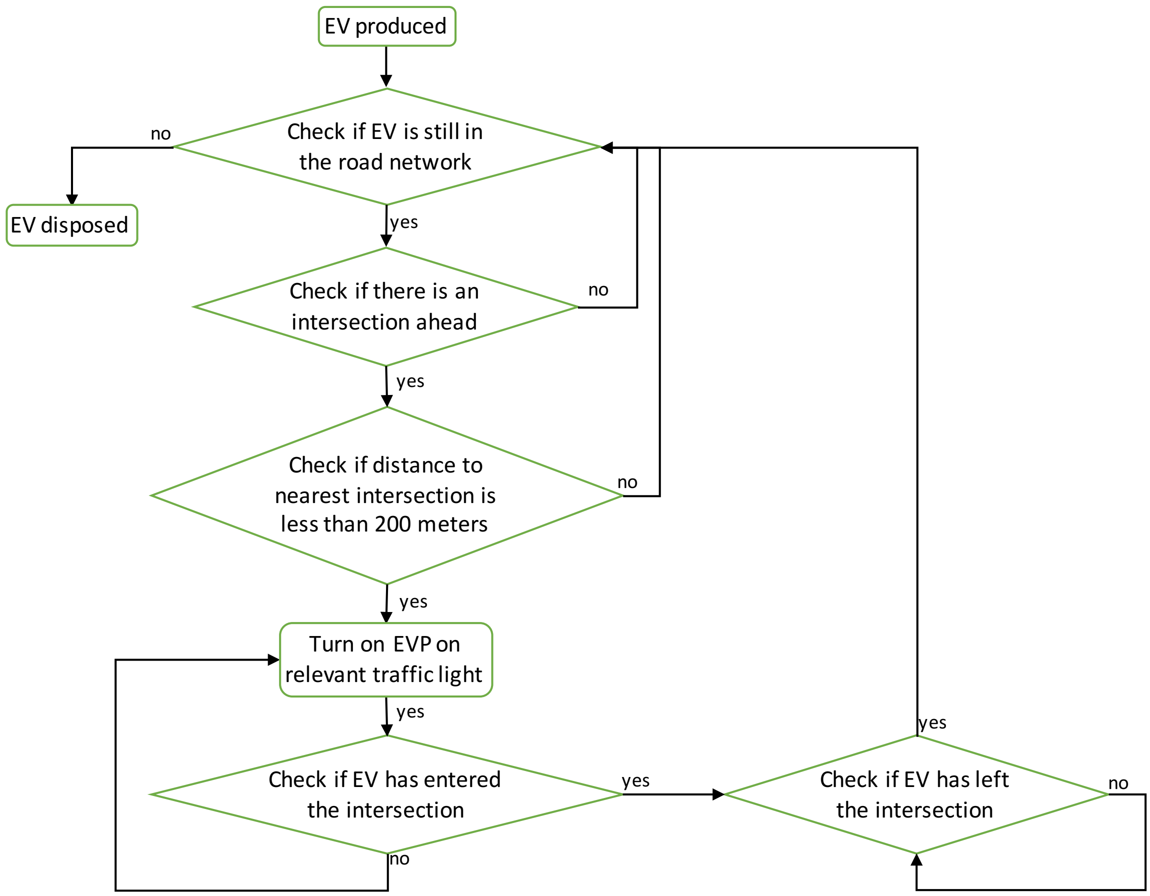

Figure 15 EV life cycle flowchart

3.2.6 EVP:

EVP consists of *Flowchart of preemption and dwell transition strategy*, *Agent-based behavior* of EV and normal vehicles, giving *Right-of-way* to EV by normal cars, *Stop* of normal vehicles after lane switching for EV.

3.2.7 Flowchart of preemption and dwell transition strategy:

The topic of EVP is of high importance because of its implications for the efficiency of emergency responses and the safety of personnel in the EV. Much work has been done on this topic already, but further research is needed to encounter for EV and give it right-of-way by other vehicles and preemption by traffic light. The EVP flowchart on Figure 16 describes how the proposed model transitions between EVP and normal signal operation.

As was described in Figure 15, preemption is started when the EV is within 200 meters of the traffic light. In this condition, a green light is given to the current approach of the EV and red lights are given to all other approaches. This allocation of green and red lights continues until the EV leaves the intersection and does not need EVP anymore. One of the main challenges is to restore traffic cycle back to its original timings so all intersections are coordinated again in the same way as before the EVP call disrupted normal operation. The Dwell transition strategy is implemented in the current research as an efficient way to restoring signal. Transition can go different ways depending on which phase EVP call came in and which phase EVP call ended in. There are five possible situations depicted in Figure 16. These situations can be illustrated in an example using intersection 2 as the intersection that needs EVP. The major phases for intersection 2 are 2 and 6, and the statechart for intersection 2 is depicted in Figure 10.

Situation a (start: main – end: same phase): The EVP call comes in phase 2 and ends in phase 2. After the EVP call ends phase 2 is turned on again for the number of seconds left (i. e. we dwell right away).

Situation b (start: main – end: different phase): The EVP call comes in phase 2 and ends in phase 3. After the EVP call ends, phase 3 is skipped and phase 1 is turned on. After phase 1 ends, phase 2 is turned on and we dwell in that phase (i.e. we add to normal duration of phase 2 the number of unused seconds from phase 3).

Situation c (start: not main– end: same phase): The EVP call comes in in phase 3 and ends in phase 3. After the EVP call ends, phase 3 is skipped and phase 1 is turned on. After phase 1 ends, phase 2 is turned on and we dwell in that phase (i.e. we add to normal duration of phase 2 the number of unused seconds from phase 3).

Situation d (start: not main– end: different phase (main)): EVP call comes in phase 1 and ends in phase 2. After EVP call ends, phase 2 is turned on again for the number of seconds left (i. e. we dwell right away).

Situation e (start: not main– end: different phase (not main)): The EVP call comes in phase 3 and ends in phase 1. After the EVP call ends, phase 1 is skipped, phase 2 is turned on and we dwell in phase 2 (i.e. we add to normal duration of phase 2 the number of unused seconds from phase 1).

The main task regardless of situation is to restore the normal traffic coordination of intersections as soon as possible.

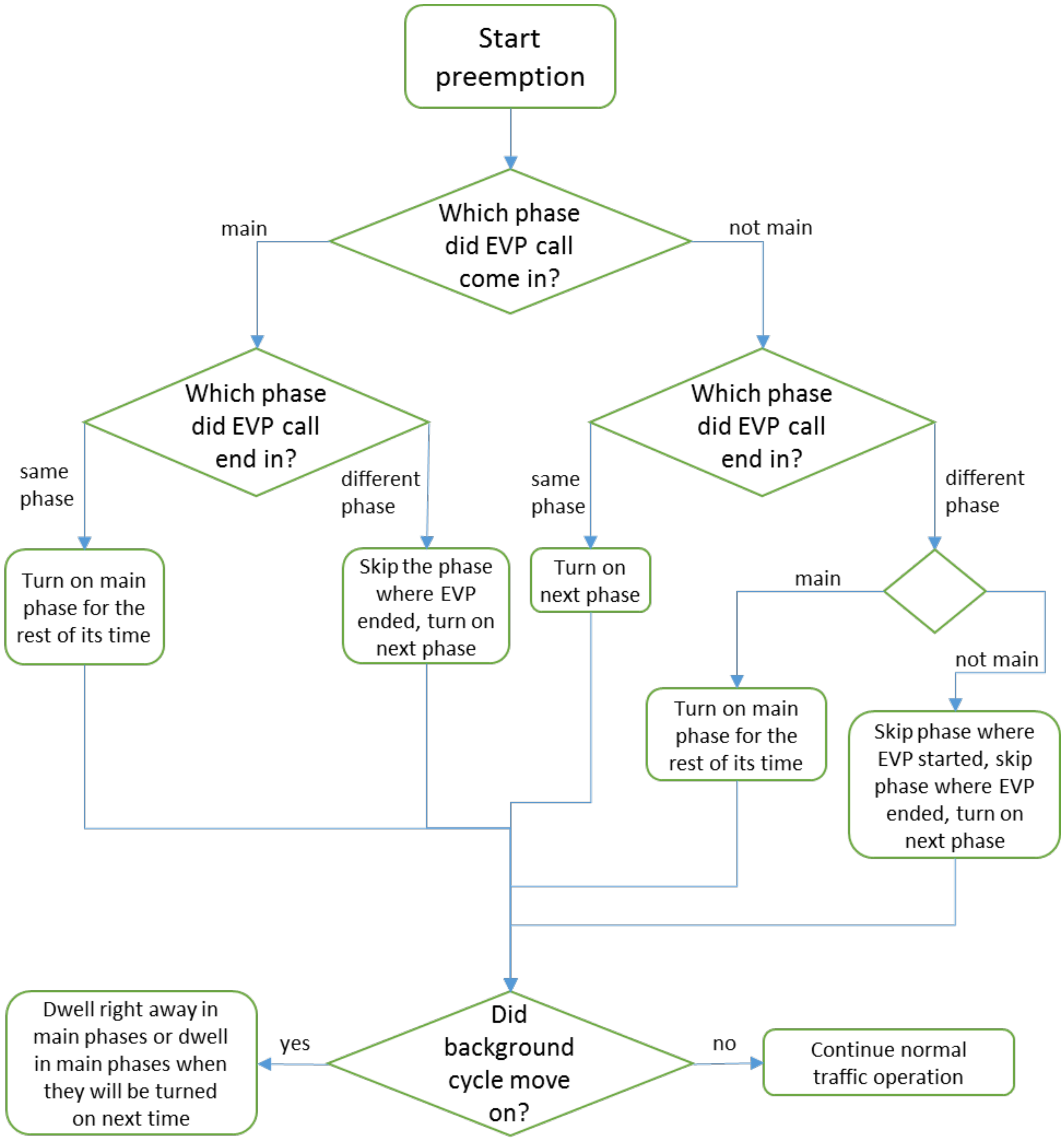

Figure 16 Flowchart of EVP with dwell transition strategy

3.2.8 Agent-based behavior:

The agent-based modeling is implemented in the current model in AnyLogic. This functionality allows normal vehicles and EV to behave like the agents and to interact with each other via messages.

