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QUANTIFYING THE EFFECTS OF MANUAL TRAFFIC CONTROL ON EVACUATION CORRIDORS

Final Report

by

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DISCLAIMER

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EXECUTIVE SUMMARY

Manual traffic control (MTC) is a key part of managing traffic during emergencies and planned special events. Despite its long history of use there has been little, if any, research on how to effectively model MTC. MTC is commonly represented as a version actuated signal control and, while this method is useful, it has significant shortcomings because it does not adequately represent the variability of police officer control actions under field conditions. In this paper, the results of recent research to develop an MTC model and integrate it into a traffic simulation system are presented. Here, the process of MTC is represented by expressing police officers decision-making in terms of a system of discrete choice equations (logit models) that compute signal phase length and green-time allocation as a function of demand, directional priority, phase length, and gaps in the approach traffic streams. The MTC discrete choice model was validated using various datasets to show that it computes phase lengths and allocates green time within a 95 percent level confidence when compared field observation. Among the general findings of this research was that manual traffic control is best suited for intersections immediately upstream of a bottleneck or for closely spaced, uncoordinated signals.

1.0 INTRODUCTION

Traffic simulation is a valuable tool to plan, design and operate transportation systems. Among its many applications is to support the design and evaluation of traffic management plans for special events (festivals, parades, and sporting events) and emergencies (evacuations, traffic accidents, road closures). Through simulation, engineers are able to evaluate the impact of congestion mitigation alternatives and strategies.

A common traffic management strategy for special events and emergency traffic is manual traffic control (MTC). MTC is an intersection control method in which trained personnel, typically police law enforcement officers, use intersection signals to facilitate the movement of traffic by allocating intersection right-of-way to approaching vehicles. It is needed because major events cause a surge in demand, which often overwhelms the available road capacity. But, because the demand is also usually directionally imbalanced, it is thought the use of police, who can directly observe the demand conditions, is a better form of control than automated traffic signals.

Police officers observe traffic conditions and allocate green time based a series of discrete choice decisions. MTC often results in significantly longer and variable cycle lengths to facilitate the movement of directionally imbalanced volumes. Variability arises within MTC is the result the stochastic nature of both the officer's decision-making and traffic in general. For this reason, it has proven difficult to evaluate the impact of MTC on evacuation corridors. The goal of this research is to quantify the effect of manual traffic control on evacuation corridor operations and to develop a quantitative model able to describe the behavior of police officers directing traffic for special events and emergencies. Using observations of police officers directing special event traffic, a logit model capable of predicting the officer's phase change decisions was developed. This model was then incorporated into a traffic simulation software VISSIM, 7.0 to model the green time allocation of the police officer. Finally, using a hypothetical grid network, the impact of MTC at key intersections within a corridor was evaluated.

1.1 RESEARCH BACKGROUND

Previous studies attempting to simulate manual traffic control have done so by assuming officers act like traffic signals, with constant cycle lengths and phase splits [1]; [2]; [3]. However, empirical observations show this is not the case. Rather, early research on the subject suggested that many of the advantages of manual traffic control come from not having constant cycle length and phase splits. Marsh [4], Eno [5], and Schab [6] found that the advantages of manual traffic control have been in an officer's ability to extend green time when needed, truncate phases, and accommodate unbalanced and uneven traffic volumes. Oversimplifying MTC in simulation models by assuming constant cycle length and phase splits could lead to an unfair comparison between alternative strategies.

Recent research on manual traffic control has also used human-in-the-loop simulation to replicate police officers directing traffic. This technology allows for real-time user input into a traffic simulation model. So, Lee, and Park [7] developed a VISSIM simulation where participants could change the phase length of a traffic signal similar to a police officer directing traffic. Ding, He and Wo [8] used a similar approach with only first responders as participants. Both of these research efforts found large variations in the performance of manual traffic control and concluded that with additional officer training, manual traffic control could be performed more effectively.

NCHRP Synthesis 309 addressed all aspects of highway management for planned special events [9]. This document made frequent reference to the use of police officers for manned traffic control points. “The advantage of using staffed traffic posts over signalized control is the presence of authority and the ability to make dynamic changes to the traffic flow”. A survey conducted in NCHRP 309 showed that MTC of intersections for special events is a common traffic management technique used around the country. Therefore, any agency looking to develop a special event traffic management plan is encouraged to use MTC. Furthermore, these agencies are encouraged to use traffic simulation in the development of management plans. However, any event utilizing MTC currently would have no reliable way of simulating the process for a comparative analysis.

The criteria for developing evacuation time estimates (ETE) for the area surrounding nuclear power plants are provided in NUREG/CR-7002 [10]. This document highlighted MTC stating, “In general, it may be assumed that manned traffic controlled intersections operate most efficiently” when compared to un-signalized, fixed-time signals and actuated signals. This document also supports the use of traffic simulation in the development of ETEs. It mandates that if MTC is proposed as a part of a traffic management plan, then the simulation model must simulate the effects of MTC. The document proposes modeling MTC as an actuated signal with a signal-timing plan that reflects more efficient operations (NRC, 2011). However, without full knowledge of MTC operations, simulating MTC as an actuated signal may not be realistic. Furthermore, no guidance was given on how to make the simulated actuated signal more efficient or how to simulate the actuated signal to produce results similar to that of MTC.

