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AGENT BASED RESILIENT TRANSPORTATION INFRASTRUCTURE WITH SURROGATE ADAPTIVE NETWORKS

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Abstract

Connected autonomous intelligent agents (AIA) can improve intersection performance and resilience for the transportation infrastructure. An agent is an autonomous decision maker whose decision making is determined internally but may be altered by interactions with the environment or with other agents. Implementing agent-based modeling techniques to advance communication for more appropriate decision making can benefit autonomous vehicle technology.

This research examines vehicle to vehicle (V2V), vehicle to infrastructure (V2I), and infrastructure to infrastructure (I2I) communication strategies that use gathered data to ensure these agents make appropriate decisions under operational circumstances. These vehicles and signals are modeled to adapt to the common traffic flow of the intersection to ultimately find an traffic flow that will minimizes average vehicle transit time to improve intersection efficiency. By considering each light and vehicle as an agent and providing for communication between agents, additional decision-making data can be transmitted. **Improving agent based I2I communication and decision making will provide performance benefits to traffic flow capacities.**

1. INTRODUCTION

Prior research has demonstrated that localized decision making within groups of robots (agents) can improve overall system decision making in stochastic environments [Chee, 2014]. In this scenario, each robot, is indistinguishable from the concept of a computational agent. Agents make independent decisions based on localized information obtained from the environment and other interacting agents, as determined by internally defined dynamic behaviors. Use of this approach enables the system to stay current with local conditions. Furthermore, rather than having a centralized controller gathering all information, each individual robot will gather data that can be interpreted and used for individual decision making. The ability for individual agents to gather data to provide information to nearby agents will allow the system to adapt to local conditions.

Research Problem and Motivation

With emerging autonomous vehicle technology, it is important to study the positive and negative effects that may occur in a connected vehicle/city environment. Further, the question of how can connected autonomous technology be used to improve performance through intersections? If this technology can lead to enhanced safety, traffic flow, and resilience a connected agent-based approach will ultimately create a positive outcome.

By treating each connected autonomous system as an agent, the potential impact of connected autonomous systems can be studied in the context of these transportation questions. The ability for each car to gather data through its own sensors as well as pull data from other local cars can be a huge technology improvement. If automobiles can relay information about current locations to nearby vehicles as well as traffic lights, the intersection can apply the received data to the immediate situation. For example, an individual intersection may be overcrowded from a high number of approaching vehicles. The improved communication between the status of intersections will allow traffic lights to communicate to provide alternative light signal times. This is just one example that displays the benefits of improved vehicle communication and decision making. This knowledge will ultimately improve traffic flow, safety and overall agent behavior.

2. BACKGROUND

The individual details of each component in the transportation infrastructure are complex, therefore highlights of current, new, and potential improvements will be discussed. Overall, there is a need and potential for improved communication between vehicles and traffic signals given emerging autonomous vehicle technology.

Current Infrastructure Technology

General traffic lights operate on a fixed timing schedule typically only allowing adjustments to the sequence based on a sensor to detect vehicles at the intersection and through expected volumes of traffic based on daily traffic routines. These common approaches are solely based on the detection of nearby vehicles. A benefit of detection devices present in a fixed light sequence traffic signal is the option to alter traffic flow directions through nearby vehicle detection given the light has not reached its maximum green light time display. Another benefit is the option to skip certain cycles if no vehicle is present in a specific direction at that intersection. This will result in an improved flow of traffic in the opposite direction. Another common technique for traffic flow optimization is the use of the concept rolling horizon [Goodall 2013]. A traffic control algorithm will optimize an objective function over a short period of time to estimate the position of vehicles over future cycles. This approach again only allows for estimation of a vehicle location as opposed to a precise recognition. With emerging autonomous vehicle technology, intersection performance can greatly be enhanced.

Furthermore, a rolling horizon quadratic programming approach was used for signal control [Aboudolas 2010]. They investigated recently developed signal control and discovered new ways to improve real-time network control in large-scale networks. The traffic responsive urban control (TUC) method was used and is based on a linear quadratic multivariable regulator which considers minimum green time constraints and cycle time. Two different strategies of first and second class were created. First class considers undersaturated traffic conditions while second class considers oversaturated traffic conditions. Overall optimization for network wide signal control of traffic was proven effective through efficiency improvement.

For over a decade, there have been several attempts to develop approaches for improving operations of self-driving vehicles through signalized intersections [Mladenovic 2014]. One main concentration for improvement has been the cooperation of the vehicles to improve safety. About 96% of traffic engineers recognize the importance of safety at intersections, while identifying the concern for respect and morality. Crashes that occur generally are due to human error. Therefore, to implement autonomous vehicles and ensure citizens are content with this improvement, a safer environment throughout the automotive transportation must be proven successful.

Connected Vehicle Technology

Although quality decision making is important in the improvement of safety, connectivity between vehicles adds an extra component to improve the traffic flow and overall safety of the vehicle. Talebpour and Mahmassani [2016] performed a study demonstrating the influence of connected autonomous vehicles and the impact on traffic flow. It was proven that connected vehicle technology can provide real-time information about nearby traffic and ultimately can increase efficiency and reliability.

In the same article published by Talebpour and Mahmassani [2016], the type of communication that can occur in an autonomous environment was discussed. Active Vehicle-to-Vehicle (V2V) communication is the ability for one vehicle to maintain an appropriate distance behind another. This is typically based on desired spacing, comfortable acceleration or deceleration, and the relative velocity between the vehicles. This specific type of communication is like adaptive cruise control (ACC) which allows a user to specify a top speed which may be reduced based on the distance behind and speed of a vehicle in front. Vehicle to Infrastructure (V2I) is also an important level of communication. Active V2I communications allow real-time data to be transmitted regarding speeds of multiple vehicles. The signal can then update an appropriate speed limit to allow the connected autonomous vehicles to work in harmony. It is concluded that the general autonomous vehicle will calculate the appropriate acceleration based on all inputs to the system from nearby vehicles and infrastructure signals. This calculation is important as the basic behavior of a vehicle begins with the ability to accelerate and decelerate appropriately.

More recent research relating to the topic of connecting autonomous vehicles and traffic signals is through [Feng 2015] paper titled “A real-time adaptive signal control in a connected vehicle environment.” Common traffic signals have been optimized to improve traffic flow based on real-real time traffic conditions. Adaptive signal controls design signal time and phasing on-the-fly based on real-time traffic demand as well as predicted traffic demand. Furthermore, they can use sensors embedded in the pavement or non-intrusive sensors, like video detectors. However, this traffic flow can be improved with advances in wireless communication technology as vehicles can communicate with each other and with the infrastructure in the emerging connected vehicle system [Feng 2015]. There have been many advances in Vehicle to Vehicle (V2V) communication as well as Vehicle to Infrastructure (V2I) communication. These technologies use dedicated short-range communication (DSRC) and this technology can be used to gather data for these specific communication scenarios.

This study considered both autonomous and non-autonomous vehicles. Applications utilizing V2I communication enable the intersection to acquire a more complete picture of the nearby vehicle states. Data from connected vehicles provide real-time vehicle location, speed, acceleration, and other status-based vehicle data. From this new source of data, traffic controllers should be able to make “smarter” decisions [Feng 2015]. This author has presented a real-time adaptive traffic control algorithm by utilizing data from connected vehicles. Algorithms for this study utilize arrival time, estimation for traffic signal timing, and phasing decision at the traffic controller.

To improve light signal timing, Goodall et al [2013] created an algorithm to control traffic signals with connected vehicles. Instead of relying on point detectors to recognize vehicles at a fixed location, traffic signals can use data transmitted from a vehicle through DSRC to gain access to previously estimated measures such as vehicle speed, position, arrival time, acceleration rates, and queue lengths [Goodall 2013]. The predictive microscopic simulation algorithm (PMSA) was then created to improve state of the practice performance by responding to real time demands while eliminating the ability to reidentify records of an individual vehicle to protect driver privacy. The algorithm initially receives data regarding the position and speed within a 300-meter distance of the light. Assuming a minimum green light signal time of 5 seconds and a maximum of 15 seconds, the most appropriate green light signal timing is determined by the time required to clear vehicles in that direction.