3.2.9 Right-of-way:

When an EV appears in the road network, it needs to move as fast as possible.

The EV knows the intended destination and is sure to occupy the appropriate lane in advance. The EV Is forced to follow the same rules as all other vehicles regarding lane assignment. For example, it cannot turn left from the right most lane because there is no physical connector between right lane and left turn. Once the EV enters the road network, it constantly sends messages to normal vehicles in front and asks them to yield right-of-way by moving to the right lane and stopping. When normal vehicles receive such messages, they try to switch lanes if possible. Rules of lane switching are displayed in Figure 17 and explained below. If switching is not possible right away, vehicles keep trying until they succeed.

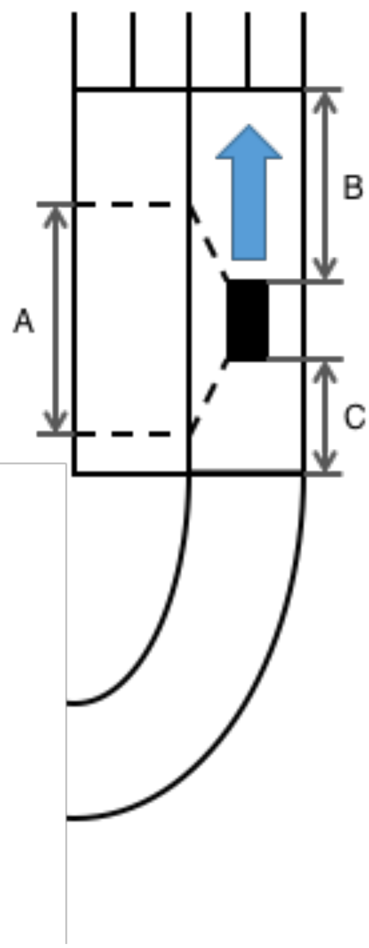

Figure 17 EV lane changing rules

Stop: After normal vehicles give right-of-way to EV by switching lanes, they stop on the right lane for a few seconds before resuming their normal motion. Stopping time is a parameter that can be configured in settings before the start of the simulation.

<u>Merging:</u>
Sometimes in the process of merging, vehicles attempt to occupy the same

space on the road at the same time. For example, one vehicle may cross the intersection going westward while another vehicle is turning left from northbound. In the real life this situation would cause a crash. In the simulation there is only an exception in the software. There is no embedded functionality to solve these merge conflicts between vehicles in the current version of AnyLogic [26]. To avoid such cases, *Lane Merge* and *Merge Resolver* algorithms were implemented. The essence of *Merge Resolver* algorithm is that the pair of arc or arc and lane combinations where collisions take place are stored in a file. Then vehicles approaching that same potentially dangerous location communicate with each other and decide who will yield the right-of-way. The dynamics of *Lane Merge* algorithm is depicted on Figure 17. A represents the search length, which includes one car length in front of the car and one car length in the back of the car. B represents the distance remaining until the division of the two lane road to a four lane road. C represents the distance between the intersection and the current position of the vehicle. Figure 17 describes the situation when EV is travelling on the right lane of a two lane road and needs to switch to the left lane of the same two lane road. To accomplish this goal, a few requirements should hold true. First, no cars should be present in road segment. Second, B should be greater than 10 car lengths from the front of the car. Third, C should be greater than 20 meters. The same rules are applied for normal (not EV) vehicles when they are trying to give right-of-way to EV.

3.2.10 VT-micro microscopic emission model

As was mentioned before, this work used the VT-micro emission model. The equation of this microscopic emission model is presented below along with the table with coefficients that were provided by the field survey [27]:

$$
\begin{aligned}
MOE = \exp(\; & C_{11} + C_{12}V + C_{13}V^2 + C_{14}V^3 + \\
& C_{21}A + C_{22}AV + C_{23}V^2 + C_{24}AV^3 + \\
& C_{31}A^2 + C_{32}A^2V + C_{33}A^2V^2 + C_{34}A^2V^3 + \\
& C_{41}A^3 + C_{42}A^3V + C_{43}A^3V^2 + C_{44}A^3V^3 \;)
\end{aligned}
\tag{8}
$$

Where,

MOE is the calculated measure of effectiveness (fuel, HC, CO, NO_x) per second,

V is Speed (km/h),

A is Acceleration (m/s2), and

C_{xy} are the coefficients provided in Table 3 [27]

Emission of every vehicle for every second is calculated based on the VT-micro model and stored in the log file in the end of a simulation.

Table 3 Coefficients of VT-Micro Emission Model

Coefficients	Fuel	HC	CO	NOx
C_{11}	-7.533E+00	-7.280E-01	8.874E-01	-1.068E+00
C_{12}	3.255E-02	2.738E-02	7.790E-02	5.094E-02
C_{13}	-3.323E-04	-2.468E-04	-9.464E-04	-2.083E-04
C_{14}	1.965E-06	2.575E-06	6.099E-06	7.518E-07
C_{21}	1.484E-01	0.000E+00	1.633E-01	2.791E-01
C_{22}	5.789E-03	1.222E-02	4.660E-03	1.864E-02
C_{23}	-2.713E-05	-1.361E-04	1.232E-04	-1.731E-04
C_{24}	8.032E-08	8.959E-07	-1.024E-06	4.755E-07
C_{31}	1.920E-02	2.814E-02	3.678E-02	1.068E-02
C_{32}	1.101E-04	-7.253E-04	-1.223E-03	3.800E-03
C_{33}	1.358E-06	5.450E-05	7.130E-05	-8.504E-05
C_{34}	-3.945E-08	-3.388E-07	-4.995E-07	3.818E-07
C_{41}	-1.571E-03	-1.232E-04	-1.781E-03	-1.256E-03
C_{42}	-8.890E-05	-1.638E-04	0.000E+00	-4.654E-04
C_{43}	4.836E-07	5.266E-06	-2.243E-06	3.091E-06
C_{44}	-7.803E-09	-3.037E-08	0.000E+00	-2.199E-08

3.3 Analysis

3.3.1 Simulation, offset variation and validation

The proposed model was developed in simulation and optimization package AnyLogic 7.2. Although this software is not traffic specific like VISSIM etc, it does include some useful classes and functionalities for traffic studies along with the Road Traffic, Analysis, Presentation, Agent, Process modeling, and Statechart libraries that were applied in the current research. The road network with four coordinated intersections, timing plans for every intersection, turning volumes were discussed previously.

Values for deceleration and acceleration are set according to comfortable rate for vehicle deceleration and acceleration (3 m/s^2 and 2 m/s^2 respectively) [28], [29]. Each simulation continues for 900 seconds. Vehicles are generated from different carSources based on the rate of vehicles per unit time that are different for every carSource. When the simulation is started, the functional layer of the road (Figure 9) becomes animated. The numbers below the road segments display vehicles on this segment with each vehicle in its corresponding state (i.e. this many vehicles entered this particular road segment carMoveTo, this many vehicles are moving, this many vehicles vehicles left). Also, the physical layer shows car movement on the road network according to lane assignments and timing plans. The physical layer also shows traffic lights changing color. Some states on Statecharts of the intersections (Figure 10) are highlighted showing which state the traffic light is currently in.

For the current research, multiple simulations were performed with different offsets. In the technique called offset variation, offsets ranging from 0 to 120 seconds were varied in 20 second increments. Altogether, 343 simulations were run in order to find optimal offsets for particular inputs such as road network, set of timing plans, and HRD. As a result of these simulations, optimal offsets were found to be 110, 20 and 20 seconds, in good agreement with offsets reported in [21].

After every simulation, we get output data in HRD format. Emissions of every vehicle in every second on each road segment are calculated based on the VT-micro model described earlier and stored in logs, which are processed later to find possible patterns in inputs.

Multiple scenarios can be run depending on EV inclusion/exclusion and emissions from each of those scenarios can be compared later on. No-EV scenario is when there is no EV in the road network. This is the base case. Scenarios EVP and EVP with right-of-way consider EV. In EVP scenario an EV gets EVP and cars move normally. In scenario EVP with right-of-way, an EV gets EVP and cars yield right-of-way. Any one of the scenarios can be chosen along with offsets before the start of the simulation in the simulation window. Later in the paper, there will be an attempt to compare the degree to which EV effects emissions in different scenarios.

The group and individual behavior of vehicles were analyzed as a way to sanity check the validity of the developed model. The vehicle flow travelling on the road network on Figure 18 represents vehicle group behavior. A red square around one of the vehicles indicates which vehicle was selected for individual profile checking.

