Using Time Series Forecasting for Adaptive Traffic Signal Control

S. Kim[1], M. Keffeler[1], T. Atkison[1], A. Hainen[2]
[1]Computer Science Department, University of Alabama, Tuscaloosa, AL, USA
[2]Civil, Construction, and Environmental Engineering, University of Alabama, Tuscaloosa, AL, USA

Abstract— *This paper presents a method of adaptive traffic signal control using time series forecasting and real time signal phase adjustment. The situation in which a green light turns red before passing an intersection is a familiar and frustrating experience to drivers. The proposed forecast based traffic signal adjustment attempts to predict and alleviate this situation by extending green lights in real time. The procedure and thought process of the implementation of the system are discussed in this paper along with results from a simulation on three intersections over the course of a week. Experimental results have shown an increase in traffic efficiency based off of a decrease in total waiting vehicles and time.*

Keywords: Adaptive Traffic Control, Time Series Forecasting.

1. Introduction

Traffic intersections are a popular form of traffic control allowing for a great amount of control. It is up to traffic engineers to time the traffic signals in order for traffic to flow efficiently across each lane. The characteristics of traffic volume at each intersection can vary, so there needs to exist a way to tailor signal timings to optimize each intersection. Manual assessment and timing of signals can be time consuming and error prone, considering the fact that traffic behavior may change over time. Congestions formed by inefficiencies in signal timing lead to wasted driving time, and raise environmental as well as safety concerns. Cutting down on waiting times will lead to less exhaust emissions, and reduce the number of accidents caused by drivers running red lights. Our proposed method attempts to increase the efficiency of traffic intersections by finding areas of improvements within existing signal timings, and dynamically adjusting signal phases to allow more vehicles to pass, leading to decreased waiting times and stoppages.

Advancements in traffic controller technology and the availability of vehicle detection sensors provide the opportunity for a more adaptive, efficient traffic assignment system. The system developed for this research aims to predict incoming vehicles and optimize signal timings to allow for more vehicle throughput and waiting time reduction at an intersection. The only tools needed for this system are packages found in R and Python, both of which are free and open source. The goal is to integrate this new system to run natively inside traffic controllers.

During heavy traffic hours, delays that are inherent in traffic intersections lead to back ups and congestion. A common occurrence in intersections is the arrival of vehicles right as a green light turns red. This problem can be lessened using a two-part adaptive traffic signal control method. First, the system must be able to predict the arrival of cars at an intersection. By reading sensor data provided by a traffic controller, the daily activity of an intersection was able to be reconstructed down to the second. This transformed data can be used to perform a time series forecast. Predictions can then be used in a real-time simulation in which signals are adjusted through the extension of green lights.

2. Background

There have been several efforts to apply forecasting methods and techniques to the problem of traffic signal control with varying levels of success. Included in these are Yi's et al. [1] work in comparing multivariate time series with univariate time series and K-nearest neighbor (KNN) nonparametric regression model. Wang's et al. [2] use Multiscale multifractal analysis of traffic signals to uncover additional more complex information in the time series of the signals. Vlahogianni et al. [3] looked at and compared several methods for short term traffic forecasting algorithms. The authors developed a framework for short-term forecasting models. Earlier work by Smith et al. [4] implemented a nonparametric regression model and applied it to two different sites, producing a forecasting model for estimating traffic flow 15 minutes in the future.

In order to solve the nonlinear problem of traffic optimization, research involving computational intelligence began as early as 1977 by Pappis and Mamdani [5]. They created a fuzzy logic traffic controller, which Chou and Teng [6] later expanded upon to incorporate multiple lanes and junctions. Spall and Chin [7] demonstrated a neural network based approach to produce an optimal signal timing strategy. Evolutionary computation has also been incorporated to the traffic problem using a genetic algorithm by Ceylan et al [8].

3. The System

The entire procedure can be broken down into three main steps. First, the data is cleaned into a form that can easily be worked with. Then, a time series of vehicle counts is input into R for forecasting. Finally, the forecasts are used to adjust the signal phases of a designated test day through a real time simulation. The data for these experiments were gathered at three different intersections along highways AL-69 and US-11 in Tuscaloosa, AL. These intersections all have advanced built-in data logging capabilities through Siemens traffic signal controllers.