Similar connected vehicle and infrastructure research was also completed for situational awareness for a connected autonomous vehicle (CAV) making a left turn at a signalized intersection [Khan 2019]. Video cameras as well as lidar and radar sensors are placed at the intersection to recognize upcoming vehicles traveling in the opposite direction of the vehicle intending to make a yielding left turn. The intersection will predict the arrival time to the intersection of the opposite direction vehicles. If the maneuver can be completed safely, the intersection sensors will notify the CAV (I2V) that it may proceed through the intersection. Furthermore, given a two-lane road, the autonomous vehicle control system can recognize behind vehicles to determine if a safe maneuver to the left turn lane can be completed [Khan 2019]. This study was completed given an aggressive non-CAV driver which is important to consider because not all vehicles on the road today are autonomous. Overall, the ability for the traffic signal to recognize upcoming vehicles from a distance was proven effective.

Multi-Intersection and Adaptive Signal Control for Traffic Optimization

SCOOT and SCAT traffic signal techniques have been used widely throughout traffic control for many decades. SCOOT is an optimization technique that incorporates a centralized system that measure traffic loads continuously [Luk 1984]. These measurements of traffic volumes adjust signal timings to minimize the average vehicle queue in specific areas per intersections [Stevanovic 2009]. Multiple details of the overall optimization include split timing, offset, and cycle length which provide smaller individual details for queue minimization. SCAT is an automated real time traffic responsive signal control strategy that incorporates local and regional computers [Stevanovic 2009]. Information from vehicle detectors regarding location is used to adjust signal timing based on the variation in traffic demand. Software program VISSIM is often used with this method and overall, signal timing is adjusted based on change in traffic flow which is monitored from the heuristic feedback system.

A connected vehicle research study based on an adaptive traffic signal in a mixed traffic stream was also completed [Khan 2019]. Connected vehicles (CV) are considered mobile nodes that communicate with nearby vehicles (connected road users) and infrastructure traffic signals. The intersection signals use an algorithm to optimize the traffic flow and adapt the timing based on vehicle load through the intersection. Initially, traffic signal timing is estimated based on the number of connected vehicles at the intersection. As vehicles travel through the intersection, dynamic offsets based on the initial signal timing can be implemented from the vehicle data load [Khan 2019]. Finally, the green time interval can be adjusted from the queue load of vehicles in the red direction. Overall, the time a vehicle is stopped at the intersection (stopped delay) can be reduced through adaptive signal timing.

Finally, multi intersection autonomous vehicle interactions have been simulated based on distributed mixed integer linear programming (MILP) to enhance traffic flow at signalized intersections [Ashtiani 2018]. Using connected autonomous vehicles (CAV), intersections solve their own optimizations given vehicle information and communicate decisions to other autonomous vehicles. Using time for a vehicle to proceed through an intersection and distance to the intersection, the controller can create a list of subscribed vehicles to neighboring intersection to find the desired access time. Overall traffic flow is optimized given these calculations.

This research was also incorporated using optimal schedule of autonomous vehicle arrivals at intelligent intersections [Fayazi 2017]. Using the mixed integer linear programming technique (MILP), a live picture of traffic conditions can be created. Notifications per vehicle can be communicated to the upcoming intersections to determine arrival time of that vehicle. Considering all subscribed vehicles to the upcoming intersection, an optimal schedule for light time can be determined to minimize intersection delay while ensuring safety. The access distance of the vehicle to the intersection allows for further calculations of the desired arrival time to ensure vehicles do not face extreme delays. Furthermore, safety is more improved through ensuring vehicles travel safely behind vehicles ahead given autonomous vehicle reaction time.

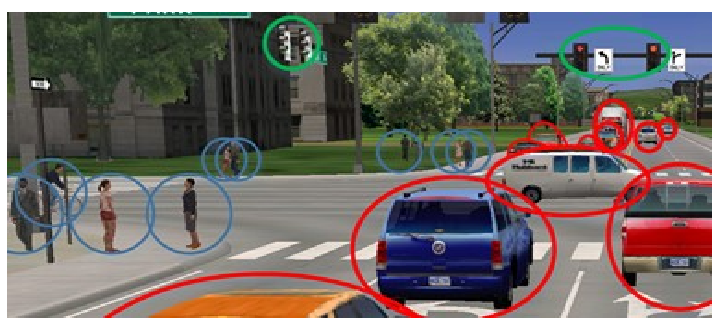

Figure 1: Full City Intersection Connectivity.

Potential for Communication Improvement

In general, studies have been completed through connecting vehicles to determine common traffic flow. This data is used to ultimately improve the traffic signal patterns. However, there is not a significant amount of research considering the communication between both vehicles and traffic signals and treating each as an individual intelligent agent. This further includes a lack in research of communication between adjacent intersections (I2I). Including this newer form of communication can create improved traffic flow across a wider range of roads. Connecting vehicle flow through multiple intersections allows for more accurate status updates that can be used to improve both vehicle and intersection status decisions. Considering previous research regarding connected vehicle behavior and implementing optimization algorithms for the addition of connected traffic signals will allow for further improvement of intersection performance. A full network of agent-based communication between autonomous vehicles and intelligent traffic signals is a new study that will be discussed and proven to be advantageous to the transportation infrastructure. Eventually, this communication can be improved to full dynamic component connectivity in a city intersection as shown in Figure 1 however, this research will only consider communication between autonomous vehicles and intelligent traffic signals.

3. METHODOLOGY

The goal is to model an intersection that connects both autonomous vehicle and intelligent traffic signal agents to understand and improve communication between intersections. Figure 2 displays the ideal coupled system at an individual intersection when considering both an autonomous vehicle and an intelligent traffic signal each as an agent. Realistically, numerous nearby vehicles and traffic signals will be in simultaneous communication. However, for simplicity, initially only the interaction between one vehicle and light is considered.

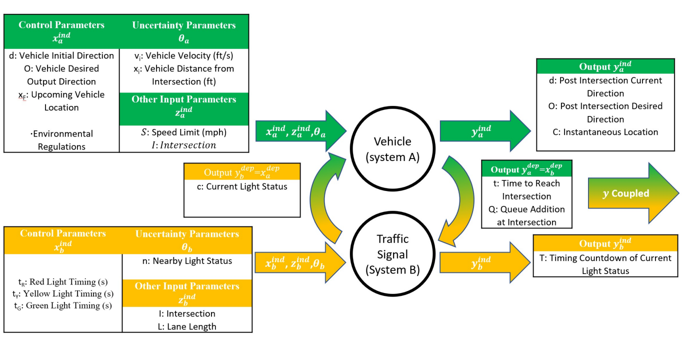

Figure 2: Coupled Agent-Based Behavior.

The importance of this experiment is to ensure the autonomous vehicle agents and intelligent traffic signal agents are working in harmony. As displayed in Figure 2, autonomous agents can communicate approach time to an intersection when necessary. The intelligent light can then put that autonomous car in queue and determine if a potential light status change is necessary based on the load of vehicles currently waiting at the light. The traffic signal will continuously gather nearby vehicle data to determine if a light status change is necessary. Furthermore, to allow two-way communication, intelligent traffic signals can relay light status to upcoming vehicles to ensure common traffic laws are obeyed.

The MATLAB model has been created to run specific simulation scenarios on the behavior of autonomous vehicles in a smart city environment. The initial model was created to demonstrate traffic flow at one individual intersection. Figure 3 displays the individual intersection model labeled with specific directional values for facilitated reference throughout this section. The direction number is based on the input or output location relative to the center of the intersection and it is assumed that all cars will travel on the right side of the road. The overall model is a fixed time step iteration-based code which calculates the desired acceleration of each individual vehicle for appropriate movement throughout the simulation. This model is based on the behavior of a realistic vehicle. As time passes, drivers change positions relative to the traveled road in the desired direction. Vehicles will continue to move throughout the simulation until their desired destination is reached.

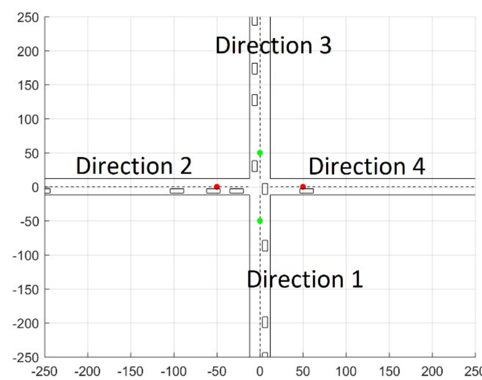

Figure 3: Individual MATLAB Simulation Intersection.