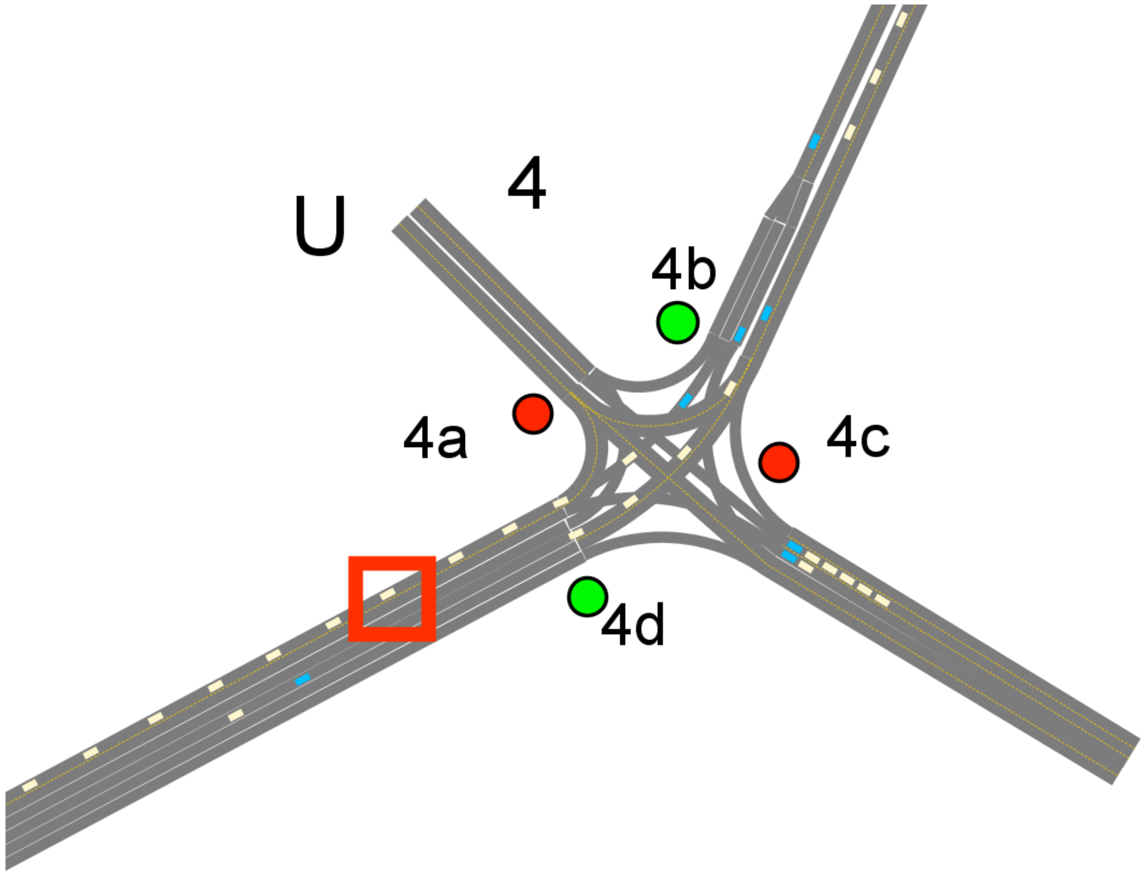

Figure 18 Group behavior of vehicles

An individual vehicle profile consisting of a time-space diagram, smoothed speed, and acceleration was extracted from a simulation shown on Figure 19, Figure 20, Figure 21.

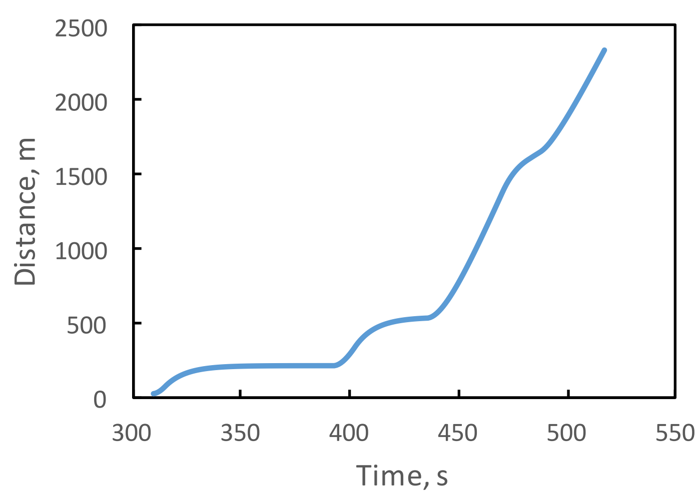

Figure 19 Time-space diagram of an individual vehicle

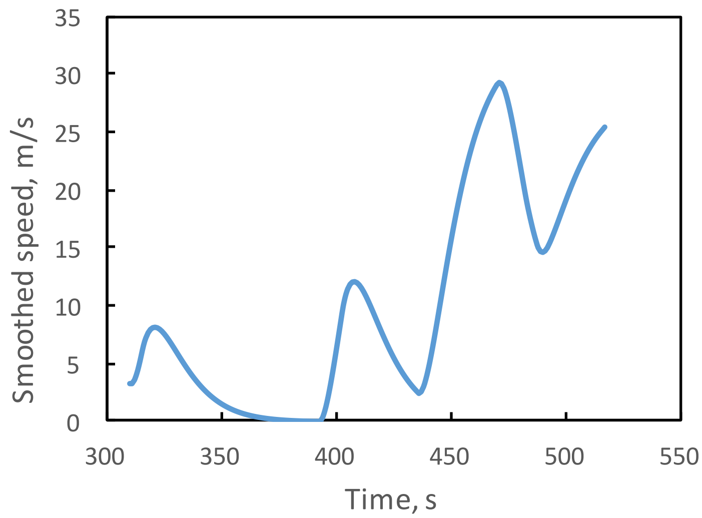

Figure 20 Smoothed speed of an individual vehicle

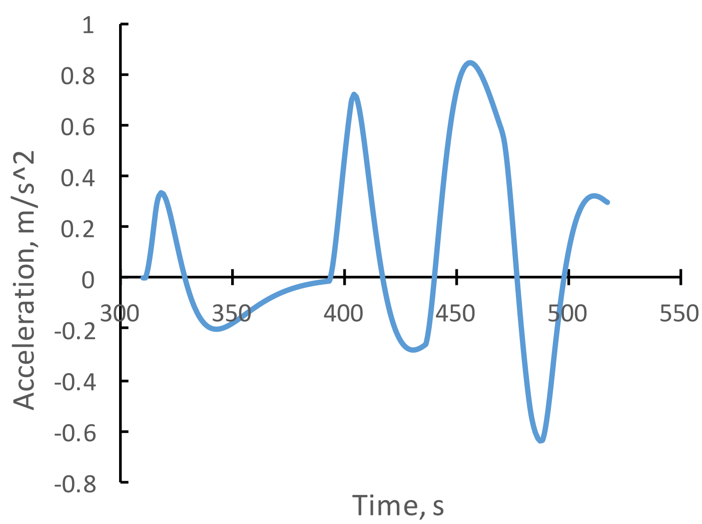

Figure 21 Acceleration of an individual vehicle

All four graphs display normal individual and group behavior of a vehicle, which, along with the good agreement of our offsets to literature values, indicates that the model is valid.

3.3.2 HRD utilization in emission prediction

There are two loop detectors in our model: 100 ft and 200 ft away from each intersection on the major approaches similar to what is displayed on Figure 22 [30]. The loop detectors are assumed to be 5 meters long.

Figure 22 Loop detector

There is a sample of HRD output from controllers of all 4 intersections in Table 4 and in
Table 5. It consists of Signal ID, Timestamp, Event code ID and Parameter. The info of green, yellow and red lights (Event code ID 1, 8 and 10) along with timeStamps are called signal phase info. The info about traffic moving on top of the detector and leaving it (EventCodeID 82 and 81) along with time stamps is called detector events info. From a combination of signal phase info and detector events info, the number of vehicles can be counted and their speeds and accelerations calculated.

Table 4 Sample of HRD from 200ft detector

Signal ID	Timestamp		Event code ID	Parameter
Intersection 1	6/11/15	30:00.0	1	2
Intersection 1	6/11/15	30:15.8	82	1
Intersection 1	6/11/15	30:16.0	81	1
Intersection 1	6/11/15	30:35.9	82	1
Intersection 1	6/11/15	30:36.1	81	1
Intersection 1	6/11/15	30:37.5	82	1
Intersection 1	6/11/15	30:37.7	81	1
Intersection 1	6/11/15	30:38.3	82	1
Intersection 1	6/11/15	30:38.5	81	1
Intersection 1	6/11/15	30:51.7	82	1
Intersection 1	6/11/15	30:51.9	81	1
Intersection 1	6/11/15	30:52.5	82	1
Intersection 1	6/11/15	30:52.7	81	1
Intersection 1	6/11/15	30:58.7	82	1

Intersection 1	6/11/15	30:59.0	81	1
Intersection 1	6/11/15	31:25.0	82	1
Intersection 1	6/11/15	31:25.2	81	1
Intersection 1	6/11/15	31:36.8	82	1
Intersection 1	6/11/15	31:37.0	81	1
Intersection 1	6/11/15	30:22.0	8	2

Table 5 Sample of HRD from 100ft detector

Signal ID	Timestamp		Event code ID	Parameter
Intersection 1	6/11/15	30:00.0	1	2
Intersection 1	6/11/15	30:16.6	82	2
Intersection 1	6/11/15	30:16.8	81	2
Intersection 1	6/11/15	30:36.8	82	2
Intersection 1	6/11/15	30:37.0	81	2
Intersection 1	6/11/15	30:38.3	82	2
Intersection 1	6/11/15	30:38.5	81	2
Intersection 1	6/11/15	30:39.2	82	2
Intersection 1	6/11/15	30:39.4	81	2
Intersection 1	6/11/15	30:52.5	82	2
Intersection 1	6/11/15	30:52.7	81	2
Intersection 1	6/11/15	30:53.3	82	2
Intersection 1	6/11/15	30:53.7	81	2
Intersection 1	6/11/15	30:59.8	82	2
Intersection 1	6/11/15	31:00.3	81	2
Intersection 1	6/11/15	31:25.7	82	2
Intersection 1	6/11/15	31:26.0	81	2
Intersection 1	6/11/15	31:37.5	82	2
Intersection 1	6/11/15	31:37.7	81	2
Intersection 1	6/11/15	30:22.0	8	2

HRD from Table 4 and Table 5 about loop detectors at 200ft and 100ft away from the intersection 2b was processed to generate the data shown in Table 6 and Table 7. For example, from Table 4 time ON (t1) and time OFF (t2) were collected that are first 2 columns in Table 6. Similarly, from Table 5 time ON (t3) and time OFF (t4) were collected that are first 2 columns in Table 7. Since the length of loop detector and vehicle occupancy are known (5 meters and (t2-t1)), speed V1 with which the vehicle was travelling on loop detector 200 ft and speed V2 with which the same vehicle was travelling on loop detector 100 ft can be calculated. Also, acceleration of a vehicle between these two loop detector can be calculated by dividing (V2-V1)/(t3-t1).

Table 6 200 ft loop detector data

t1	t2	V1
15.90	16.07	28.60

35.96	36.17	24.10
37.52	37.72	24.38
38.32	38.52	24.38
51.71	51.91	24.59
52.51	52.71	24.59
58.77	59.00	22.12
85.14	85.30	32.16
96.85	97.02	28.93

Table 7 100 ft loop detector data

t3	t4	V2
16.63	16.81	28.60
36.83	37.04	24.10
38.38	38.59	24.38
39.20	39.41	23.81
52.56	52.77	24.59
53.39	53.77	13.33
59.86	60.34	10.31
85.80	85.95	32.16
97.58	97.75	28.93

Using Table 6 and Table 7 (from 200 ft away and from 100ft away) we create Table 8.