3.1 Data Cleaning

Before the forecasting of vehicles can occur, the raw data must be cleaned. Data taken from a traffic controller is read as lines of events with corresponding timestamps, type of event, and lane number. By extracting traffic light and detector change events, a table of time bins with vehicle counts and traffic signal state can be constructed for each lane. Representing the data in this way allows for easy data manipulation and an easy to read visualization of traffic behavior. The time bins can be input into R to perform time series forecasting, or read in by a program for the simulation of traffic signal adjustment. Data for each day is broken down into two sections. The five hour periods between 6-11 a.m. and 3-8 p.m. were used to capture both morning and evening rush hours. Time periods outside of this range are unlikely to experience congestion at the intersections used in the experiment, and were therefore ignored to save computational time during testing.

Table 1

EXAMPLE OF RAW DATA

SignalID	Timestamp	EventCode	EventParam
63069008	2016-12-11 00:00:00.2000000	82	11
63069008	2016-12-11 00:00:00.2000000	43	6
63069008	2016-12-11 00:00:00.4000000	81	11
63069008	2016-12-11 00:00:00.4000000	44	6
63069008	2016-12-11 00:00:00.9000000	81	1
63069008	2016-12-11 00:00:00.9000000	44	2
63069008	2016-12-11 00:00:01.5000000	82	6

Table 2

EXAMPLE OF RAW DATA TRANSFORMED INTO TIME BINS

Timestamp	Vehicle Count	Signal State
2016-12-12 18:29:30	2	G
2016-12-12 18:29:40	1	G
2016-12-12 18:29:50	2	G
2016-12-12 18:30:00	4	G
2016-12-12 18:30:10	3	G
2016-12-12 18:30:20	2	G
2016-12-12 18:30:30	4	G
2016-12-12 18:30:40	1	G
2016-12-12 18:30:50	0	R
2016-12-12 18:31:00	2	R

Table 1 shows how the events from the traffic controller are stored in a `.csv` file. Table 2 shows an example of how the time bins are stored as text after the conversion of the traffic data. In each row, the first item gives time, the second gives vehicle count, and the third gives a signal state.

The intersections in this research contained both magnetic advance detectors and induction loops. Magnetic advance detectors, specifically called induction or search coil magnetometers, work by detecting changes in the magnetic field when a metal object, such as a car, passes. Therefore, these detectors are placed before the stop bar as they cannot detect stopped cars [9]. Induction loops work by embedding a wire loop into the pavement connected to an oscillator. The presence of a vehicle causes a decrease in the loop inductance which changes the frequency of loop cycles. When changes are detected above a threshold, a signal is sent to the traffic controller to indicate that a vehicle is present [10].

When conducting vehicle counts on a lane, magnetic advance detectors work very accurately. Adding a lag time to the detector reading gives an accurate timestamp of when a vehicle arrives at an intersection. An induction loop, however, cannot distinguish the number of vehicles that passed as accurately as a magnetic advance detector. In the case that vehicles pass through the stop bar bumper-to-bumper, the induction loop may not be able to distinguish between different vehicles. Since it is common that vehicles pile up in this manner during a red light, the number of seconds the loop stays on once the light turns green is counted and divided by 2.5 in order to estimate the number of vehicle arrivals during a red light.

3.2 Creating the forecast

Massaging the raw traffic controller data into a table of time bins essentially provides a time series of vehicle counts and traffic light states. Forecasting models can be used with this time series in order to predict the presence of vehicles in the future. When performing time series analysis, it is important to understand how the data behaves in regards to seasonality, trend, and noise. In the case of traffic flow counts, it is expected to have multi-seasonality in daily and weekly activity. This is due to morning and evening rush hours, as well as the Monday to Friday work week. A gradual change in vehicle counts may likely occur in the data depending on changes in population size and business activity in an area. Noise in the data is introduced due to sensor downtime and road accidents. When adopting a forecasting method, these components must be taken into consideration.