A review of the literature has shown that currently there is no way to effectively simulate MTC in a traditional sense. The use of actuated controllers employs a repeating cycle length that is uncharacteristic of MTC. Human-in-the-loop simulation provides the most realistic approach to date but requires constant user input, can only simulate a single intersection at a time, and is time consuming. There is a need for a simulation tool that can replicate the primary control decisions of police officers conducting MTC in real-time and implement their actions to quantify the impact on evacuation corridors.

2.0 RESEARCH METHODOLOGY

Broadly, the research methodology consisted of four primary tasks. The first task was the collection and processing of video footage of police officers directing traffic. The second task was the development of a discrete choice model capable of explaining right-of-way allocation decisions made by the police officers. The third task was programing the discrete choice model into the microscopic traffic simulator, VISSIM 7.0, to simulate police officers directing traffic. This was accomplished through Vehicle Actuated Programing (VAP), which "replaced" the intersection signal controller logic with the discrete choice model developed in the previous task. This task also included the calibration and validation of the traffic simulation model. The final task was to evaluate the MTC within an evacuation corridor. The following sections detail the methods and results of each of these tasks.

2.1 DATA COLLECTION AND PROCESSING

The data requirements for discrete choice modeling (logit model) required an extensive collection effort. Data was collected from four intersections after five college and professional football games in Baton Rouge, LA and Miami Gardens, FL. In both study areas, intersections were chosen because of their proximity to the football stadiums and their location on heavily utilized routes. The data collection effort spanned over four months starting in the Fall 2012. In total, video data from over 320 hours of special event traffic was collected, viewed and cataloged. From the video footage, a total of 26 hours and 27 minutes (less than 10% of the total footage collected) was of police officers actively directing traffic.

In Baton Rouge, three intersections were selected for data collection during four Louisiana State University football games. These intersections were Stanford and Perkins, Nicholson and Roosevelt and Nicholson and Lee. In Miami Gardens, FL cameras were placed at the intersection of NW 183 St. and NW 27 Ave. near Sun Life Stadium for one football game.

Through the data reduction process, the video footage was systematically categorized it into numeric observations. The end product of data reduction was a time-line, capturing the events (phase changes, phase length, lane groups, vehicle departures, etc.) that took place within the intersection. This process was completed in two-steps. The first step required manually recording lane groups, phase length and phase sequence for the periods immediately before, during, and immediately after the officer was directing traffic. During this time, observations of red-light running, emergency vehicle movements, and other abnormal road user behavior were also noted.

The next step was to time-stamp individual vehicle departures, platoon gaps and intersection blockages. Vehicle departures were time-stamped manually. Temporary gaps in the traffic platoon which typically occur when vehicle platoons break-up due to poor coordination, lack of demand, or travel conditions between intersections were also cataloged. Additionally, durations when vehicles were stopped or prevented from proceeding through the intersection due to downstream congestion were noted. Using the coded data, a second-by-second timeline was created to incorporate departures for all intersection movements, lane groups, phase length and phase sequence, and intersection blockages and gaps.

2.2 DISCRETE CHOICE MODELING

At signalized intersections police officers direct traffic from the controller box. Using a push-button device within the controller cabinet, an officer can switch between signal phases. Fundamentally, an officer directing traffic using this method is faced with a binary discrete choice process, to change the signal during a time interval or let the current phase remain green. Important to note here, is that phase sequence, the order in which one phase leads to the next was not decided by the police officer. Once the officers pushes the button, the signal changes to the next default option. This is a function of the controller and its programing and not the officer. The controllers in both Baton Rouge and Miami Gardens functioned in this manner under MTC. To model the choice by the officer to push the button, binary logit modeling was used. Other discrete choice models were applicable for this purpose but since the simulation model must ultimately calculate the choice probabilities every time-step, it was assumed that a more complex choice model would increase the computational time during the simulation process.

The logit model choice probability that an officer (*n*) would change phases (choose alternative *i*), was a function of the utility of changing phases (U_{in}). This relationship is shown in Equation (1) [11]:

$$P_n(i) = \frac{e^{U_{in}}}{e^{U_{in}} + e^{U_{jn}}} \tag{1}$$

The utility of changing phases in any time interval was dependent upon a vector of independent variables (x_{in}) observed in the traffic stream and the degree to which these variables influence this decision (vector β_k). For example, if x_1 was a variable determined to affect the officer's decision-making, then x_1 contributed to the utility of changing phases by a factor of β_1, as observed in Equation 2. The parameter coefficient vector β_k, was econometrically inferred from a sample of *N* observations using the maximum likelihood estimation procedure [11].

$$U_{in} = \beta_o + \beta_1 x_{in1} + \beta_2 x_{in2} + \cdots + \beta_k x_{ink} + \varepsilon_{in} \tag{2}$$

2.3 VARIABLE SELECTION

The data collection and reduction process resulted in a second-by-second time-line of events, which took place in the traffic stream. This time-line was then used to develop the dependent and independent variables for the logit model analysis. The time interval used in this research was one second. As a result, the discrete choice represented by the logit model was between an officer changing phases over a one second interval (dependent variable y=1) and the officer not changing phases during this second (y=0). Prior to the generation of the independent variables, the intersection clearance time (the yellow and all-red time, which transitions between signal phases) was removed from the timeline to not bias the model toward selecting the intervals.