Updated behavior parameters calculated from the previous iteration to be used for the current iteration include the current position (x_i) and velocity (v_i) of an individual vehicle. The main objective of each iteration per car is to calculate the appropriate acceleration given the situation. Four main types of accelerations are calculated per iteration and the most appropriate acceleration is implemented in the final car movement calculation. The accelerations are highlighted in Table 1 and explained in detail throughout this section.

$$x_{PS} = -28 - v_{id} * t_Y \tag{3.1}$$

$$x_{PR} = -22 - v_{id} * t_Y + \frac{1}{2} * a_{id} * t_Y^2 \tag{3.2}$$

$$x_{PL} = -16 - v_{id} * t_Y + \frac{1}{2} * a_{id} * t_Y^2 \tag{3.3}$$

Table 1: Individual Iteration Acceleration Options

Distance Acceleration	Maintaining an appropriate following distance behind a car given the desired headway time.
Light Status Acceleration	Determining the appropriate acceleration given no cars ahead, the current light status, and an intent to proceed straight through the intersection
Right Turn Acceleration	Calculated instantaneous acceleration given no cars to impede upcoming progress and a desire to make a right turn at the upcoming intersection
Left Turn Acceleration	Calculated instantaneous acceleration given no cars to impede upcoming progress and a desire to make a left turn at the upcoming intersection

Equations 3.1, 3.2 and 3.3 based on the desired turn are calculated to determine if the vehicle at the current speed will make it through the intersection if the light were to change immediately from green to yellow. Considering the same direction 2, if the current x_i position is greater than the through intersection calculation position, it is highly likely the vehicle will make it through given an immediate yellow light change. The equations are evaluated only with a green light at the upcoming intersection. An additional value used is the yellow light time (t_Y). These equations calculate the passing position (through point) based on ideal behavior for a straight (x_{PS}), right (x_{PR}), and left (x_{PL}) turns.

These equations are used to determine if a vehicle will pass through the intersection and to provide opposite direction vehicle status to confirm if a vehicle can proceed through an unprotected left turn. If no cars in that opposite direction have reached the through point, the yielding vehicle can proceed safely across the lanes of traffic. Figure 4 displays a comparison between the straight (x_{PS}), right (x_{PR}), and left (x_{PL}) turns values for a vehicle with an intensity rating of 5. It is clear from the graph that a vehicle traveling straight can be the furthest distance away from the center of the intersection but still make the light given a potential yellow light change. This is because no deceleration is required for a vehicle proceeding straight assuming no nearby vehicles are impeding the progress. Vehicles turning left and right are required to slow down to complete the turn safely.

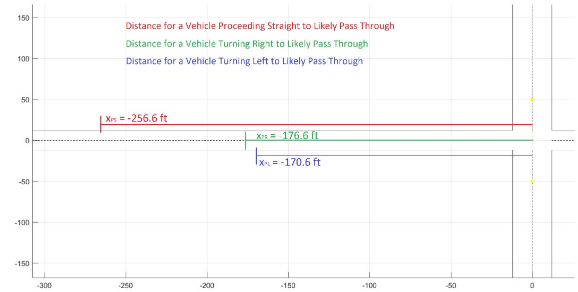

Figure 4: Distance from Intersection to Likely Proceed Through Based on Desired Turn.

Overall, vehicles in the simulation behave typical traffic laws in a single intersection model with one lane input and output per direction. The light timing at the four-way intersection is fixed with varying green times per simulation and a fixed yellow light time based on the speed limit. The individual intersection is then used to create a grid scenario like a city environment.

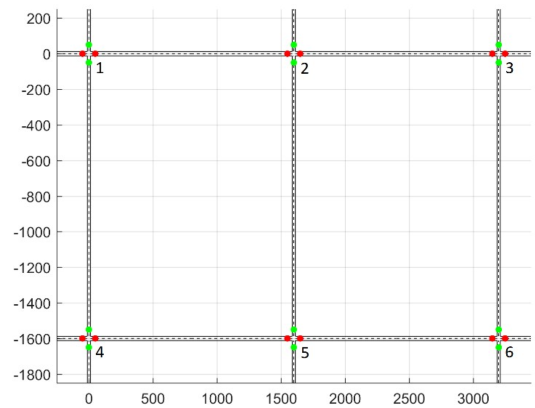

Figure 5: 2 x 3 Intersection Grid.

Intersection Grid with Fixed Timing Signals

Upon completion of the basic intersection model, individual intersections are then connected to create a city environment. The initial evaluation of traffic flow through the intersection is evaluated using fixed timing signals. This objective is critical for understanding the status and behavior of previously constructed intersection or city models. Once the behavior of a basic city environment can be evaluated, approaches to improve the efficiency of these models while ensuring a safer environment for the transportation infrastructure can be determined.

Initially, basic intersection modeling was carried out. A simple intersection model has been created with vehicles passing through the intersection based on light status. Next, the basic intersection model was scaled to simulate a city environment with fixed timing signals. This is important so the efficiency of the grid setup and an average vehicle time through individual intersections can be calculated. Overall, these parameters will be calculated given fixed green light signal times to establish a baseline for improvement in each city grid scenario.

MATLAB Modeling for Connected Intersections

The initial MATLAB code was created to simulate vehicles traveling through one specific intersection. To consider a city scenario, individual intersections are placed in new locations throughout a mapped area with one lane road transitions connecting each adjacent intersection. An example of a 2x3 intersection setup is shown in Figure 5. The center of each individual intersection was placed at a specific (x_I, y_I) coordinate on the map based on the lane length (L) of the intersection, the intersection grid row (R) count and intersection column (C) count. Furthermore, the intersection number (I) is established as well as the direction (d) per intersection. The single intersection 1 used direction numbers 1 – 4 to establish north, south, east, and west surrounding the intersection; intersection 2 will possess directions 5 – 8. This numbering process will continue for the total amount of intersections in the grid (N = R*C).

The center location of the individual intersection is based on the lane length (L). In Figure, L = 800 ft. Due to the intersections all possessing the same length, the location of each intersection center must be exactly L*2 ft away from an adjacent intersection to represent a square setup. The grid setup in Figure 5 is not displayed to scale.

The iteration process per vehicle is very similar compared to the single intersection acceleration determination process. The main difference is the overall location evaluation per vehicle. Individual calculations regarding position are all based on the center location of the intersection. For example, the through intersection equations now include an additional x_I center location term. Furthermore, the specific direction number 2 from the individual intersection cannot always be referenced however, the west direction relative to an individual intersection will still be considered. The new through intersection evaluation equations are listed as

$$x_{PS} = x_I - 28 - v_{id} * t_Y \tag{3.4}$$

$$x_{PR} = x_I - 22 - v_{id} * t_Y + \frac{1}{2} * a_{id} * t_Y^2 \tag{3.5}$$

$$x_{PL} = x_I - 16 - v_{id} * t_Y + \frac{1}{2} * a_{id} * t_Y^2 \tag{3.6}$$

which still directly relate to the individual intersection equations. All equations from section 3.3.1 can be used for any direction west of an intersection given the center x coordinate. This consistency highlights the scalable ability of the individual intersection to a grid city model.

Evaluation of Fixed Timing Intersection Performance

The initial evaluation of intersection performance will begin by modeling a select few basic intersection networks to build a framework for the experiment. To evaluate the performance of this intersection, we will consider the average time for each car to proceed through an intersection. Individual vehicle timing can be evaluated using the actual simulation start time (t_s) of the vehicle when it is located at the beginning of the intersection and the final intersection departure time (t_d). The actual time through the simulation (t_a) can be found using the equation

$$t_a = t_d - t_s \tag{3.7}$$

To compare the quality of this value, we can study how long it may take for each individual car to pass through based on the typical behavior of that driver (desired speed, following time, desired acceleration). We can determine the time it would take for an individual driver to pass through this intersection given a green light and no other cars to impede the progress. This calculation will be used as an ideal time (t_{id}) scenario per car.