The decision of the period length for the time series is dictated by the meaningfulness of the resulting forecasts. Forecasting vehicle counts for each hour in the day can produce accurate results; however, this hourly information is harder to incorporate into the decision-making of a signal adjustment algorithm. A short period length of 10 seconds can be used as a base unit of time extension when optimizing at a per green-red cycle level.

Hyndman's "forecast" package in R, provides several different forecasting model implementations from which to choose. Common approaches to forecasting seasonal data are to use a seasonal ARIMA model or an exponential smoothing method such as Holt-Winters. Williams and Lester [11] showed the effectiveness of the seasonal ARIMA model in fitting traffic flow data. However, the related functions provided did not support time series forecasting of non-standard seasonal periods. Because of this, the STL method, developed by Cleveland et al. [12], was used as it provides the advantage of allowing periods of any length. The specific model used relies on the STL method to remove seasonality from the series, and applies a non-seasonal exponential smoothing model with additive errors. The result is then re-seasonalized to a given period. The STL method captures daily patterns in the data, but in order to deal with the multi-seasonal weekly patterns, a day of the week is chosen in advance and the following days are extracted and spliced together. For example, if the test day is on a Monday, the previous Mondays will be spliced together into the training set.

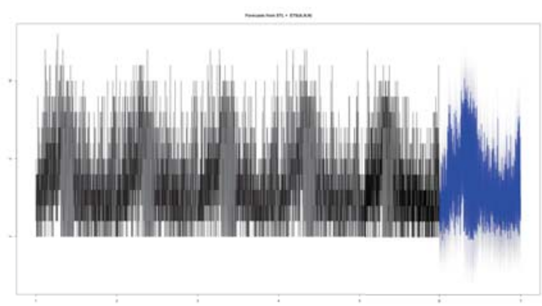

Fig. 1
EXAMPLE FORECAST PLOT

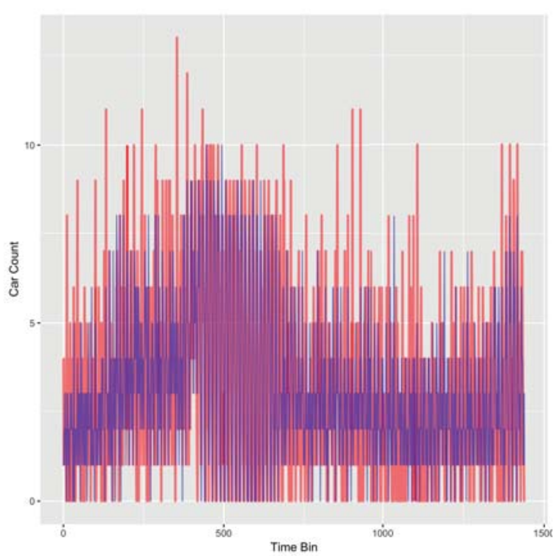

Fig. 2
COMPARISON OF FORECAST TO ACTUAL VALUES

The STL decomposition method produced reasonably accurate forecasts of vehicle count. Figure 1 shows the results of the forecast of a morning rush hour period on a northbound lane using a training set of five days, with time series period lengths of 10 seconds. In Figure 2, the forecasted values from the blue section of Figure 1 are overlaid onto actual vehicle counts from the same period. Lanes with high traffic volume and magnetic advance detectors tended to produce more accurate forecasts. Lanes with low traffic volume and loop detectors performed worse, due to lack of activity, or susceptibility to noise.

3.3 Signal adjustment simulation

To simulate the behavior of the method in real time, the algorithm is run on a series of 1 second time bins taken from the test day. The signal states of these time bins are adjusted based on the forecast values and a set of conditions as the algorithm walks through each bin.