Fundamentally, there were three independent variables used in this research: “Time”, “Gap”, and “Phase”. The “Time” variable was the phase length duration, or how long a phase has received a green indication. The “Gap” variable accounted for periods of time in which no vehicles entered an intersection despite having a green indication (time-headways greater than 4-seconds). These “gaps” were generally the result of the breaking down of vehicle platoons. The “Gap” variable took a value of one, if one of the intersection approaches had a “gap”; two, if two of the approaches had a “gap” during the same time interval and zero if no gap was present. The “Phase” variable was a set of four binary variables that indicated which phase was receiving the green indication. Each of these four variables represented a phase (northbound/southbound thru, northbound/southbound left, etc.). The four “Phase” variables were labeled according to the priority they received from the police officers. These are “Primary”, “Secondary, “Tertiary, and “Quaternary”.

The Primary variable (*Prim (1)*), represented the phase that received the largest proportion of the green time allocated by the officer. For example, if the northbound/southbound thru phase received more green time than any other phase, this phase would be labeled as the “Primary” phase. This was done to compare “Primary” phases between intersections regardless of the intersections’ geometric characteristics. As such, Secondary (*Secon (2)*), Tertiary (*Ter (3)*), and Quaternary (*Qu (4)*) represent the phases green time proportions. It was also hypothesized that the impact of time and the presence of gaps had on the officer’s decision making varied for each direction. These variables were tested for their interaction and included in the study. The variable representing the interaction of the “Priority” phase and “Time” was labeled *Time (1)*. As such, the interaction between the “Gap” variable and the “Priority” phase was labeled *Gap (1)*. The same labeling system was used for the interaction between “Secondary”, Tertiary” and “Quaternary” phase for both “Time” and Gap” (*Time (2)*, *Gap (2)*, etc.) The resulted indicated that interaction did occur and the contribution to the decision making process made by the “Time” and “Gap” varied, depending on which phase was green.

3.0 LOGIT MODEL RESULTS

From these variables, a total of nine logit models were developed in this research, one for each intersection/event observation. The tables which display the logit model results are first presented then each of the variable types (“Priority”, “Time”, and “Gap” are discussed. Table 1 shows the results of the four logit models estimated from the intersection of Nicholson and Roosevelt, in Baton Rouge, LA, from four separate special events (LSU football games). Also developed from Baton Rouge Data, Table 2 and Table 3 show the model results from Nicholson and Lee, and Stanford and Perkins for two special events, respectively. Table 4 show the results from SW 183 St. and SW 27 Ave. in Miami Gardens, FL from one speicle event.

These tables show the variable coefficients (coef), the standard error (St.Er) of these coefficients, and their P-value (*P*>/*z*/), which test the statistical significance of the variables. P-vales less than or equal to 0.05 were determined to contribute to the officer’s decision making [14]. Also shown in the tables are the goodness-of-fit measures (GoF) used to evaluate the accuracy of the model i.e. how well the model predictions match the observed choices made by the police officers. The Goodness-of-fit was quantified using three metrics: the pseudo R-squared (ρ^2) value, the Hosmer-Lemeshow chi-square statistic (χ^2) and the area under the receiver operator curve (ROC). For reference, the GoF line in the tables also displays the log likelihood (LL) of the maximum likelihood parameter estimation and the number of observations (OBS) the model was built from.

Table 1: Nicholson and Roosevelt Model Results

	1-1: Nicholson and Roosevelt, Observation Event on 10/13/12								
	Prim (1)	**Second (2)**	**Ter (3)**	**Time (1)**	**Time (2)**	**Time (3)**	**Gap (1)**	**Gap (2)**	**Gap (3)**
Coef	-5.34	-2.01	0	0.01	0.02	0.07	2.81	1.23	2.02
St.Er	1.1075	0.4856	0.0000	0.0015	0.0035	0.0075	44.90	0.1786	0.0622
P>|z|	0.00	0.02	1.00	0.00	0.01	0.17	0.00	0.00	0.00
GoF	ρ^2 = 0.2774		χ^2 = 0.4866		ROC = 0.864		LL = -316.97		Obs. = 7534