The ideal time is based on the output direction relative to the input direction. Given different output directions of straight, right, or left, the following three equations for the ideal time (t_{id}) can be determined.

$$t_{idS} = \frac{2L}{v_{id}} \tag{3.8}$$

The right and left turn equations require more detail regarding deceleration and acceleration time as it is necessary to slow down to complete a turn safely.

$$t_{idR} = 2\left[\frac{-28 - v_{id}\left(\frac{v_{id} - v_T}{a_{id}}\right) + \frac{1}{2}(a_{id})\left(\frac{v_{id} - v_T}{a_{id}}\right)^2 + L}{v_{id}}\right] + 2\left(\frac{v_{id} - v_T}{a_{id}}\right) + \frac{6}{v_T} \tag{3.9}$$

$$t_{idL} = 2\left[\frac{-20 - v_{id}\left(\frac{v_{id} - v_T}{a_{id}}\right) + \frac{1}{2}(a_{id})\left(\frac{v_{id} - v_T}{a_{id}}\right)^2 + L}{v_{id}}\right] + 2\left(\frac{v_{id} - v_T}{a_{id}}\right) + \frac{10}{v_T} \tag{3.10}$$

Eventually, an overall real average time per car is evaluated to determine the efficiency of the intersection given the average ideal calculation.

Given details from the MATLAB model from a fixed timing intersection, there is room for improvement. Autonomous vehicles are moving in a positive direction possessing new vehicle recognition and 5g technology. This creates the ability for vehicles to communicate. Building on this initial model and improving intersection performance by light and vehicle communication is a challenging problem. These initial basic steps will help determine the best approach for intersection evaluation.

Implementing Coordinated Traffic Signals

After evaluating and modeling multiple basic intersections, agents will be introduced in traffic signals. As previously stated, an agent is an autonomous decision maker whose decision making is determined internally but may be altered by interactions with the environment or other agents. Therefore, to ensure a proper functioning network, individual traffic signal agents will have their own internal behavior function and will gather data from nearby intelligent intersections to build and improve the model. These coordinated traffic signals communicate light status to optimize traffic flow for safety and resilience improvement for the transportation network.

MATLAB Modeling for Coordinated Traffic Signals

Given the basic intersection model for city grid scenarios, intelligent traffic signals are now implemented. Nearby intersections view the status of adjacent intersections and adapt their own status based on average time for a vehicle to travel between intersections. The average time for a vehicle to travel between intersections (t_b) is

$$t_b = \frac{2L}{S} \tag{3.11}$$

where L is the lane length and S is the speed limit. This is the approximated time a vehicle will take to travel from the center of one intersection to another. Given fixed values of L = 800 and S = 40 mph (58.6667 ft/s) for all simulations run, the average vehicle time between intersection t_b = 27.27s. This calculation considers vehicles traveling at the full speed limit throughout the transition. Realistically, a range of drivers will travel above and below this value however, this is used as a reasonable approximation for this scenario. This value is used to initialize the adjacent intersection green light countdown.

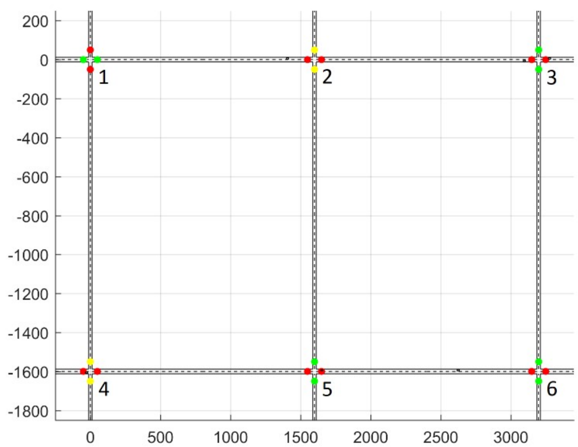

Figure 6: Coordinated Intelligent Intersection Setup.

In this example, the 2 x 3 intersection setup will be used. Figure 6 displays a sampled view of the coordinated traffic signal intersection setup. All traffic is initially routed to pass through each intersection in the north and south directions (Figure 5). Note the intersection numbers displayed in Figure 6. For this coordinated traffic scenario, intersection 1 has the leading fixed signal. This intersection behaves similarly to the fixed timing lights based on the maximum green light time. All other intersections in this simulation will adapt to the nearby intersections relative to the west or north depending on location.

Based on the overall mapping, the direction of coordinated traffic flow will be in the southeast direction. Intersections 2 and 4 are informed when intersection 1 changes state to a yellow light and will immediately start a countdown for their individual light change generally based on the average time for a vehicle to travel between intersections (t_b = 27.27s).

Referring to the display in Figure 6, intersection 1 has already allowed traffic to pass through in the east and west directions while the north and south traffic is held at a red light.

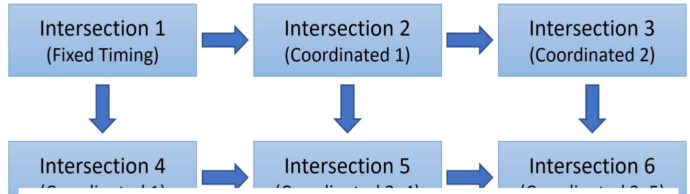

Figure 7: Coordinated Traffic Signal Logic.

Intersections 2 and 4 have switched to a yellow light which has started a countdown for intersections 3 and 5 to adjust to their yellow light. Figure 7 shows the coordinated logic for a 2x3 intersection example.

Coordinated Traffic Signals

Overall, various maximum green light times were run to simulate alternative traffic scenarios. To coordinate traffic appropriately, the intersections receive the instant yellow light change and create a countdown for their individual light change based on either the maximum green light time (t_G) or the average time for a vehicle to travel between intersections (t_b). The appropriate choice is determined by which numerical value is smaller.

Figure 8 displays a section of the Traffic Light matrix from the MATLAB code which displays the light number, the status of the light, the countdown of that specific light status, and the intersection at which the light is placed. For the status, green = 2, yellow = 1, and red = 0. For reference, the individual intersection setup in Figure 3 can be directly labeled as intersection 1. Intersections 2 – 6 contain the same relative direction numbers as intersection 1. The traffic light status in Figure 8 can be directly related to the visual light status representation in Figure 6. An equation relating light status countdown from coordinated intersections (3 coordinated from 2) is important to consider.

Light #	Status	Countdown	Intersection
1	0	0	1
2	2	4.5341	1
3	0	0	1
4	2	4.5341	1
5	1	3.5	2
6	0	0	2
7	1	3.5	2
8	0	0	2
9	2	9.5	3
10	0	0	3
11	2	9.5	3
12	0	0	3
13	1	3.5	4
14	0	0	4
15	1	3.5	4
16	0	0	4
17	2	9.5	5
18	0	0	5
19	2	9.5	5
20	0	0	5
21	2	79.4773	6
22	0	0	6
23	2	79.4773	6
24	0	0	6

Figure 8: Individual Traffic Signal Status.

$$t_Y - T_5 = t_G - T_9 \tag{3.12}$$

From Figure 8, given a yellow light time of 4 seconds (t_Y = 4) and a maximum green light time of 10 seconds (t_G = 10), it can be observed that intersection 2, which contains lights 5 and

7 has communicated information to intersections 3 (lights 9 and 11) and 5 about the recent light status change from green to yellow (0.5 seconds have passed since the light change). Therefore, the simulation logic is accurate as the countdown time that has passed in intersections 3 and 5 is exactly 0.5 seconds less than the maximum green light time. This logic is repeated for the duration of the simulation and the average vehicle time through individual intersections is evaluated.

MATLAB Modeling for Adaptive Traffic Signals

The main addition to the MATLAB model is the ability for a traffic light to recognize the level of vehicles waiting in a specific direction at the intersection. This is referred to as the queue (Q) of the light. For each experiment, the queue of each individual intersection throughout the overall simulation is a fixed value. Each intersection will add up the number of vehicles waiting in the red-light direction and when the current queue value reaches the maximum ($Q \geq Q_{max}$) set in the simulation, a new countdown for the green light direction may be applied.