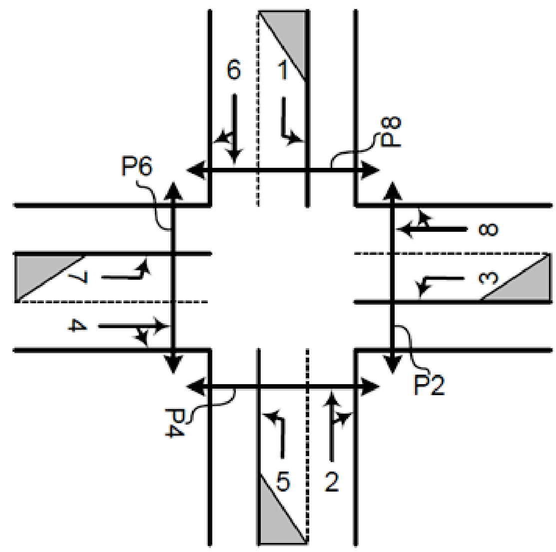

Fig. 3
DIAGRAM LABELING AN 8-PHASE INTERSECTION

Figure 3 illustrates a 4-way intersection with a standard numbering scheme for each lane. Using this scheme, a conflict lane matrix is defined. An example of an element in the matrix would be $M[2] = \{1, 4, 7, 3, 8\}$, as none of these lanes can be green while lane 2 is green. With the conflict matrix and forecasted bins read, the algorithm can begin to walk through the test data time bins.

The adjustment of the signal phases is a deterministic problem; therefore, the algorithm is nested in a loop that runs for each of the eight lanes. For each lane, the algorithm walks through each time bin and stops when a green light is about to turn red. The algorithm checks the forecasted bins to see if more vehicles are predicted to arrive in its current lane than vehicles from all other conflict lanes. If this is true, the green light will be extended to the end of the forecasted time bin. As a result, vehicles that would normally have to wait an entire red light cycle can pass the intersection without any stoppage. Since the signal adjustment algorithm runs in linear time, it would perform well in a real time scenario. It is also important to consider latency issues in a traffic control system. Thus, fast decision-making should be a priority.

Figure 4 shows a visualization of the changes made to a busy lane over the course of a five-hour period. Each value in the x-axis corresponds to one complete green to red cycle. The red lines indicate the end of red phases, and the green lines for the end of green phases. The dotted blue line in between

ISBN: 1-60132-453-7, CSREA Press ©

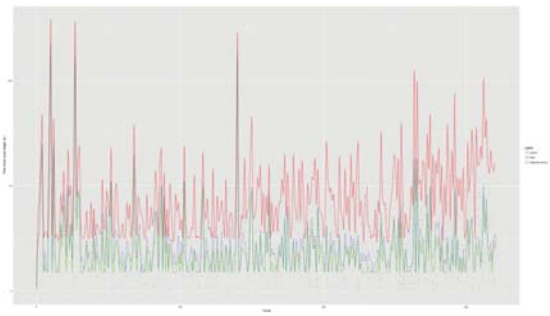

Fig. 4
VISUALIZATION OF GREEN EXTENSION

shows the changes in green phases as they are extended to allow more cars through the light.

4. Results

In order to evaluate the improvements of the method, a function was created that counts the total number of vehicles that had to stop at a red light, and the total seconds waited for each vehicle. Comparing these totals before and after running the algorithm provides the basis of our evaluation.

Tables 3 through 8 are designed to gauge the effects of the method in traffic efficiency. Improvements in vehicle stoppages and wait times are indicated by row pairs, which are taken for each day of the test week. Each column of values represents the improvement metric for one of the eight lanes in the intersection, as depicted in Figure 3. Improvement values are calculated as a percent decrease in stopped vehicles or total wait time from values taken before and after the method.

4.1 Results for Intersection 1

Table 3
INTERSECTION 1 - AM

		Improvement %							
		P1	P2	P3	P4	P5	P6	P7	P8
12/11	Vehicle	0.0	10.8	0.0	0.0	0.0	10.6	0.0	0.0
	Time	0.0	17.3	-0.6	0.0	0.0	17.9	-0.3	-1.2
12/12	Vehicle	0.0	9.2	0.0	0.0	0.0	11.9	-0.8	0.0
	Time	0.0	14.2	-0.3	-0.4	0.0	18.1	-0.4	-0.1
12/13	Vehicle	0.0	16.2	0.0	0.0	0.0	17.6	-0.3	0.1
	Time	-0.1	26.0	-0.6	-0.4	0.0	29.6	-1.0	0.1
12/14	Vehicle	0.0	10.0	0.0	-0.7	0.0	17.6	-0.8	0.0
	Time	0.0	17.6	-1.4	-0.6	0.0	28.0	-2.0	-0.1
12/15	Vehicle	0.0	6.5	0.0	0.0	0.0	13.2	0.0	0.0
	Time	-0.4	9.5	-0.7	-0.2	-1.0	23.9	-1.1	0.0
12/16	Vehicle	0.0	13.8	-0.8	1.4	0.0	13.9	0.0	0.0
	Time	-0.1	24.3	-1.0	2.5	0.0	22.8	-1.0	-0.2
12/17	Vehicle	0.0	6.0	0.0	0.0	0.0	13.8	0.0	0.0
	Time	0.0	11.2	0.0	-0.3	0.0	23.1	-0.2	-0.5