Table 8 Data extracted from HRD

200 ft, t1	200 ft, t2	100 ft, t3	100 ft, t4	200 ft, V1	100 ft, V2	200-100ft,A
15.90 (82)	16.07 (81)	16.63 (82)	16.81(81)	28.60	28.60	0.00
35.96 (82)	36.17 (81)	36.83 (82)	37.04 (81)	24.10	24.10	0.00

Similarly, this table becomes filled with the data from all vehicles in all simulations. A separate table for each major approach is made (8 tables in total). As of now, the columns V1 and V2 are the most important ones. Then in every one of these 8 tables one more column named speed between 200ft and 100 ft was added so now the average speed for each approach is available with all simulations included. Now only cars that stopped anywhere on this particular approach that we are dealing with need to be selected. In the simulation this selection is done by a script to select stopped vehicles because we have full control over vehicles. In a reality only speeds and accelerations of the cars are available from HRD so a prediction based on speeds and accelerations must be made. It is known that stopped cars are the main contributors to vehicle emissions since when they accelerate they produce much more emissions than cruising cars. Therefore, the frequency distribution of the speeds between two detectors and accelerations of all stopped cars are plotted to identify the most frequent speeds and most frequent accelerations. In order to estimate the number of stopped cars in individual simulations, all cars that fall within the range of one standard deviation around the mean are selected. So, the most frequent speeds of the cars that will stop need to be considered. That is why the speed range of 1 standard deviation is selected and that should give good enough prediction. So, all vehicles on a particular road segment whose speeds fall within this range are counted. This is how stopped vehicles are predicted on the particular approach based on speed. Similarly, all vehicles on a particular road segment whose accelerations fall within identified range are counted. This is the way stopped vehicles are predicted on the particular approach based on accelerations. Also, cars that satisfy both speed-based ranges and acceleration-based ranges are selected. The number of stopped vehicles on a particular approach will be used for an analysis in the following sections.

3.3.3 Finding classifier and its threshold

As was stated in the introduction, vehicle emissions depend on timing plans, traffic volume and traffic characteristics. That is why it makes sense to start searching for significant inputs approach-wise such average speed, average acceleration, standard deviation speed, standard deviation acceleration. Offset is insignificant so it is omitted.

As a result of all 343 simulations, a summary excel file with the essence of every simulation is produced. For example, intersection 4 has these outputs:

- total network emission within particular simulation
- offsets values
- westbound approach emission
- eastbound approach emission
- average speed on 4b
- average acceleration on 4b
- standard deviation in speeds on 4b
- standard deviation in acceleration on 4b
- average speed on 4d
- average acceleration on 4d
- standard deviation in speeds on 4d
- standard deviation in acceleration on 4d
- stopped vehicles on approach 4d based on speeds
- stopped vehicles on approach 4b based on speeds

There are three scenarios that have been simulated in this paper, namely No EV, EVP, EVP with right-of-way. Thus, there are three summary excel files – one for every scenario.

In every scenario, CO emission, HC emission, NOx emission at the 4th intersection was sorted one after another. The 15 minimum and 15 maximum values were taken and used to produce graphs of number of stopped vehicles on two major approaches 4b and 4d of intersection 4. Figure 23 does not display a clear pattern as we see some overlap between minimum emission cases and maximum emission cases in No-EV scenario. In contrast, patterns in Figure 25 and Figure 27 are clear. EV makes scenarios more distinct. Regression analysis was applied to intersections 4 for all three scenarios with all available inputs. The predicted models shown in Figure 24, Figure 26, Figure 28 had R^2 values of 70%, 78%, 80% correspondingly.

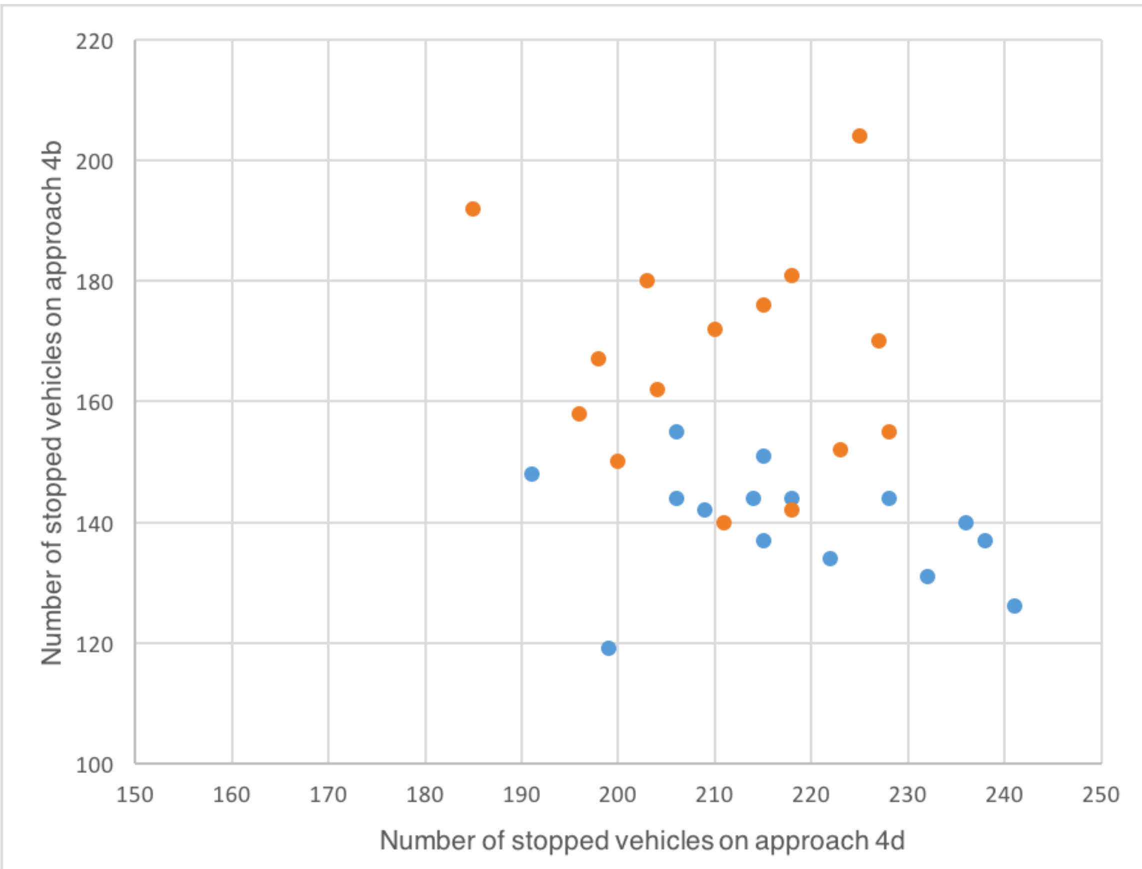

Figure 23 Stopped vehicles on approaches 4d and 4b in minimum emission no EV case (blue) vs maximum emission no EV case (red)

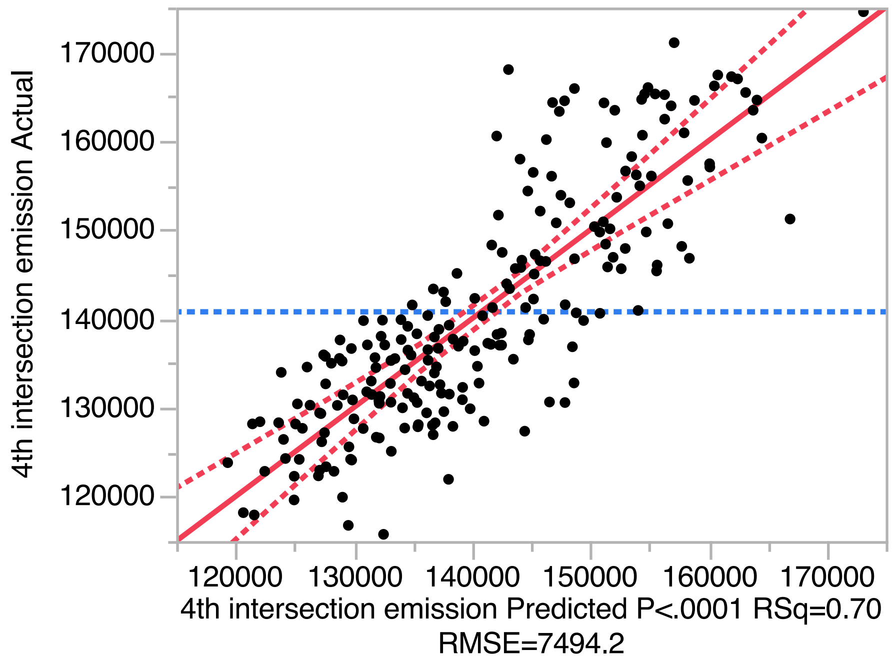

Figure 24 Prediction of the proposed model for intersection 4 in No-EV scenario

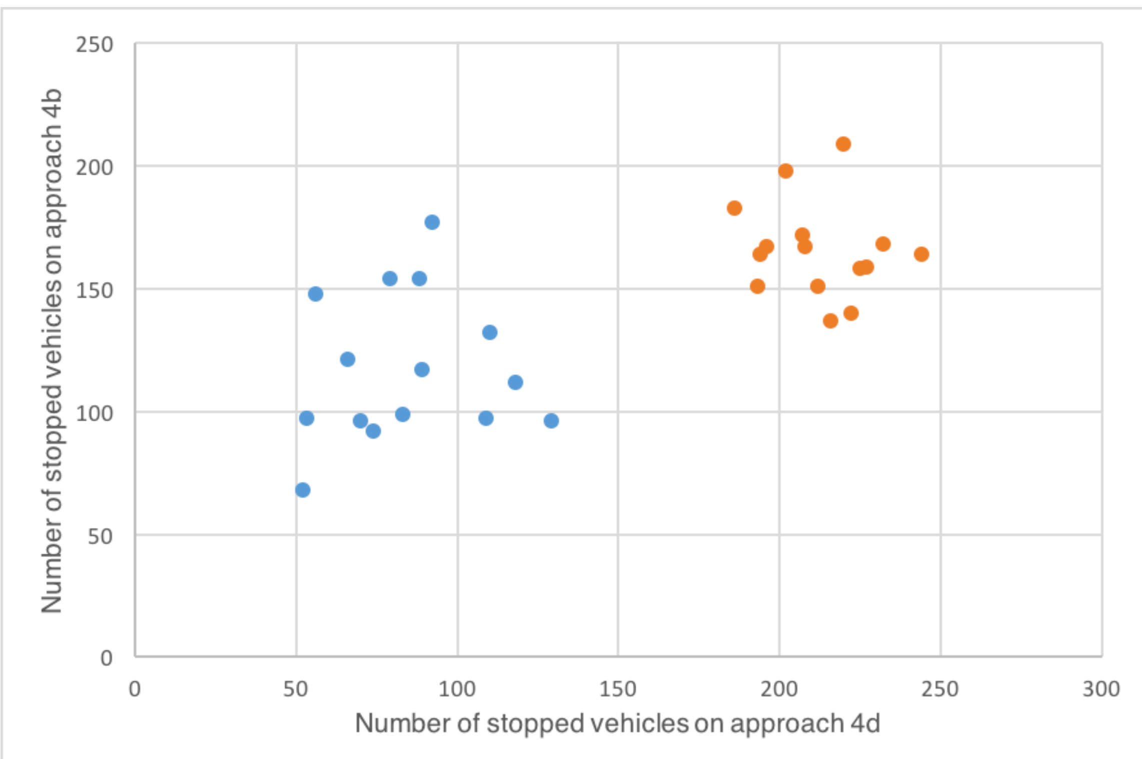

Figure 25 Stopped vehicles on approaches 4d and 4b in minimum emission EVP case (blue) vs maximum emission EVP case (red)