	1-2: Nicholson and Roosevelt, Observation Event on 11/03/12								
	Prim (1)	**Second (2)**	**Ter (3)**	**Time (1)**	**Time (2)**	**Time (3)**	**Gap (1)**	**Gap (2)**	**Gap (3)**
Coef	-2.23	0.41	0	0.01	0	-0.04	1.03	2.12	2.2
St.Er	2.1572	1.0122	0.0000	0.0022	0.0028	0.0032	31.50	0.1838	0.2177
P>|z|	0.30	0.84	1.00	0.00	0.68	0.01	0.00	0.00	0.04
GoF	ρ^2 = 0.2229		χ^2 = 0.8067		ROC = 0.8546		LL = -378.39		Obs. = 6385

	1-3:Intersection Nicholson and Roosevelt, Observation Event on 11/10/12								
	Prim (1)	**Second (2)**	**Ter (3)**	**Time (1)**	**Time (2)**	**Time (3)**	**Gap (1)**	**Gap (2)**	**Gap (3)**
Coef	-7.56	-2.42	0	0.02	0.04	0.49	3.28	1.61	1.05
St.Er	1.6306	0.7652	0.0000	0.0049	0.0088	0.0344	28.60	0.3765	0.0962
P>|z|	0.00	0.09	1.00	0.00	0.03	0.03	0.00	0.02	0.09
GoF	ρ^2 = 0.2774		χ^2 = 0.4518		ROC = 0.9346		LL = -153.27		Obs. = 3141

	1-3: Intersection Nicholson and Roosevelt, Observation Event on 11/17/12								
	Prim (1)	**Second (2)**	**Ter (3)**	**Time (1)**	**Time (2)**	**Time (3)**	**Gap (1)**	**Gap (2)**	**Gap (3)**
Coef	-4.35	-1.32	0	0.02	0.03	1.19	1.05	1.41	0.01
St.Er	1.8263	0.6531	0.0000	0.0041	0.0060	0.0660	60.90	0.2016	0.0887
P>|z|	0.02	0.31	1.00	0.00	0.03	0.02	0.01	0.00	0.98
GoF	ρ^2 = 0.2870		χ^2 = 0.4747		ROC = 0.8858		LL = -168.00		Obs. = 3134

Table 2: Nicholson and Lee Model Results

	2-1: Nicholson and Lee, Observation Event on 11/03/12								
	Prim (1)	**Secon (2)**	**Ter (3)**	**Time (1)**	**Time (2)**	**Time (3)**	**Gap (1)**	**Gap (2)**	**Gap (3)**
Coef	-2.45	-0.42	0	0.02	0.01	0.04	0.47	0.31	1.32
St.Er	0.6991	0.4542	0.00	0.0030	0.0033	0.0061	21.3000	0.2899	0.1085
P>|z|	0.00	0.51	1.00	0.00	0.00	0.03	0.00	0.44	0.00
GoF	ρ^2 = 1448		χ^2 = 0.1075		ROC = 0.8276		LL = -417.81		Obs = 6898

	2-2: Nicholson and Lee, Observation Event 11/10/12								
	Prim (1)	**Secon (2)**	**Ter (3)**	**Time (1)**	**Time (2)**	**Time (3)**	**Gap (1)**	**Gap (2)**	**Gap (3)**
Coef	0.34	2.82	0	0.01	0.01	0.28	-0.18	-0.24	1.35
St.Er	1.6213	0.8306	0.0000	0.0030	0.0036	0.0207	23.8000	0.2046	0.0971
P>|z|	0.83	0.06	1.00	0.00	0.20	0.00	0.01	0.51	0.00
GoF	ρ^2 = 0.1901		χ^2 = 0.2345		ROC = 0.8173		LL = -201.02		Obs = 4581

Table 3: Stanford and Perkins Model Results

	Pr (1)	Se (2)	Te (3)	Qu (4)	T (1)	T (2)	T (3)	T (4)	G (1)	G (2)	G (3)	G (4)
3-1: Stanford and Perkins, Observation Event 11/10/12												
Coef	-8.06	-3.1	-1.61	0.00	0.01	0.03	-0.03	0.11	2.66	1.51	2.4	0.95
St.Er	1.888	0.598	0.388	0.00	0.004	0.006	0.010	0.024	41.1	0.224	0.388	0.264
P>|z|	0.00	0.01	0.11	1.00	0.00	0.04	0.30	0.13	0.00	0.00	0.02	0.25
GoF	$\rho^2 = 0.2244$		$\chi^2 = 0.3796$		ROC = 0.89		LL = -158.98			Obs = 3486		
3-2: Stanford & Perkins, Observation Event 11/17/12												
	Pr (1)	**Se (2)**	**Te (3)**	**Qu (4)**	**T (1)**	**T (2)**	**T (3)**	**T (4)**	**G (1)**	**G (2)**	**G (3)**	**G (4)**
Coef	-3.91	1.08	-30.99	0.00	0.02	-0.01	0.03	0.06	2.04	3.25	17.46	1.93
St.Er	2.355	1.231	0.000	0.00	0.006	0.009	0.008	0.022	30.6	0.405	0.238	0.327
P>|z|	0.10	0.59	0.00	1.00	0.00	0.39	0.07	0.26	0.00	0.00	0.00	0.02
GoF	$\rho^2 = 0.3662$		$\chi^2 = 0.98$		ROC = 0.9575		LL = -141.98			Obs = 3987		