Table 4
INTERSECTION 1 - PM

		Improvement %							
		P1	P2	P3	P4	P5	P6	P7	P8
12/11	Vehicle	0.0	6.3	0.0	0.0	0.0	13.1	0.0	0.0
	Time	0.0	10.7	0.0	0.0	0.0	19.2	0.0	0.0
12/12	Vehicle	0.0	13.7	0.0	-0.6	0.0	15.1	-1.7	0.0
	Time	0.0	24.3	-2.2	-0.9	0.0	23.3	-2.5	-0.3
12/13	Vehicle	0.0	8.0	0.0	0.0	0.0	20.3	0.0	0.0
	Time	0.0	15.4	-0.3	-0.4	0.0	35.2	-0.3	0.0
12/14	Vehicle	0.0	11.5	0.0	-3.5	0.0	15.9	-0.6	0.0
	Time	0.0	22.1	-0.4	-0.5	0.0	31.1	-0.7	0.1
12/15	Vehicle	0.0	12.8	0.0	-0.7	0.0	14.3	-0.5	0.0
	Time	0.0	20.8	-0.2	-0.5	0.0	28.1	-1.3	0.0
12/16	Vehicle	0.0	13.3	-3.1	0.0	0.0	15.4	-0.9	0.0
	Time	0.0	24.7	-2.0	-0.6	0.0	29.9	-1.1	0.0
12/17	Vehicle	0.0	6.8	0.0	0.0	0.0	16.3	0.0	0.0
	Time	0.0	12.2	0.0	-0.1	0.0	24.1	0.0	-0.1

Table 3 represents the changes for intersection 1 (along Highway AL-69) during the morning rush hour period between 6-11 am. Lane 2 and 6 show consistent improvement around the 10-20% range. These are the north and southbound lanes, which experience the most traffic. On the contrary, every other lane experienced a negligible decrease. However, lane 4 noticed a slight increase on Friday of that week. Table 4 shows values for the same intersection during the afternoon rush hour period between 3-8 pm. The amount of change is similar to that of the morning period. While lanes 1 and 5 show no change, the maximum decreases in performance have slightly risen in lanes 3 and 4. However, Lanes 2 and 6, the lanes with the most traffic, had a marked improvement. Lane 2 improved 6-24%, and Lane 6 improved 13-35%.

4.2 Results for Intersection 2

Table 5
INTERSECTION 2 - AM

		Improvement %							
		P1	P2	P3	P4	P5	P6	P7	P8
12/11	Vehicle	-0.4	3.8	0.3	-1.1	0.0	10.4	-0.3	0.0
	Time	-0.3	5.5	-0.5	-0.4	-0.1	15.3	-1.0	-0.2
12/12	Vehicle	0.0	10.3	-2.2	0.0	0.0	2.3	-0.8	0.0
	Time	0.0	17.5	-1.7	-0.1	0.0	4.1	-1.7	-0.2
12/13	Vehicle	0.0	11.4	-1.0	0.0	0.0	4.5	-1.1	0.0
	Time	0.0	19.3	-2.4	-0.1	0.0	9.7	-2.6	-0.2
12/14	Vehicle	0.0	8.8	-0.4	0.0	0.0	5.0	-0.6	0.0
	Time	0.0	14.3	-1.4	-0.1	0.0	10.4	-1.4	-0.1
12/15	Vehicle	0.0	7.3	-0.8	-0.9	0.3	5.5	-1.7	0.0
	Time	0.0	13.1	-1.9	-0.1	0.7	11.7	-2.0	-0.1
12/16	Vehicle	0.7	7.2	-0.9	0.0	0.0	3.5	-0.9	0.0
	Time	1.1	12.0	-1.5	0.0	0.0	7.7	-2.2	-0.2
12/17	Vehicle	0.0	4.1	0.0	0.0	-0.4	11.2	-1.3	0.0
	Time	-0.1	7.6	-1.6	-0.1	-0.1	18.4	-1.8	-0.1