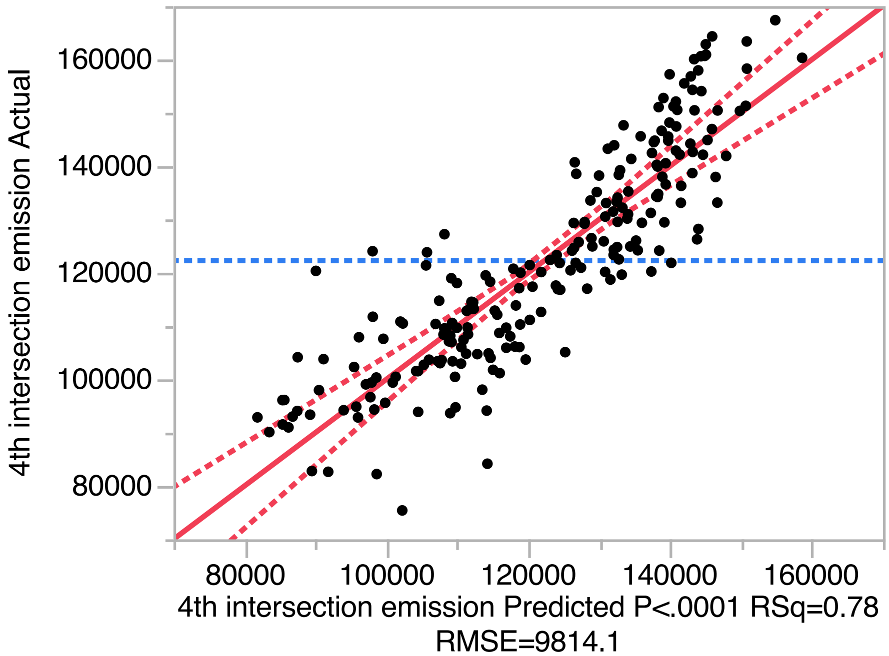

Figure 26 Prediction of the proposed model for intersection 4 in EVP scenario

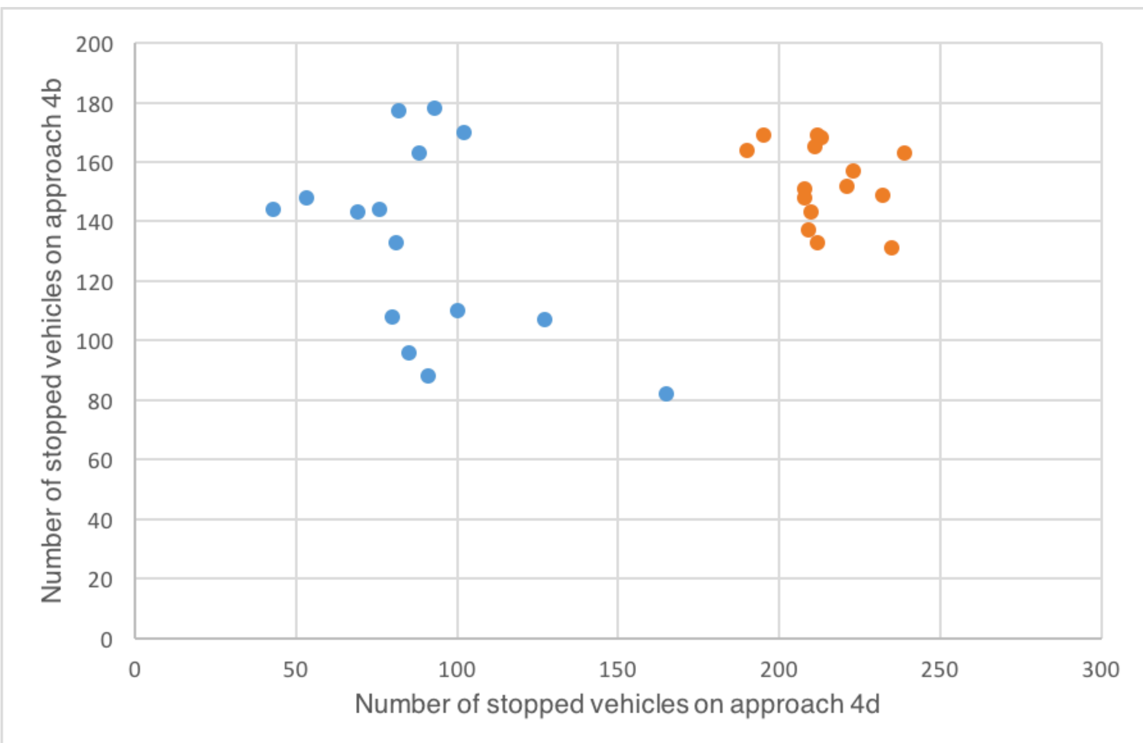

Figure 27 Stopped vehicles on approaches 4d and 4b in minimum emission EVP with right-of-way case (blue) vs maximum emission EVP with right-of-way case (red)

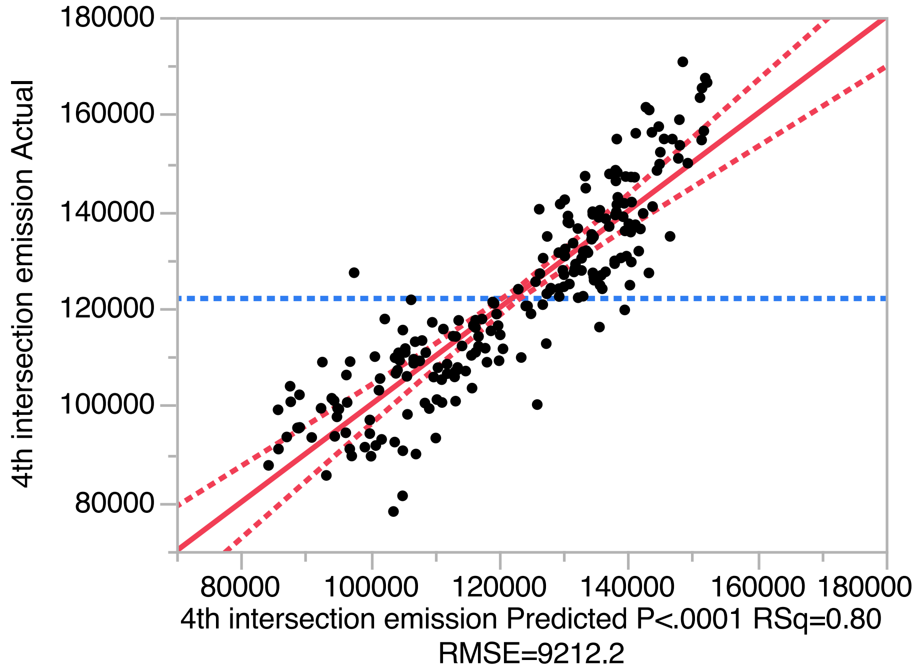

Figure 28 Prediction of the proposed model for intersection 4 in EVP with right-of-way scenario

Discriminant analysis has proved in the past to be a useful tool for finding significance of the factors and the equation, that is why it was used to find a classifier for vehicle emissions based on HRD. Discriminant analysis was applied to intersection 4 based on stopped vehicles on 4b approach and stopped vehicles on 4d approach for No-EV, EVP and EVP with right-of-way scenarios. For every scenario, CO emission, HC emission, NOx emission was considered separately. Graphs for all 9 scenarios are shown on Figure 29 through Figure 37. The following figures show the reports generated by JMP statistical software.