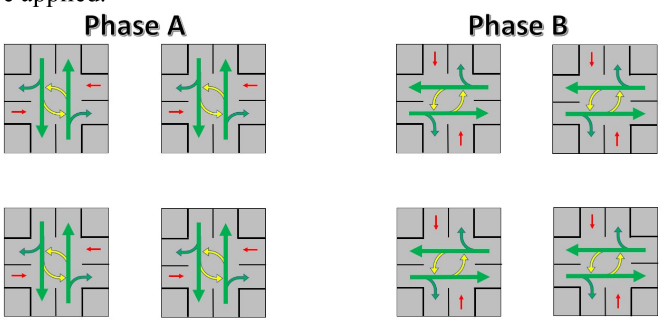

Figure 9: 2x2 Fixed Timing Signal Sequence

Overall, the intelligent coordinated traffic signal environment is still implemented. However, the status may be altered due to a large queue. For consistency, the basic intersection directions from Figure 3 will be referenced in this scenario. If directions 1 and 3 (north and south) currently display a green light, directions 2 and 4 (east and west) will display red to avoid intersection collisions. As the countdown to a yellow light continues, traffic from the direction with a red light will build up. A car will be officially added to the queue count when it is completely stopped at the intersection ($v_i = 0$) while waiting for the light to change. When the Q_{max} value is reached in either direction 2 or 4, a calculation to determine the amount of time it will take for the furthest vehicle in a green light direction (1 or 3) to reach the intersection (t_v) is carried out.

Initially, the code determines the furthest vehicle in each direction from the intersection that is within the lane length range. A situation may occur where no upcoming vehicles are present in the green light directions. In this scenario, the green light countdown will automatically be reduced to 1. This will ensure the vehicles in the red-light direction are not waiting more time when no traffic is present for a green light.

The time each vehicle will take to reach the intersection in each direction (t_{v1} and t_{v3}) will be evaluated. For simplicity, only the evaluation for direction 1 will be explained. First, a calculation is completed to determine the minimum distance the individual vehicle can be from the intersection to make it through given ideal behavior in the event of an immediate change to a yellow light. These calculations are the same compared to the through intersection calculations. They are shown here again as equations 3.13, 3.14, and 3.15 and are based on the desired output direction straight (x_{PS}), right (x_{PR}), or left(x_{PL}).

$$x_{PS} = -28 - v_{id} * t_Y \tag{3.13}$$

$$x_{PR} = -22 - v_{id} * t_Y + \frac{1}{2} * a_{id} * t_Y^2 \tag{3.14}$$

$$x_{PL} = -16 - v_{id} * t_Y + \frac{1}{2} * a_{id} * t_Y^2 \tag{3.15}$$

Next a calculation is completed to determine how long it will take the vehicle to reach this specific point. Realistically, depending on the true output direction of the vehicle, any of the three above equations could be used. For this scenario, the displayed calculation assumes the upcoming vehicle will make a right turn therefore, variable (x_{PR}) will be used. The time for the vehicle in direction 1 (t_{v1}) is calculated as

$$t_{v1} = \frac{x_{PR} - x_{1i}}{v_{1i}} \tag{3.16}$$

given current vehicle speed (v_{1i}) and position(x_{1i}).

A comparison for calculated values t_{v1} and t_{v3} is completed. The greater value will be used as the ultimate t_v value which is then compared to the light countdown. In this scenario, $t_{v1} > t_{v3}$ is assumed therefore, $t_v = t_{v1}$. The individual light countdown in direction one (T_1) is then compared to the calculated value t_v. If $t_v < T_1$, the new countdown value will be t_v. This will allow all vehicles in each green light direction to proceed through the light and ensures that once this happens, vehicles in the red-light direction will not have to wait unnecessarily. Alternatively, if $t_v > T_1$, the light will continue its normal countdown (T_1) to keep traffic continuously moving. In this research, no additional time will be given to a green light countdown.

Simulation Goals of the MATLAB Model

The MATLAB code can run simulations regarding either the fixed, coordinated, or adaptive timing signal network. Furthermore, based on details explained throughout chapter 3, a variety of inputs can be adjusted to vary the intersection simulation (car load, intersection grid setup, etc.) These varying parameters allow a user to determine how efficient an intersection may be based on the input details and the signal performance choice. The overall evaluation and explanation regarding the performance difference of each scenario will be explained throughout Section 4. The appendix contains the main MATLAB code for an adaptive traffic signal setup.

4. SIMULATION RESULTS

To determine if this adaptive approach improves intersection performance in city environments, evaluations per car will be completed. These evaluations will be completed by comparing overall distance traveled through the entirety of the intersection and time it takes to reach the destination from the initial starting point. Evaluations were initially completed from the fixed timing intersection model to establish a baseline and to confirm there is potential for improvement. The evaluations of the fixed timing signal are compared to the coordinated signal setup as well as the adaptive signal setup. Comparison criteria will be the intersection grid setup, the number of vehicles in the setup, and the queue count for the various adaptive signal options.

Fixed Timing Evaluation Results

Timing is the most important factor that will be considered during this evaluation. Performance will be evaluated for overall time through intersections. The key factor in this research is reducing wait times at intersections (stopped delay). Figure 9 displays the fixed timing intersection sequence in two phases given a 2x2 intersection setup. Due to the fixed timing evaluation, the only varying parameters are the intersection setup, the number of vehicles on the road, and the maximum green light time. The main comparisons are the intersection setup and the number of vehicles present on the road. The green light time varies and average traffic flow time and overall efficiency through an intersection is evaluated. The maximum green light ranges from a time of 10 – 50 seconds and the number of vehicles on the road per intersection ranges from 5 – 60 cars. The intersection setups evaluated for the fixed timing signal are 1x1, 2x2, 2x3, and 3x3.

Efficiencies per scenario are also compared. To maintain consistency for minimizing parameters, the inefficiency will be measured and displayed using the following equation:

$$I_{eff} = 1 - \%E = \left(1 - \frac{t_{id}}{t_a}\right) \tag{4.1}$$

where t_{id} is the average ideal time and t_a is the average actual time for a vehicle to proceed through the intersection.

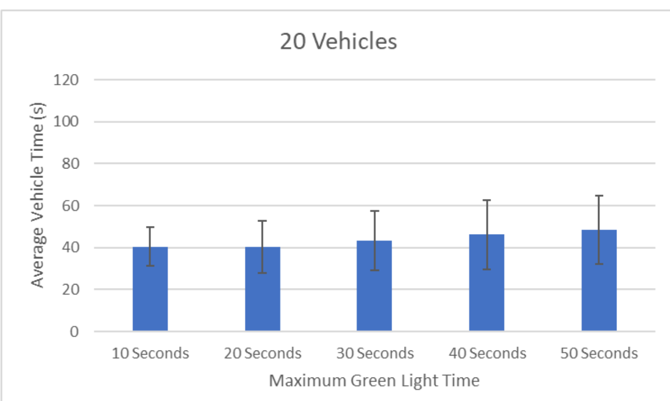

Figure 10: Average Time, Fixed, 20 Vehicles

A graph summarizing the data for a 2x2 intersection grid can be displayed in the Figure 10. The detailed comparisons show the difference in vehicle time through each intersection based on the vehicle load, the green light times per direction, and the intersection setup. Generally, the average vehicle time is based on the longer light time as well as the increased number of vehicles on the road. It can be seen that longer green light times are more beneficial for a larger vehicle count.