Table 6

INTERSECTION 2 - PM

		Improvement %							
		P1	P2	P3	P4	P5	P6	P7	P8
12/11	Vehicle	0.4	8.1	-0.7	0.0	-0.5	9.2	-1.2	0.0
	Time	-0.1	12.1	-2.7	-4.7	-0.7	13.2	-3.7	-1.3
12/12	Vehicle	0.0	6.5	-1.5	-2.9	0.0	4.6	-1.9	-8.3
	Time	-0.3	10.4	-3.6	-0.6	0.0	7.6	-3.6	-0.2
12/13	Vehicle	0.0	7.3	-1.4	-2.6	0.2	4.2	-1.4	0.0
	Time	-0.1	12.1	-2.7	-0.5	0.6	6.6	-3.1	-1.8
12/14	Vehicle	0.0	6.1	-1.2	0.0	0.0	5.6	-1.5	-11.1
	Time	-0.1	10.8	-2.9	-0.9	0.0	9.5	-2.5	-0.2
12/15	Vehicle	0.0	7.1	-1.2	0.0	0.0	4.2	-1.0	0.0
	Time	0.0	10.7	-2.2	-0.3	0.0	7.2	-2.6	0.0
12/16	Vehicle	0.0	7.6	-0.9	0.0	0.0	3.3	-1.3	0.0
	Time	-0.2	11.4	-3.4	0.0	0.0	5.3	-3.6	0.0
12/17	Vehicle	0.0	15.8	-1.7	0.0	-0.8	8.2	-1.1	0.0
	Time	-0.7	23.7	-4.1	-0.6	-0.4	13.8	-11.8	0.0

Tables 5 and 6 show changes at intersection 2 (along Highway AL-69). While lanes 2 and 6 showed improvements, similar to intersection 1, the averages sit closer to 10%. The effects of other lanes seem to be around the same as intersection 1. The values for intersection 2 show two interesting outliers. First, there is a significant jump in performance on the Saturday of that week in both morning and afternoon hours. Second, on that same day, there is an 11% increase in waiting time. One possibility is that a sudden jump in traffic volume was experienced on that day, which affected those lanes. The preferential bias toward lanes with expected heavy traffic can become more evident from such an event.

4.3 Results for Intersection 3

Table 7

INTERSECTION 3 - AM

		Improvement %							
		P1	P2	P3	P4	P5	P6	P7	P8
12/11	Vehicle	-0.4	3.8	0.3	-1.1	0.0	10.4	-0.3	0.0
	Time	-0.3	5.5	-0.5	-0.4	-0.1	15.3	-1.0	-0.2
12/12	Vehicle	0.0	10.3	-2.2	0.0	0.0	2.3	-0.8	0.0
	Time	0.0	17.5	-1.7	-0.1	0.0	4.1	-1.7	-0.2
12/13	Vehicle	0.0	11.4	-1.0	0.0	0.0	4.5	-1.1	0.0
	Time	0.0	19.3	-2.4	-0.1	0.0	9.7	-2.6	-0.2
12/14	Vehicle	0.0	8.8	-0.4	0.0	0.0	5.0	-0.6	0.0
	Time	0.0	14.3	-1.4	-0.1	0.0	10.4	-1.4	-0.1
12/15	Vehicle	0.0	7.3	-0.8	-0.9	0.3	5.5	-1.7	0.0
	Time	0.0	13.1	-1.9	-0.1	0.7	11.7	-2.0	-0.1
12/16	Vehicle	0.7	7.2	-0.9	0.0	0.0	3.5	-0.9	0.0
	Time	1.1	12.0	-1.5	0.0	0.0	7.7	-2.2	-0.2
12/17	Vehicle	0.0	4.1	0.0	0.0	-0.4	11.2	-1.3	0.0
	Time	-0.1	7.6	-1.6	-0.1	-0.1	18.4	-1.8	-0.1