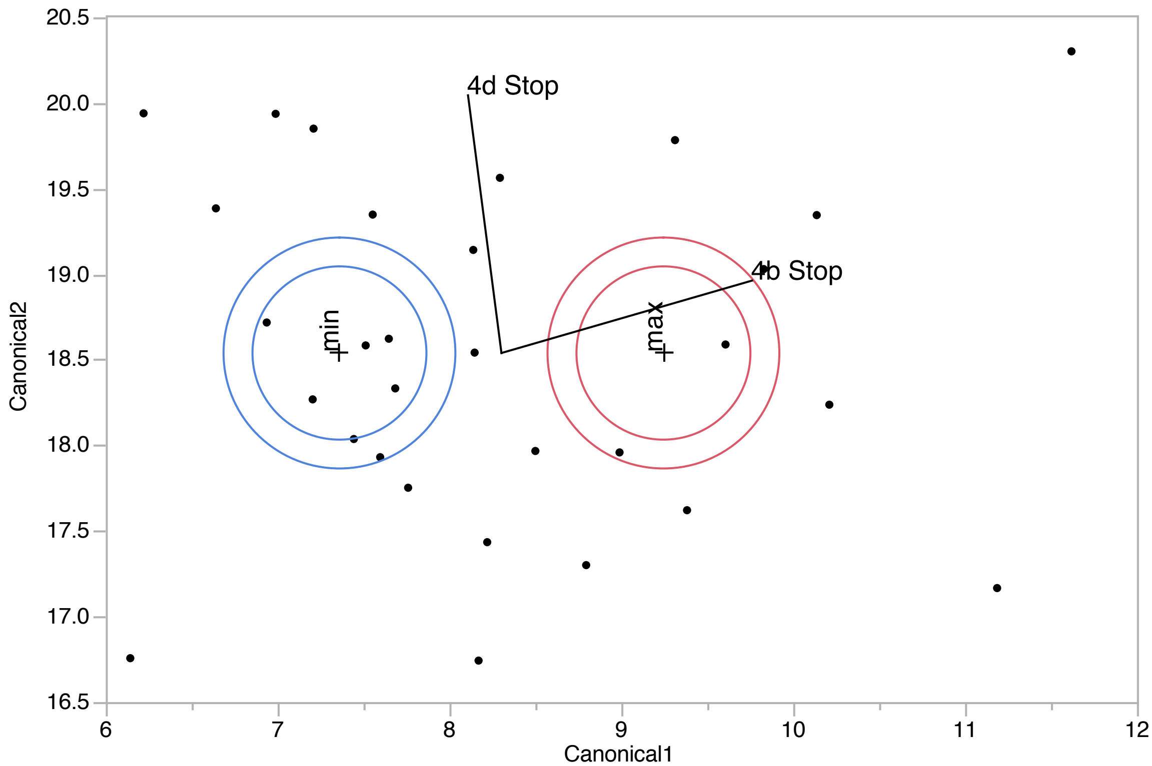

Figure 29 Discriminant analysis of intersection 4 based on stopped vehicles in No-EV scenario for CO emission

The equation for classifier for No-EV case for CO emission is provided below.

Canonical1 = -0.009*4d stopped cars + 0.067*4b stopped cars *(9)*

Calculated value of the classifier (threshold) less than 8.303 indicates acceptable level of emission at an intersection, greater than 8.303 belongs to unacceptable level of emission. Depending on the value for the classifier, decision can be make whether the emissions are within acceptable ranges or some changes are required for a particular intersection to bring down the emissions.

Minimum and maximum cases do not overlap and can be distinguished. Difference in CO emission between minimum average and maximum average cases in No-EV scenario is 36.1%.

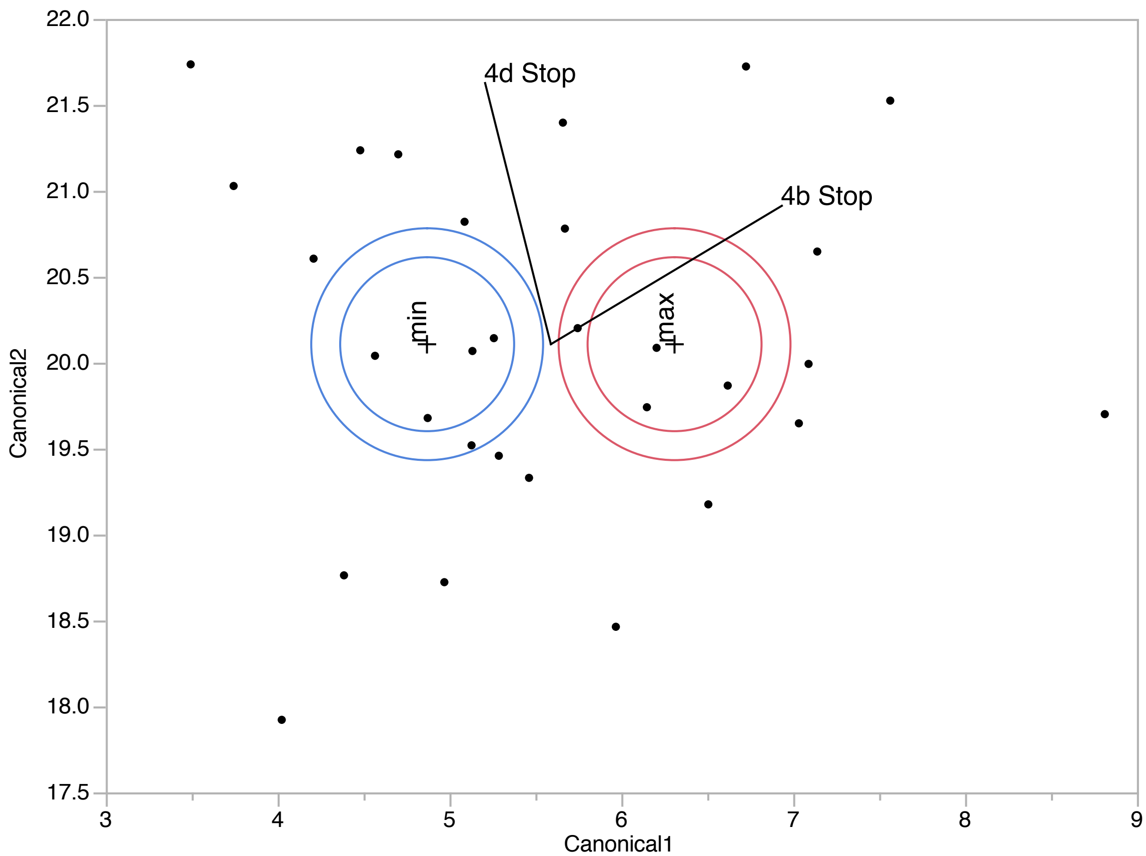

Figure 30 Discriminant analysis of intersection 4 based on stopped vehicles in No-EV scenario for HC emission

The equation for classifier for EVP case for HC emission is provided below.

Canonical1 = - 0.017*4d stopped cars + 0.062*4b stopped cars *(10)*

Threshold is 5.590.

Minimum and maximum cases do not overlap and can be distinguished. However, they are very close to one another. Difference in HC emission between minimum average and maximum average cases in No-EV scenario is 50.6%.

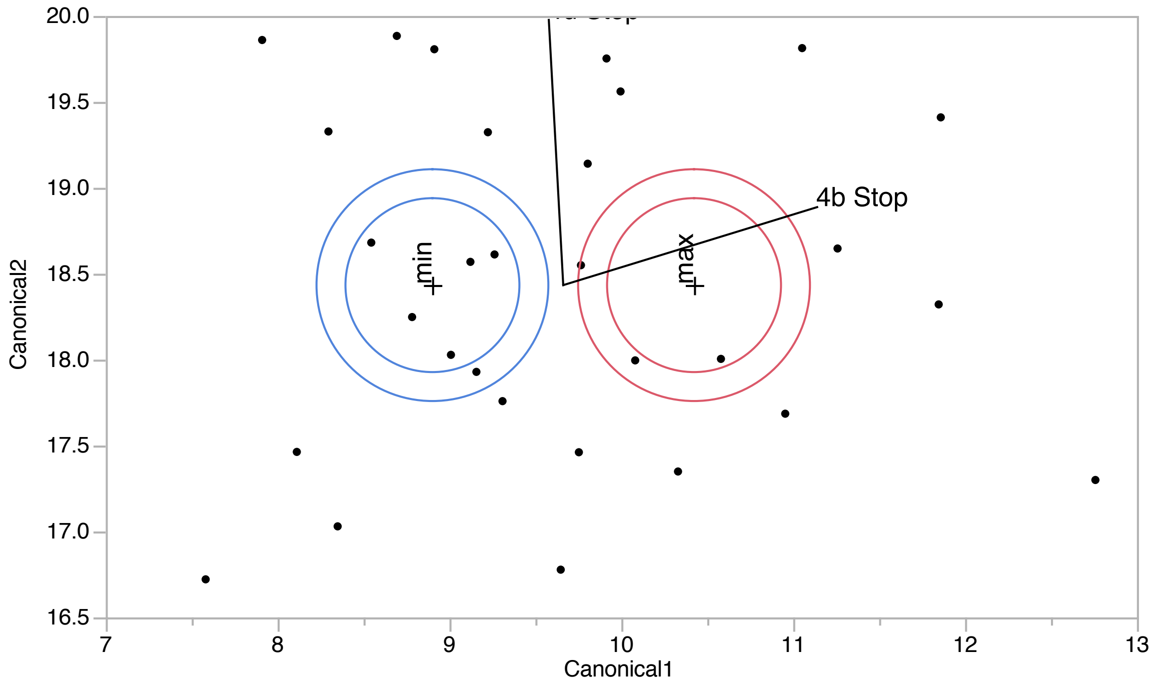

Figure 31 Discriminant analysis of intersection 4 based on stopped vehicles in No-EV scenario for NOx emission

The equation for classifier for EVP case for NOx emission is provided below.
Canonical1 = - 0.004*4d stopped cars + 0.070*4b stopped cars *(11)*
Threshold is 9.662.
Minimum and maximum cases do not overlap and can be distinguished. However, they are very close to one another. Difference in NOx emission between minimum average and maximum average cases in No-EV scenario is 41.0%.

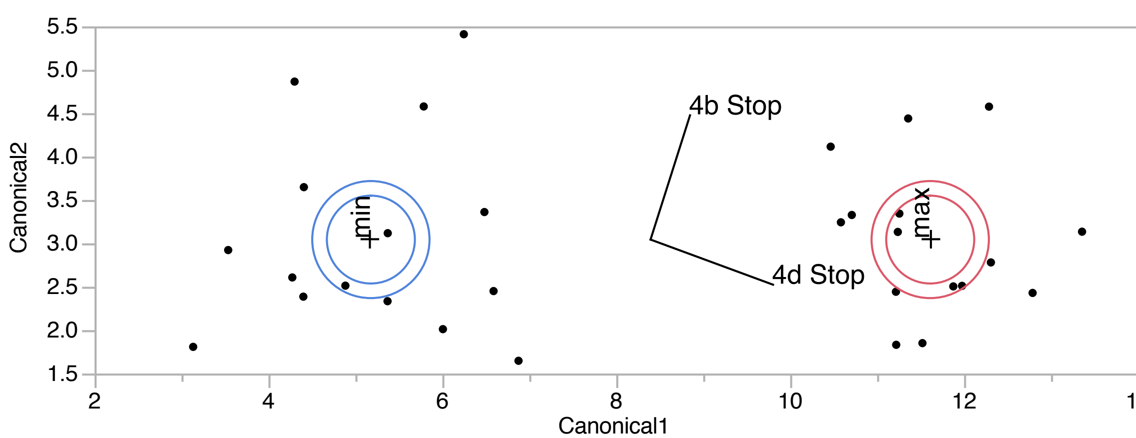

Figure 32 Discriminant analysis of intersection 4 based on stopped vehicles in EVP scenario for CO emission

The equation for classifier for EVP case for CO emission is provided below.