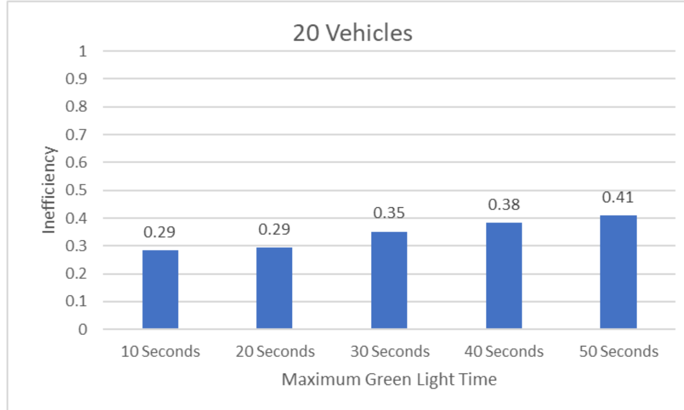

Figure 11: Inefficiency, Fixed, 20 Vehicles

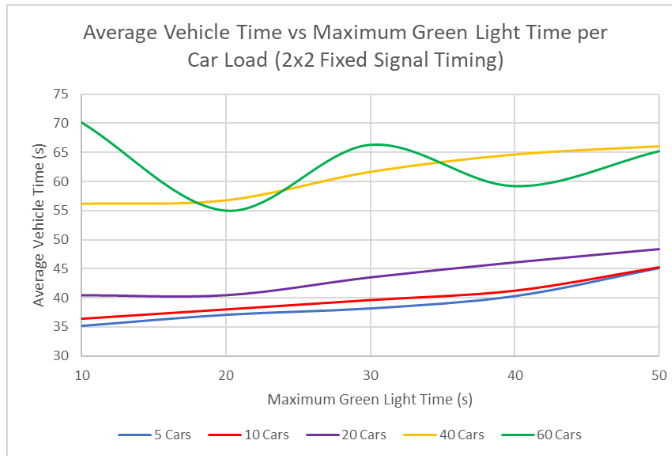

Figure 12: Average Vehicle Time for 2x2 Intersection, Fixed Signal

Coordinated Signal Evaluation Results

The coordinated traffic signal is the first step for improving the intersection performance. As discussed in Section 3, the nearby light sequences are now adaptable based on nearby intersection signal changes which includes rudimentary I2I communication. A representation of this light sequence in ongoing phases for a 2x2 intersection is displayed in Figure 13. The exact phase changes may not be represented by the exact figure but overall, the upper left intersection will change first to allow the opposite directional traffic to flow. The next phase includes the adjacent intersections compared to the initial. Finally, the bottom right intersection will adjust the direction. Other situations could occur where the initial intersection may change back to allow north and south traffic to flow before the last intersection has the option for a change. This ultimately will depend on the maximum green light time.

Graphic Displays of Coordinated Light Sequence

The data displayed for each graph will also be for a 2x2 intersection grid setup for consistency. More traffic creates an overall longer wait time. However, the wait times are more consistent given the longer green light time in scenarios with a higher number of vehicles. This is also consistent for the inefficiency of the intersection.

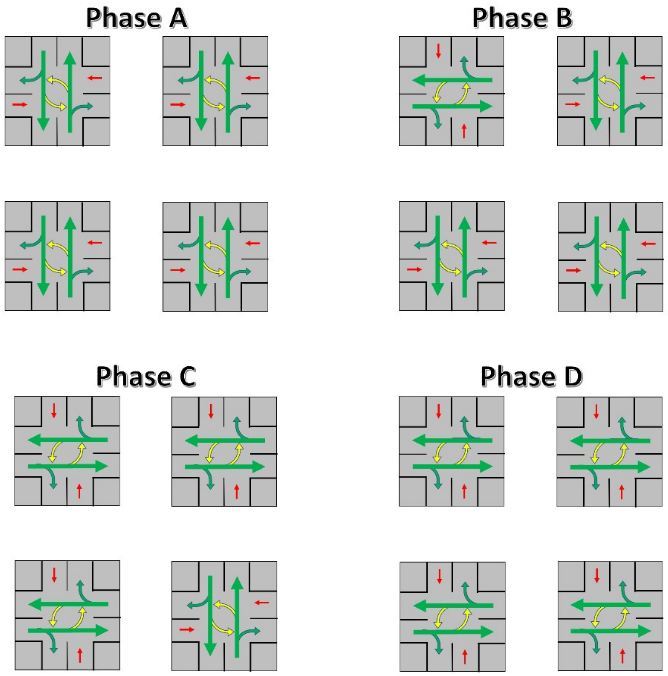

Figure 13: Coordinated Signal Light Sequence

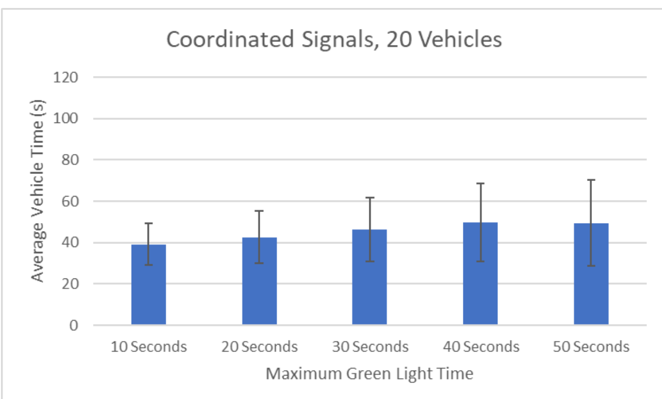

Figure 14: Average Time, Coordinated, 20 Vehicles

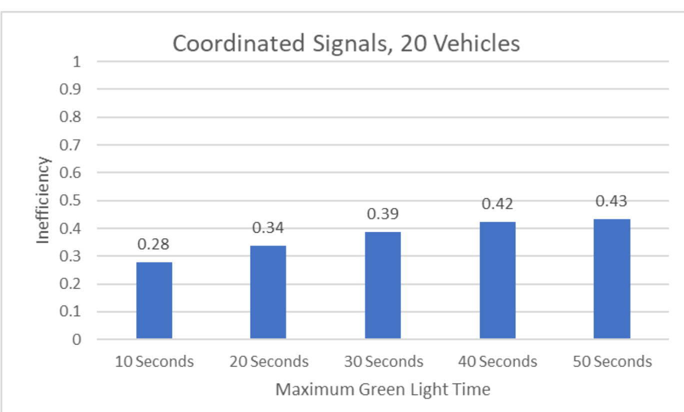

Figure 15: Inefficiency, Coordinated, 20 Vehicles

To demonstrate the importance of the light signals, Figure 17 shows the light status as run through a 2x2 simulation with 20 vehicles on the road per intersection (80 total). These values specifically are identified as the west directional light statuses per intersection in the 2x2 setup. Light 2 is the upper left intersection, light 6 is for the upper right, light 10 references lower left, and light 14 refers to the lower right intersection. Figure 16 shows the light locations for a 2x2 intersection setup. The light patterns can be compared, and it is evident that as light 2 changes to a yellow, it is within a certain amount of time that lights 6 and 10 will alter their status. It is furthermore clear that lights 6 and 10 are on the exact same track as they both alter their status based on light 2.

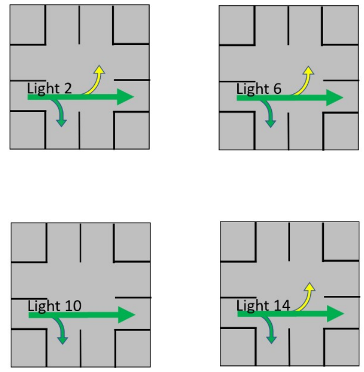

Figure 16: 2x2 Intersection Light Number Locations

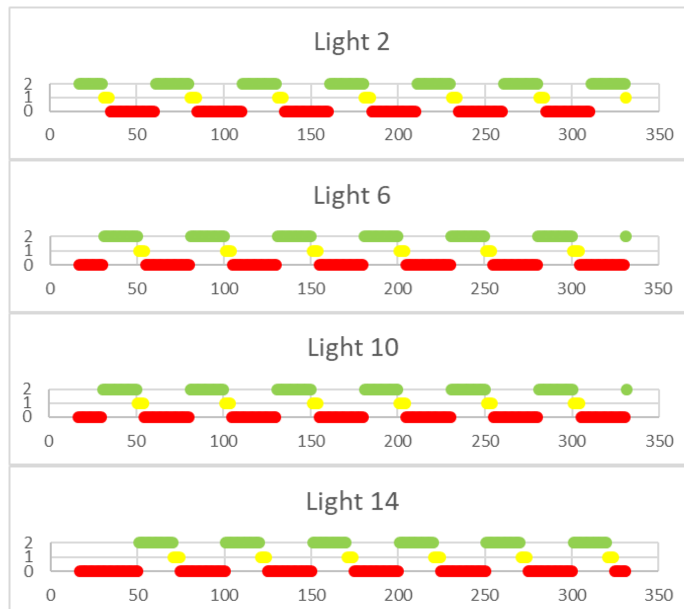

Figure 17: Visual Status Representation of Coordinated Traffic Signals

Trendlines can again be formed from evaluations of the 2x2, 2x3, and 3x3 intersection grid setups. Data from the 2x2 intersection is show in Figure 18. Again, like the fixed signal timing, it is evident that longer wait times occur with more vehicles on the road and with longer green signal times. Higher loads of vehicles contain trends where longer green light times improve the overall efficiency. This is due to more vehicles allowed through the intersection in one cycle.