Table 4: SW 183 St. and SW 27 Ave. Model Results

	Pr (1)	Se (2)	Te (3)	Qu (4)	T (1)	T (2)	T (3)	T (4)	G (1)	G (2)	G (3)	G (4)
4-1: SW 183 & SW 27 Ave, Observation Event on 01/07/13												
Coef	-5.56	-2.44	-1.52	0.00	0.03	-0.02	-0.02	-0.05	1.48	2.21	1.7	1.9
St.Er	0.804	0.330	0.260	0.00	0.005	0.006	0.009	0.010	20.2	0.176	0.160	0.122
P>|z|	0.00	0.00	0.01	1.00	0.00	0.21	0.29	0.07	0.00	0.00	0.00	0.00
GoF	$\rho^2 = 0.2214$		$\chi^2 = 0.752$		ROC = 0.8739		LL = -565.08			Obs = 6541		

3.1 PHASE VARIABLES

Broadly, the preference shown by the officers to a particular direction this was related to approach volume. In general, the coefficient values for the "Priority" variables are negative and most of them are statistically different than zero (p-values less than 0.05). The negative sign of the coefficient indicates the officers' reluctance to changing phases when this particular phase is receiving a green indication. The higher the magnitude of the negative coefficient, the larger the preference was shown to that phase by the officer. This indicates that the officer assigned an ordinal priority (primary, secondary, tertiary, etc.) to each phase of the intersection, likely based on demand. For example, the "Primary" (*Pri (1)*) direction has a negative coefficient value with the highest magnitude. This suggests that the officer was less likely to change phases from this phase when compared to the others i.e. this was the officers "favorite" phase.

In general, the magnitude of the coefficient was less for the *Secondary* direction and even less for the *Tertiary* direction. For intersections with only three phases, no priority was given to the *Tertiary* direction (the officer's least "favorite" phase). The same was true for four phase intersections and the *Quaternary* direction (being the officer's least "favorite" out of the four possible phases). This was intuitive because the logit model can only estimate the relative difference in the priorities. If the officer favored one direction most, by default the officer must not favor one of the directions at all. The logit model determined this independently and assigned a coefficient value to this variable of zero.

3.2 TIME VARIABLES

The "Time" variable represents the impact of phase duration on the phase change decision. From the tables it is evident that the importance of *Time* is weighted differently depending on which phase is receiving a green indication. In general, the impact of the *Time* variable is positive, suggesting that as phase duration increases, so too does the probability the officer will change phases. In addition, the magnitude of the coefficient was inversely proportional to the contribution of the variable, i.e. the larger the coefficient value, the shorter the phase duration. From the figure, relatively small coefficient values are observed for the "Priamry" direction (*Time (1)*), suggesting these phases are longer in duration when compared to other phases. For the "Tertiary" direction for three phase intersections (Nicholson & Lee and Nicholson & Roosevelt), the "Time" coefficients were much higher than the other two phases. It is likely that officers, wanting to limit this low demand phase, allowed a green indication for a much smaller proportion of time. This phenomenon was also observable in the video footage.

3.3 GAP VARIABLES

In general, the coefficient values for the "Gap" variables were positive and significantly different than zero. This suggests that the "Gap" variable did in fact contribute the phase change decision and shows that when gaps were present, the officers were more likely to change phases. This indicates the officers directing traffic wanted to avoid these gaps in the flow of traffic, because they waste green time, decrease vehicle flow rate, and take away usable time to move cross-street traffic.

Looking at tables as a whole, there appears to be an interplay between "Time" and "Gap" variables. As one of these variables becomes larger and more statistically significant (smaller P-values), the other tends to decrease and/or become less significant (higher P-values). In general, the duration of green time (phase length) made little difference to the officers for high priority directions. As such, the presence of gaps in the traffic took on a more relevant role. While this was not necessary the case in all observations, it is a general trend and makes logical sense. Furthermore, the logit models do include, at times variables that are insignificant (P-values greater than 0.05). These variables were included because it was desirable to have the same independent variables between models. This is also intuitive in that officers would likely rely on similar events to make their right-of-way allocation decisions. The definitive significance of these variables, as quantified by the P-value, is undoubtable related to the data collection and process methodology used. In this sense, it is more important to look for general trends in the data and logit models then any one, individual parameter or model.

3.4 GOODNESS-OF-FIT

In general, the model fit was in the "good" to "outstanding" range, suggesting that the manner in which the officers made phase changes decisions was consistent throughout the observation period. However, the models estimated for intersection of the Nicholson and Lee did dip into the “acceptable” range [12], suggesting the officers at this intersection were less consistent with the allocation of signal green time when compared to the other intersections.

4.0 SIMULATION MODELING RESULTS

The predictive logit models quantified the phase change decisions of the police officers that were observed in the field. These models were then integrated into a microscopic simulation software, VISSIM 5.3 for the purpose of simulating the officer's decision making [13]. The traffic simulation was conducted in three steps. The first step was to program the geometric design and special event traffic demand for each observation into the simulation software. The second step was to program the logit models, developed in the previous chapter, into VISSIM to act as the signal controller. The final step was to calibrate and validate the simulation model to verify the performance of the proposed methodology.