Canonical1 = 0.044*4d stopped cars + 0.012*4b stopped cars (12)
Threshold is 8.395.
Minimum and maximum cases do not overlap and can be well distinguished. Difference in CO emission between minimum average and maximum average cases in EVP scenario is 79.4%.

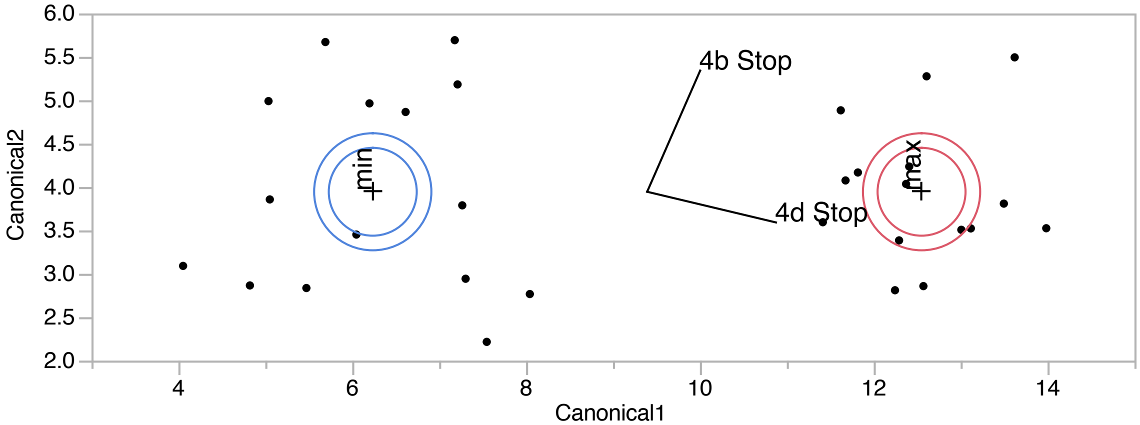

Figure 33 Discriminant analysis of intersection 4 based on stopped vehicles in EVP scenario for HC emission

The equation for classifier for EVP case for HC emission is provided below.
Canonical1 = 0.046*4d stopped cars + 0.017*4b stopped cars (13)
Threshold is 9.393.
Minimum and maximum cases do not overlap and can be well distinguished. Difference in HC emission between minimum average and maximum average cases in EVP scenario is 86.8%.

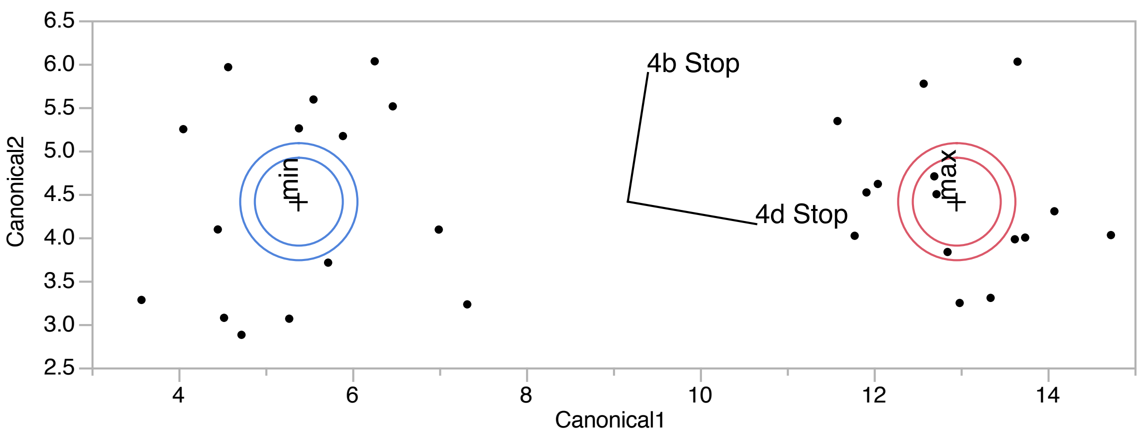

Figure 34 Discriminant analysis of intersection 4 based on stopped vehicles in EVP scenario for NOx emission

The equation for classifier for EVP case for NOx emission is provided below.
Canonical1 = 0.056*4d stopped cars + 0.006*4b stopped cars (14)

Threshold is 9.171.
Minimum and maximum cases do not overlap and can be well distinguished. Difference in NOx emission between minimum average and maximum average cases in EVP scenario is 81.2%.

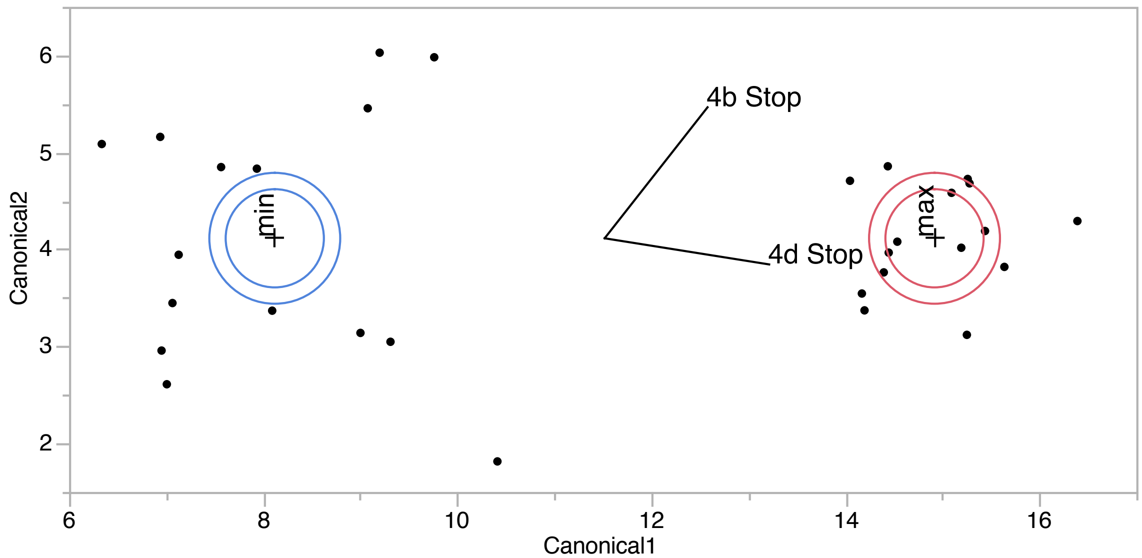

Figure 35 Discriminant analysis of intersection 4 based on stopped vehicles in EVP with right-of-way scenario CO emission

The equation for classifier for EVP case for CO emission is provided below.
Canonical1 = 0.048*4d stopped cars + 0.030*4b stopped cars *(15)*
Threshold is 11.520.
Minimum and maximum cases do not overlap and can be well distinguished. Difference in CO emission between minimum average and maximum average cases in EVP with right-of-way scenario is 78.6%.

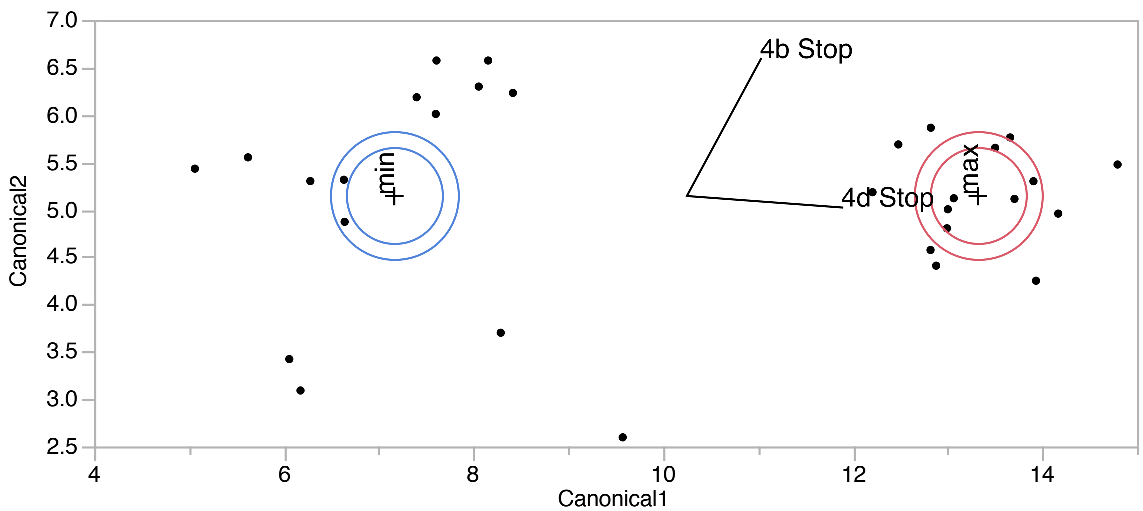

Figure 36 Discriminant analysis of intersection 4 based on stopped vehicles in EVP with right-of-way scenario CO emission

The equation for classifier for EVP case for HC emission is provided below.

Canonical1 = 0.048*4d stopped cars + 0.021*4b stopped cars (16)

Threshold is 10.250.

Minimum and maximum cases do not overlap and can be well distinguished. Difference in HC emission between minimum average and maximum average cases in EVP with right-of-way scenario is 90.8%.