Table 8

INTERSECTION 3 - PM

		Improvement %							
		P1	P2	P3	P4	P5	P6	P7	P8
12/11	Vehicle	0.0	6.9	-1.2	-9.4	0.0	7.9	-1.3	-50.0
	Time	1.5	11.8	-4.3	-1.6	0.0	13.4	-4.6	-2.2
12/12	Vehicle	0.0	4.5	-0.7	-0.6	0.0	4.3	-1.0	0.0
	Time	-0.1	7.3	-2.5	-0.2	0.0	7.5	-2.2	0.2
12/13	Vehicle	0.0	3.6	-0.8	-1.1	0.0	5.4	-1.5	0.0
	Time	0.0	6.1	-2.2	-0.4	0.0	9.2	-2.8	0.0
12/14	Vehicle	0.5	1.6	-1.1	0.0	0.0	4.9	-0.9	0.0
	Time	1.0	2.2	-2.1	0.7	0.0	8.5	-2.2	0.0
12/15	Vehicle	0.0	2.8	-1.2	-1.0	0.0	5.7	-1.6	0.0
	Time	0.0	5.4	-2.4	-0.1	0.0	10.4	-2.1	0.0
12/16	Vehicle	0.0	7.9	-2.4	0.0	0.0	5.5	-2.3	0.0
	Time	0.0	12.1	-2.5	0.0	0.0	9.0	-2.7	0.0
12/17	Vehicle	0.0	6.0	-2.0	-6.7	0.0	6.5	-1.8	0.0
	Time	0.0	10.3	-3.8	-2.6	0.0	12.1	-4.2	0.0

Tables 7 and 8 represent changes for intersection 3 (along Highway US-11). Results from the morning period mimic those of intersection 2. However, the afternoon period of this intersection found the smallest changes in improvement. An outlier of -50% is found for vehicle stoppages on lane 8 on Sunday of that week. Upon inspection, this is due to the change from two stoppages to three. Because of this, it is important to consider the actual values, as a means of evaluation.

4.4 Results for Aggregate Intersections

Table 9

AGGREGATE - AM

	Intersection 1		Intersection 2		Intersection 3	
	Vehicle Diff	Time Diff (s)	Vehicle Diff	Time Diff (s)	Vehicle Diff	Time Diff (s)
12/11	34	650	71	2373	77	1468
12/12	136	3730	225	10139	133	4751
12/13	246	9475	292	12915	140	4604
12/14	247	6916	248	10587	162	6035
12/15	145	4454	222	9903	147	4901
12/16	190	7094	182	8522	149	4586
12/17	44	1061	131	5637	210	4859

Table 10

AGGREGATE - PM

	Intersection 1		Intersection 2		Intersection 3	
	Vehicle Diff	Time Diff (s)	Vehicle Diff	Time Diff (s)	Vehicle Diff	Time Diff (s)
12/11	121	3852	233	12780	213	7452
12/12	306	10313	142	9539	170	7619
12/13	275	10268	171	12285	178	8467
12/14	216	8288	266	19329	131	6152
12/15	245	8990	198	12953	98	5072
12/16	213	6770	177	11918	304	19816
12/17	148	4748	423	22940	240	10662

In order to get a better understanding the results, Tables 9 and 10 have been constructed to show the exact number of vehicles stoppage and wait time reductions. Table 9 shows the results of running our method through the same morning rush hour period. Each row represents values totaled for that day. Three different intersections were tested from the same period, each having two values, giving six total columns. In each column pair for a given intersection, the first column represents the number of cars that would have had to stop at a red light if no changes occurred. The second column shows the difference in waiting times of cars that had to stop at a red light. Table 10 uses the same format, however, the results are from the afternoon period of 3-8pm. Keep in mind that these values have been aggregated from all lanes for the given five hour durations.

In all cases, the number of vehicles that had to stop, and the total amount of time waited decreased as a result of our method. The results of Tables 3-8 show that some intersections benefitted more than others. For example, intersection 1 saw the most gains in percentage improvement. However, Tables 9 and 10 indicate that intersection 2 had the highest instances of improvements. Therefore, the values in each set of tables are relative to what is being compared. Tables 9 and 10 give a clearer picture in evaluating the effect of the time of day. Results were generally better during the afternoon period, as more cars are flowing through the system.