4.1 GEOMETRIC DESIGN AND DEMAND MODELING

The coding of the simulation model required the geometric design of the intersections and the vehicle demand as model inputs. The geometric design of the four study intersections was programmed into VISSIM 5.3 using open source high-resolution satellite images provided by Google™. The accuracy of these measurements was also verified during site visits. Using the traffic count and turning movement information from the intersection event time-lines, the intersection discharge flow rate observed in the videos was aggregated into 15-minute flow rates and programed into the simulation.

4.2 LOGIT MODEL PROGRAMING

The integration of the logit models into VISSIM was accomplished using Vehicle Actuated Programming (VAP). The VAP allowed for a real-time exchange of information between the simulation software and a VAP program file, which contained the logit models (PTV, 2007). The VAP received the intersection detector information to create the independent variables used in the logit model. From these variables it was possible to estimate the probability that the observed police officer, when placed in a similar situation, would change phases.

Through the VAP interface, the phase change probability was calculated every simulation time-step (1-second). These probabilities were then compared to a threshold value. If the probability of changing phases was higher than or equal to the threshold value, the VAP notified the signal controller inside the VISSIM model to change phases and proceed to the next time step. If the threshold value was not reached, the VAP allowed VISSIM to proceed with the next time-step without a phase change.

The threshold value was assumed to be a random variable from a uniform distribution. By randomly changing the threshold value, phase to phase, it was possible to more accurately represent the variability of manual traffic control, which was observed in the field. At the end of each phase, the threshold value for the next phase was calculated using Equation 6. The threshold value (k_p) of phase *p*, was computed by adding and subtracting a pseudo-random number to a static threshold value (S_p). The value of the static threshold was chosen empirically from the data collection video. For example, if 30 phase changes were observed in the video, the static threshold (S_p) was set to the value of the 31st highest choice probability estimated by the logit model. This ensured that, on average, 30 phase changes would likely occur during the same time period, permitting the simulation and observed intersections to have approximately the same number of phase changes.

The upper and lower bound of the random number was confined by the calibration variable α_p. This allowed the degree to which the threshold value varied to be calibrated to match the observations in the field. This was done by adjusting this variable up or down until the standard-deviation for the simulated phase lengths was equal to the standard deviation observed in the videos. The calibration variable α_p was multiplied by a pseudo-random number between zero and one. This value was calculated using a linear congruential random number generator (Wilson, 2009). This formulation of the pseudo-random number generated also required a seed value to calculate the initial random variable. The value of the seed number varied for each simulation.

$$k_p = S_p \pm \alpha_p * \frac{(aX_n + c) \bmod m}{m} \tag{6}$$

Where,

k_p is the threshold value for phase *p*

s_p is the static cut-point value

$\alpha_p$is the calibration parameter

X_n is a random number generated in the previous/initial time step
a is 1,597,
c is 51,749,
m is 244,944.

4.3 CALIBRATION

The goal of the calibration process was to have the simulation output match the field measurements with statistical certitude. The calibration process was important because data that could not be observed in the video footage but was necessary for the simulation model to produce the correct results, was inferred from making incremental changes to the input parameters. There were three parameters that needed to be estimated through the calibration process that were unique to each simulated intersection, the logit model coefficients (β_k), the variance of the cut-point (α_p), and the approach demand.

The calibration of these three parameters was conducted in parallel because each of these parameters was interdependent. For example, by adjusting the logit model coefficients, the signal timing would change, altering the intersection throughput. An added complexity to this was the stochastic nature of the simulation runs. As a result, multiple simulation runs were required to estimate if the changes observed in the simulation model were a result of calibrating the relevant parameters or the stochastic nature of the simulation model.

Once calibrated, an analysis was conducted to determine the number of simulation runs required to estimate reliable results. This analysis used the average cycle length to estimate the number of simulation runs required. It was determined that anywhere between three to nine simulation runs were required for each model to ensure that the average cycle length was consistent between runs. Therefore, to assure consistent results, each event was simulated ten times and the results averaged.

4.4 SIGNAL TIMING CALIBRATION

The estimated logit model coefficients provided a range of values within the 95% confidence interval. The values of the coefficients that result in the correct green time allocation can fall anywhere within this range. Therefore, the coefficient values for each variable used in the logit model was modified within the range of the 95% confidence interval until the average simulated phase length match the field observations. Adjusting these values affected the mean value of the simulated signal. However, to adjust the variance of this mean, the calibration variable (α_p) had to be estimated through an iterative calibration process until the standard deviation of each phase length, approximately matched the observed standard deviation.

The signal timing calibration results for each observation event are shown in Figure 1. This figure shows the observed average phase length and the simulated average phase length and their respective standard error. To compare the observed phase length and standard deviation from the video footage to the simulation model, a two-sample student t-test and f-test was conducted, respectively. All observations failed to reject the null hypothesis, that the observed and simulated phase length and standard deviation of the phase length were equal. Therefore, the simulation model was assumed to replicate the observed actions. This can be seen in the figure by comparing the error bars.