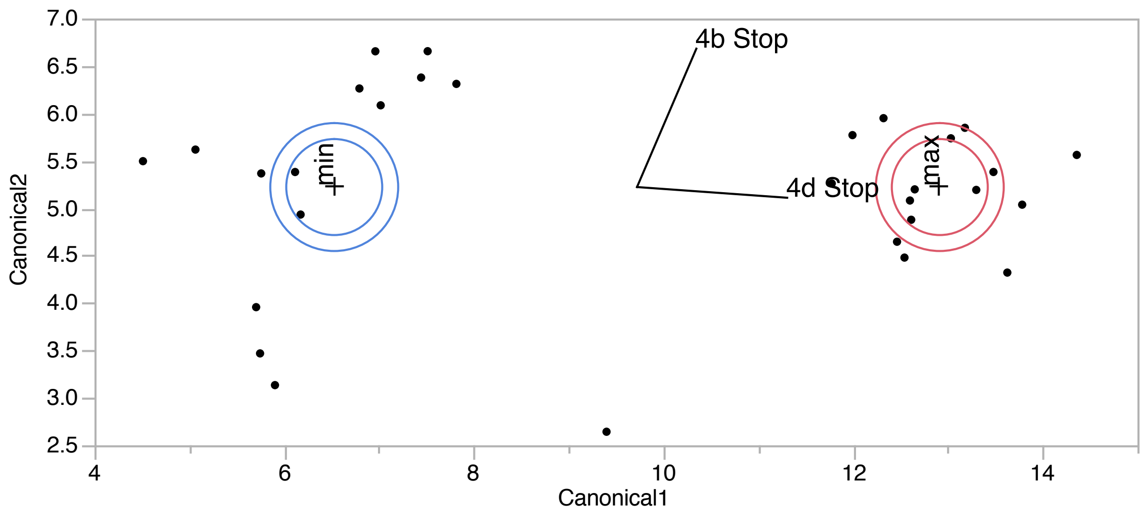

Figure 37 Discriminant analysis of intersection 4 based on stopped vehicles in EVP with right-of-way scenario CO emission

The equation for classifier for EVP with right-of-way case for NOx emission is provided below.

Canonical1 = 0.049*4d stopped cars + 0.017*4b stopped cars (17)

Threshold is 9.722.

Minimum and maximum cases do not overlap and can be well distinguished. Difference in NOx emission between minimum average and maximum average cases in EVP with right-of-way scenario is 82.8%.

Comparison of discriminants is provided in Table 9.

Table 9 Comparison of discriminants

	No-EV	EVP	EVP with right-of-way
CO	8.303	8.395	11.520
HC	5.590	9.393	10.250
NOx	9.662	9.171	9.722
Total emission	8.3	8.5	10.8

In No-EV scenario discriminant based on CO captures the difference between maximum and minimum cases. In EVP and EVP with right-of-way scenarios all three discriminants capture the difference between maximum and minimum cases.

CO discriminant is not sensitive to No-EV and EVP scenarios. However, CO discriminant is different in EVP with right-of-way scenarios. HC discriminant in all

3 scenarios is sensitive. It increased from 5.590 in No-EV scenario to 9.393 in EVP scenario and further increased to 10.250 in EVP with right-of-way scenario. NOx discriminant is not sensitive to any of the 3 scenarios. Total emission, that is a sum of CO, HC and NOx emissions, approximately reflects CO discriminant in all 3 scenarios.
NOx seems to be a good classifier since it does not change scenario to scenario and dos not depend on EV presence. NOx discriminant has average value of threshold around 9.5.

3.3.4 Impact of EV presence on emissions

As was mentioned earlier, there is an attempt to find out whether presence of EV changes emissions and if it does to what extent. Outputs from offset variation for No EV scenario found previously are compared to offset variation for EVP scenario (EVP is given and vehicles move normally) and EVP with right-of-way scenario (EVP is given and vehicles yield to EV). All three scenarios are plotted for the westbound approach on Figure 38.

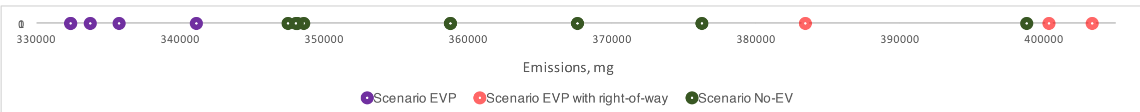

Figure 38 Comparison of maximum emissions in scenarios No-EV, EVP and EVP with right-of-way in westbound approach

Emissions observed for all scenarios are provided in Table 10. Emissions in EVP scenario are 9% less than in the No-EV scenario. Emissions in scenario EVP with right-of-way are 16.5% bigger than in No-EV scenario.

Table 10 Comparison of maximum emissions in all scenarios

Scenario EVP	Scenario No-EV	Scenario EVP with right-of-way
Emission on westbound approach	Emission on westbound approach	Emission on westbound approach
341187.33	398861.64	444058.0614
335803.21	376287.81	439058.0614
333821.21	367660.71	403429.9788
332428.35	358795.10	400429.9788
332428.35	358795.10	423429.9788
328813.58	348648.04	423429.9788
327171.11	348151.54	383429.9788
325216.41	348151.54	424429.9788
325216.41	348040.63	412429.9788
324342.04	347497.08	439429.9788

However, different relationships between scenarios may occur if compared at the intersections or at the individual approaches.

3.4 Results and Discussion

A new way to leverage HRD is proposed in the paper. An indicator that emissions are affected by delay is estimated by calculating the number of stops. Vehicle emissions are also affected by traffic characteristics such speeds and acceleration. With the methods described in this paper, a Traffic Engineer may use the developed classifier to justify whether any changes are to be made to reduce emissions at intersections. As a result, intersections with excessive emissions can be quickly identified and given priority in efforts to improve performance just by utilizing HRD from an office instead of measuring emissions in the field. Our research is significant due to its potential in estimating vehicle emissions and pointing out any existing problems. Furthermore, it was found out that the presence of EVs significantly affect vehicle emissions on road network. Vehicle emissions in EVP case is 8% less compared to No-EV scenario emission. Vehicle emissions in EVP with right-of-way is 16.5% more compared to No-EV scenario emission. Reduced emissions will make Environment and Economics healthier and Transportation more reliable and efficient.

3.5 Conclusion and Future Research

The road network WV-705 with four intersections was implemented in AnyLogic 7.2 software and signals were coordinated. The VT-Micro emission model was incorporated in AnyLogic to calculate emission from the vehicles. Process for calculating individual vehicle speeds and accelerations from HRD and analyzing them tom predict number of stopped vehicles was shown. Development of the classifier to predict emissions based on stopped vehicles from HRD was presented, its thresholds and equation were reported.

Future research consists of, but is not limited to, developing and analyzing different road networks to refine classifier and make it more precise. New ways of utilizing HRD can be found.

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Chapter 4: Conclusions

One important role of Traffic Engineers is to develop and implement strategies to improve the performance of intersections, test intersection performance in terms of emissions level, and then develop further improvements as needed. This process is reiterative and mandatory. Some methods to improve intersection performance are common knowledge to everyone in Transportation or related disciplines and are widely implemented. Some novel methods, such as those described in this paper are in development and require thinking outside of the box. They are currently difficult to implement, but they have the potential to surpass the performance of existing methods.

Current research considered gathering vehicles into platoons as one of possible ways to improve performance of the intersection in terms of emissions and delay. A model to connect emissions with platoon algorithm thresholds through cycle length was proposed. Vehicles were joined into platoon through a developed platoon identification algorithm, which is based on an extensive proposed flowchart. The algorithm was responsible for the platoon life-cycle, i.e. it was making a decision whether and when to start a vehicle platoon, sustain it, end it or refine its end times. The algorithm was sensitive to sudden flow increase or decrease, thus switch between its phases was based on these attributes.

A few parameters of a platoon identification algorithm and traffic signal coordination were optimized with minimum emission as an objective function. The optimized parameters included the platoon identification parameters such as identification interval, sustaining interval, and ending interval, which were found to be 1, 16, and 10 seconds respectively. This optimization reduced emissions to 410 mg, which was the lowest reported in that study. The upper and lower bound parameter of the traffic flow that the normal flow was compared to in some phases of the algorithm were also varied to show that there is little correlation between upper/lower bound parameters and emissions. This result is evidence that the upper/lower bound parameters can be ignored. Our research also indicates that the platoon identification parameters from our algorithm are sensitive to traffic volume. The traffic signal coordination parameter that was optimized was offset between two intersections. Results showed that an offset of 24 seconds minimized emissions. A comparison between minimum and maximum emission scenarios indicated that if algorithm is in place, total network delay can be reduced by 22.4% and total network emissions by 15.5%.

Although implementing vehicle platoon mechanisms has the potential to significantly improve an intersection and reduce emissions, Traffic Engineers need to estimate emissions afterwards and check if they are acceptably low. Previous research proved that stored HRD from traffic controllers can be an effective tool to estimate emissions for two reasons. First, if detectors are already installed near the intersections, HRD in form of controller's logs are most likely already stored and available for analysis. Utilizing this data saves the time and high costs involved in conducting a survey to obtain necessary data. Second, HRD is a stored in a format that is widely-accepted and commonly-known. Thus it is relatively easy for engineers to understand the data and use it in traffic analysis. These reason justify the use of HRD. The HRD used in this paper was taken from the Morristown WV-705 corridor. The number of stopped vehicles at an intersection in this corridor was determined based on event codes and timings from the controller's log. Also, speeds and accelerations of the vehicles were calculated based on HRD to use later in emissions calculations with the VT-micro microscopic emission model. HRD and emission values from a few most and least optimal emission cases of one of the intersections were fed into statistical

software and processed with discriminant analysis. A classifier threshold value of 14.2 along with its formula based on stopped vehicles were developed to help traffic engineers estimate emission at the intersection judging by HRD only.
Besides analysis of normal traffic, HRD is an effective tool to process info about EVs, specifically EVP call ON and OFF events. This allows evaluation of the effect EVP has on emissions. This information is critical because EVs are a very important participant of a road network and should be given right-of-way over other cars if possible. The work presented in this paper compared scenarios with and without EVP to test the hypothesis that EVP affects emissions. Results indicate that vehicle emissions in EVP case without other cars yielding to EV is 8% less compared to emission from No EV case. Vehicle emissions in EVP case with other cars giving right-of-way to EV is 16.5% more compared to No EV case emission.

4.0 Future research

Future research consists of, but would not be not limited to, further platoon dispersion considerations in traffic signal optimization. Future research could also handle the situation when multiple platoons in close temporal proximity are accommodated within a single cycle. In addition, car input can follow any probability distribution instead of the rate of vehicles per unit time.
Future research consists of, but is not limited to, developing and analyzing different road networks to refine classifier and make it more precise. New ways of utilizing HRD can be found.