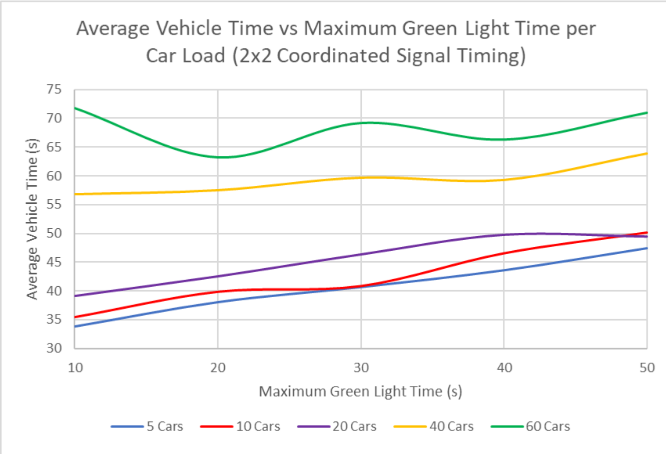

Figure 18: Average Vehicle Time for 2x2 Intersection, Coordinated Signal

Adaptive Signal Results

Overall, the best improvement for the vehicles to proceed through the intersection is the addition of the adaptive signal. This will allow the lights to adjust their light signal from neighboring traffic light status as well as the vehicle queue at a specific intersection. There is no specific phase diagram for this sequence. The initial light changes are based on the phases from Figure 13, but may be altered based on the queue size of cars at each intersection in the direction of the red light. In this research, the queue is not adjusted per simulation.

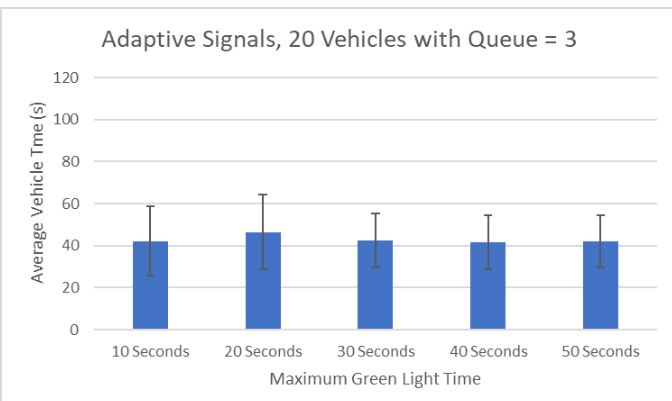

Figure 19: Average Time, Adaptive, 20 Vehicles

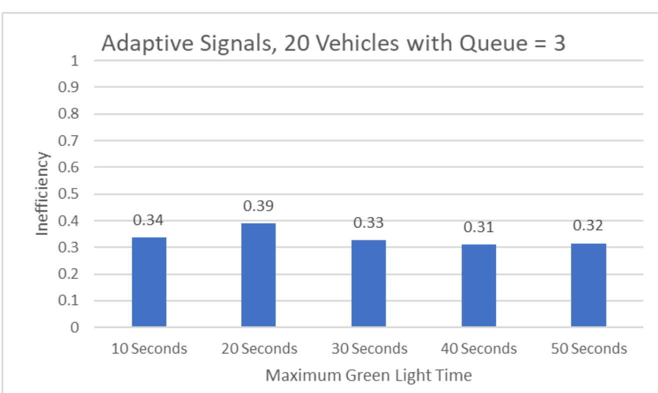

Figure 20: Inefficiency, Adaptive, 20 Vehicles

Furthermore, the light sequence status can be viewed as well. Like the coordinated signal setup, these lights are all based on the west direction from each intersection as displayed in Figure 16. Individual lights now have their own specific agenda based on the queue count but can also be altered from the neighboring light status. Light 14 in Figure 21 has a red-light section that lasts a very large amount of time. This scenario may occur when no vehicles are present in a specific direction. In this case, no vehicles are waiting for the lights at the intersection approaching from both the east and west input directions. This allows for the north and south signals to be green for an extended period as it is unnecessary to alter the status for no upcoming vehicles.

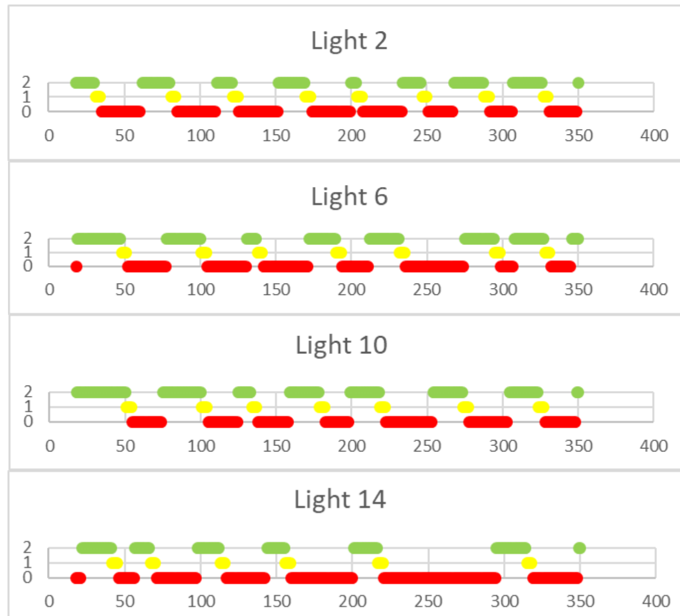

Figure 21: Visual Status Representation of Adaptive Traffic Signals

The overall comparisons from the different intersection setups compared to the queue values can be evaluated. Note that a lower count of vehicles on the road has better performance with a smaller queue as the lights need to adapt more recently. The larger queue though is more beneficial for a higher number of cars on the road and the trendline is steadier for the varying light times. By using this data appropriately, an adaptive queue can be implemented in future work.