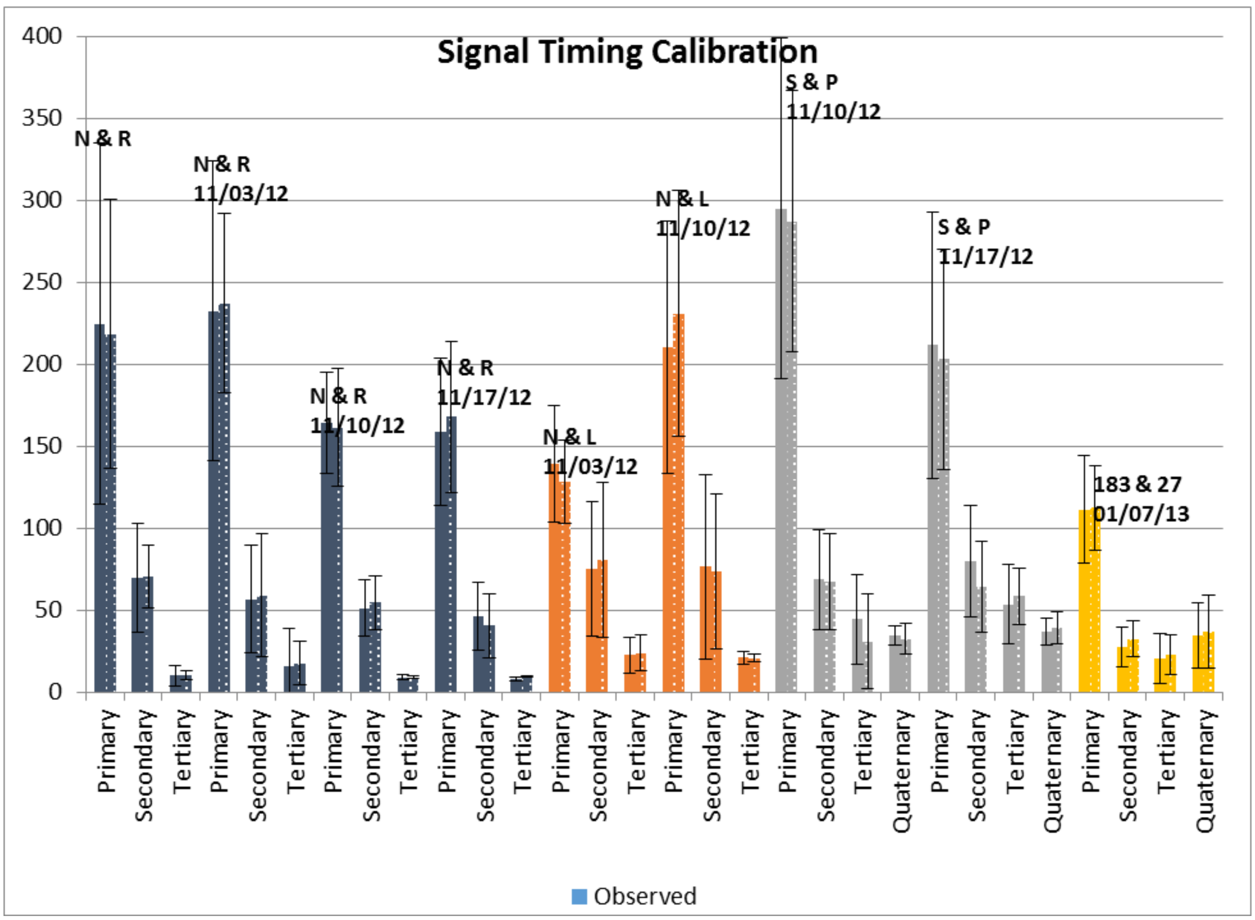

Figure 1: Signal Timing Calibration

4.5 VALIDATION

The goal of the simulation validation process was to evaluate the consistency of simulated police officer control with those observed in the field. Validation was undertaken using *model transfer*, whereby the officer actions logit model at one intersection was used to simulate the actions at another intersection. In effect, this process would be like moving an officer directing traffic from one intersection to another in the study. This was accomplished by transferring the calibrated VAP files from one intersection to another. Validation, for the purposes of this research, was achieved when the transferred model produced statistically similar results, both temporally and spatially, with the observations made in the field.

For the purposes of validation, the intersections were broken up into two datasets: calibration and validation. The calibration dataset represents the models that were transferred. The validation dataset represents the data on which the calibration parameters were being transferred to.

The intersection of Nicholson and Lee was validated by transfer the model estimated on 11/03/12 to the data collected on 11/10/12. Likewise, the validation of Stanford and Perkins was conducted by transferring the model estimated on 11/10/12 onto the data collected on 11/17/12. Since, only one data collection day was available for the intersection of NW 183 St. and NW 27 Ave. this intersection was validated using the model for Stanford and Perkins on 11/10/12. The intersection of Nicholson and Roosevelt was validated by combining the data collected on 10/13/12, 11/03/12, and 11/10/12, and testing this combined model onto data collected on 11/17/12.