Differences in the amount of improvement is heavily linked to the day-to-day activity of each intersection. Taking a look at each intersection, it became clear that some lanes undergo little to no changes. Lanes with less traffic volume contain lower forecasted arrivals along with fewer green to red cycle changes, allowing few opportunities for signal adjustment to take place. For this same reason, weekdays tended to show greater instances of improvement compared to weekends.

5. Future Work

The goal of future developments would be to improve the decision-making of the signal adjustment algorithm, and explore more advanced models in prediction. The system is at a point in which all intermediary steps are automated through scripts. This would allow traffic controllers using the system to continually adapt to trends and patterns overtime with minimal supervision. The automation also allows for quick testing of adjustments made to different parameters in order to discover ways to improve the system. For example, we tested our method using time bins of 5, 10, and 15 seconds, and the results from the simulation showed that time bins of 10 seconds provided a sweet spot in forecast bin length.

Currently, the signal adjustment step only uses local traffic data to apply a greedy algorithm in deciding to extend green phases. In the future, we hope to find ways of communicating information between a traffic network to create a more sophisticated decision making model.

6. Conclusion

The current solution to traffic management can be improved upon by utilizing a more adaptive decision based model. Minimizing the oversaturation of roads and inefficiencies of fixed signal timings reduces the amount of time wasted, while providing environmental and safety benefits. Utilizing time series forecasting, our system was able to identify and alleviate some of the inefficiencies found on real traffic data.

References

[1] Y. Yin and P. Shang, "Forecasting traffic time series with multivariate predicting method," *Applied Mathematics and Computation*, vol. 291, pp. 266–278, 2016.

[2] J. Wang, P. Shang, and X. Cui, "Multiscale multifractal analysis of traffic signals to uncover richer structures," *Physical Review E*, vol. 89, no. 3, p. 032916, 2014.

[3] E. I. Vlahogianni, J. C. Golias, and M. G. Karlaftis, "Short-term traffic forecasting: Overview of objectives and methods," *Transport reviews*, vol. 24, no. 5, pp. 533–557, 2004.

[4] B. L. Smith and M. J. Demetsky, "Traffic flow forecasting: comparison of modeling approaches," *Journal of transportation engineering*, vol. 123, no. 4, pp. 261–266, 1997.

[5] C. P. Pappis and E. H. Mamdani, "A fuzzy logic controller for a trafc junction," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 7, no. 10, pp. 707–717, 1977.

[6] C.-H. Chou and J.-C. Teng, "A fuzzy logic controller for traffic junction signals," *Information Sciences*, vol. 143, no. 1, pp. 73–97, 2002.

[7] J. C. Spall and D. C. Chin, "Traffic-responsive signal timing for system-wide traffic control," *Transportation Research Part C: Emerging Technologies*, vol. 5, no. 3, pp. 153–163, 1997.

[8] H. Ceylan and M. G. Bell, "Traffic signal timing optimisation based on genetic algorithm approach, including drivers routing," *Transportation Research Part B: Methodological*, vol. 38, no. 4, pp. 329–342, 2004.

[9] L. E. Y. Mimbela and L. A. Klein, "Summary of vehicle detection and surveillance technologies used in intelligent transportation systems," 2000.

[10] R. Koerner, M. Bienhoff, M. Henderson, J. Higbee, and S. Koerner, "Inductive loop detector system," Mar. 9 1976, uS Patent 3,943,339. [Online]. Available: https://www.google.com/patents/US3943339

[11] B. M. Williams and L. A. Hoel, "Modeling and forecasting vehicular traffic flow as a seasonal arima process: Theoretical basis and empirical results," *Journal of transportation engineering*, vol. 129, no. 6, pp. 664–672, 2003.

[12] R. B. Cleveland, W. S. Cleveland, and I. Terpenning, "Stl: A seasonal-trend decomposition procedure based on loess," *Journal of Official Statistics*, vol. 6, no. 1, p. 3, 1990.