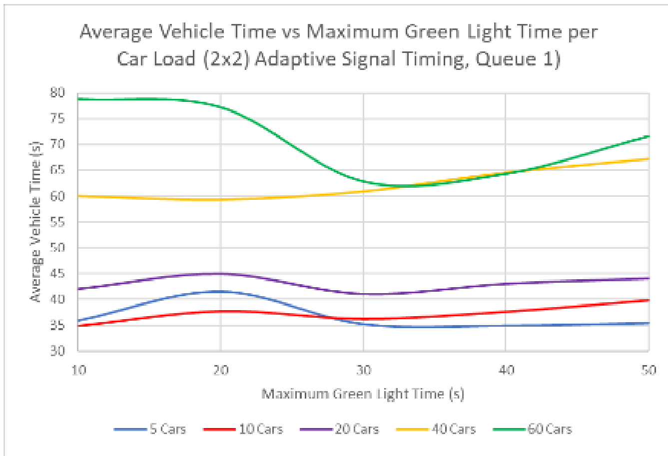

Figure 22: Adaptive Signal Timing, Queue 1

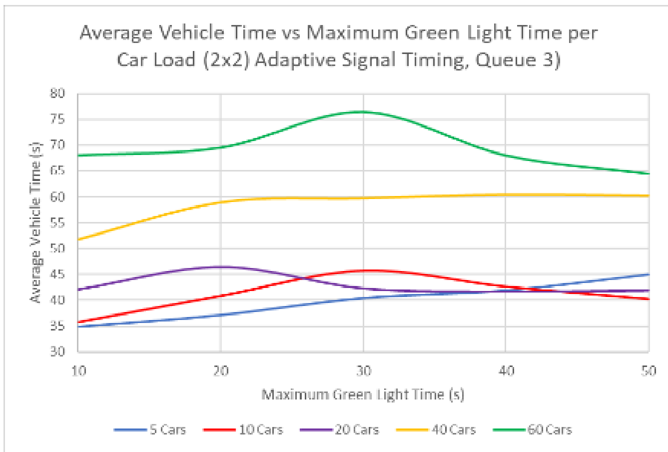

Figure 23: Adaptive Signal Timing, Queue 3

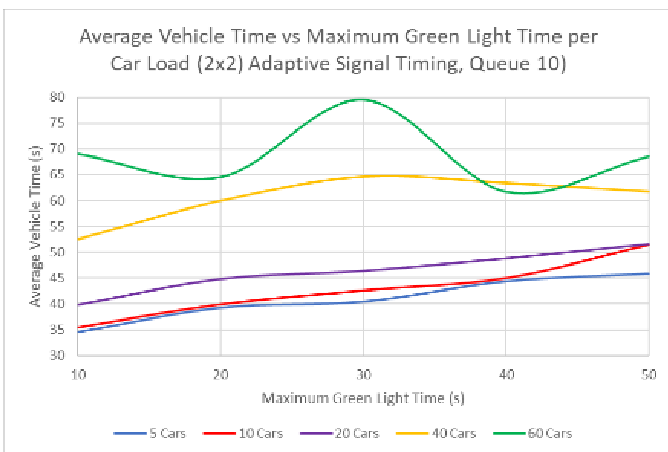

Figure 24: Adaptive Signal Timing, Queue 10

Light Sequence Comparison

Furthermore, to consider the benefits of the adaptive traffic signal, details of each traffic light in a 2x2 scenario can be observed based on the gathered data. For consistency, the 2x2 intersections graphs will be compared while 40 vehicles are on the road. Figures 22, 23, and 24 display trendlines of the average vehicle time by comparing all car counts and signal types for a 2x2 intersection setup.

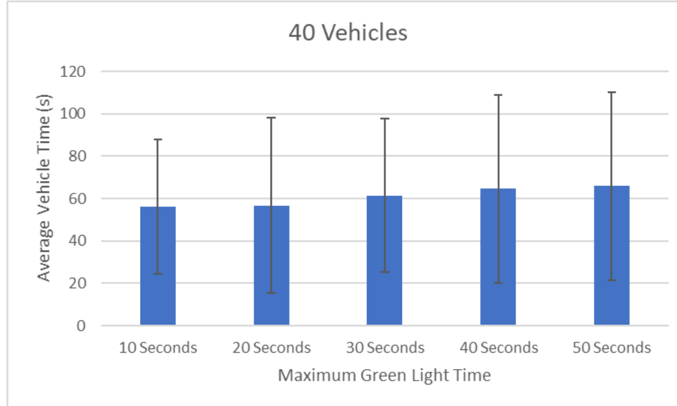

Figure 25: Average Time, Fixed, 40 Vehicles

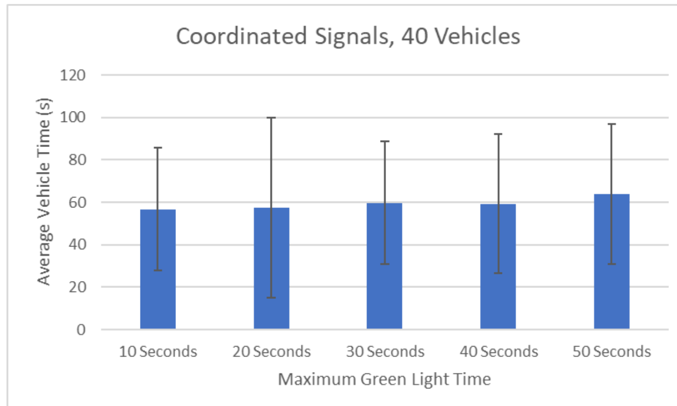

Figure 26: Average Time, Coordinated, 40 Vehicles

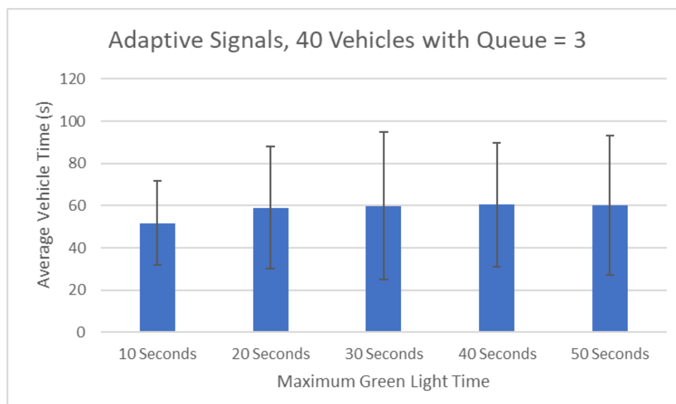

Figure 27: Average Time, Adaptive, 40 Vehicles

As can be seen here, by comparing the basic light timing sequence to the coordinated and adaptive sequences, the overall average time per vehicle is reduced as well as the inefficiency especially with 40 vehicles on the road. In some cases, the coordinated signal may be more beneficial compared to the adaptive but that is generally based on the maximum queue value. As previously mentioned, this research only considers a fixed queue value per simulation and overall, a lower vehicle load will require a smaller queue value to improve traffic flow.

It will eventually be beneficial to consider an adaptive queue for greater intersection improvement.

5. CONCLUSIONS & FUTURE WORK

All in all, the use of agent-based communication for improved decision making has been proven effective. Referring to the design statement, it has been shown that improving agent-based Infrastructure to Infrastructure (I2I) communication and decision making does provide performance benefits to traffic flow capacities.

The initial communication of queue size from the vehicle to the traffic light (V2I) allows the intersection to make an appropriate decision for the status based on the load of traffic. This change of state based on the queue is then communicated to nearby traffic signals. Next, the addition of agent communication between traffic signals allows for further improved decision making. The I2I addition is the main area of improvement for the transportation infrastructure. This improved ability allows intersections to communicate status effectively and the coordinated approach demonstrates success of this improvement. From the individual light status change based on the level of traffic to the communication between intersections, a level of connectivity is created between vehicles and traffic lights that are at different intersections. The traffic flow is then further optimized as the intelligent signals communicate and adjust individual status based on nearby intersection signal updates.

The decision-making process and improved communication through intersections (I2I) is proven effective and can be implemented throughout the real world as overall vehicle technology improves. This has been proven through multiple scenario simulations regarding various city intersection setups, load of traffic present throughout the simulation, and for alternative maximum green signal times. The overall ability to reduce average vehicle time through an intersection and reduce inefficiency is possible through adaptive signals and nearby intersection communication.

Future Work

Future work for this research can be taken in several directions. First, in this specific research, the queue size was fixed for different scenarios. A new research method would be to implement an adaptive queue size for the number of vehicles on the road or the duration of vehicles in the queue. The data already gathered from this research can be used to create a linear or quadratic maximum queue count for individual intersections or the overall intersection setup. This could depend on the number of vehicles proceeding through one intersection which may require that specific intersection to allow for an adaptive queue size.

Another opportunity for future work would be the individual intersection setup. Common intersections today have 2 or more lanes approaching from an individual direction. Many intersections also include a designated left turn lane which may assist with traffic flow improvement as well. Allowing these different types of intersections to communicate with each other (I2I) as well as with nearby vehicles (I2V) adds complexity on a new level. Queue sizes will need to then be adjusted potentially per number of lanes and for a potential left turn lane. Given the wide variety of intersection setups that are seen today, the possibilities are endless.

A final opportunity for future work is related to the different types of connected agents. In a real intersection, more types of dynamic components are found throughout. Examples of more components may include but are not limited to pedestrians, bikers, electric scooters, and pets. For improved safety, it will be beneficial to consider these components as agents as well. This will ensure autonomous vehicles will know one of these components is nearby regardless of camera technology ability. These extra possibilities that can be considered will add more complexity to the system but the ability to model this will be beneficial for improving safety.

With overall implementation of this future work, intersection performance can be evaluated and improved regarding average vehicle time, resilience, and safety. The newer technologies for individual autonomous vehicles allow for connected vehicles in city intersections to be implemented. The addition of agent-based communication for improved performance will greatly enhance the transportation infrastructure.

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