Figure 2 illustrates the traffic signal timing results for the validation dataset. Present in the figure are the average phase duration and the standard deviation of this value, represented by error bars. Error bars which overlap indicate that the simulated validation results and the observed signal timing were statistical similar (failure to reject the null hypothesis that these values are equal). The analysis from a two-sample, two-tailed student t-test failed to reject the null hypotheses for all but one observations. Suggesting the validation simulation preformed in a similar fashion, compared to the observed signal timings. The single exception was seen for the tertiary direction at the intersection of Nicholson and Roosevelt and was likely do to an extraordinarily small standard deviation observed during in the validation dataset. F-testing conducted on the variance of these values also showed them to be statistically similar (failure to reject the null hypothesis that these values are equal) for every observation with the exception noted prior. Therefore, in general, the validation model was successful at replicating the observed signal timings.

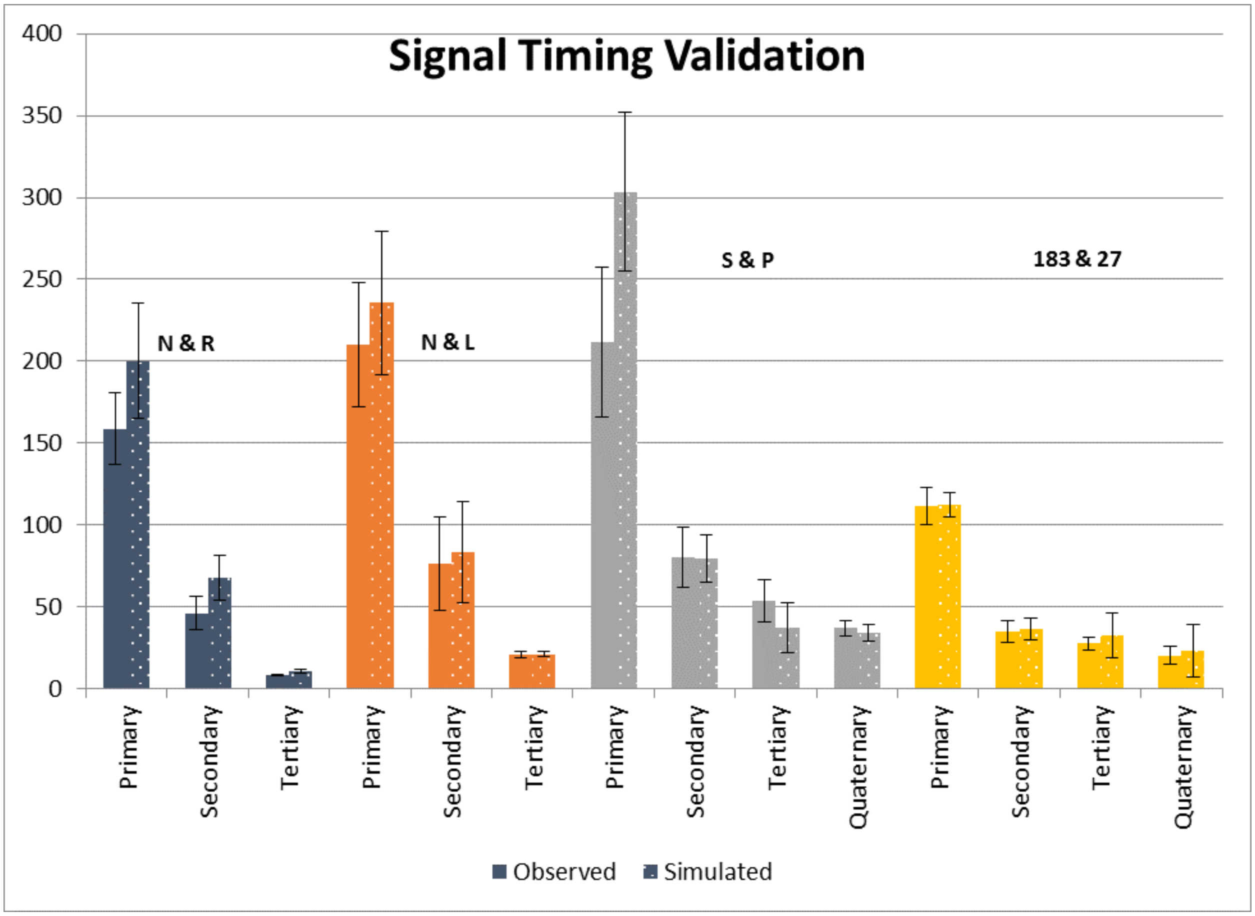

Figure 2: Signal Timing Validation

5.0 SIMULATED CORRIDOR NETWORK

A hypothetical urban grid network, originally developed by El-Metwally and Murray-Tuite [16], was used to evaluate the application of MTC for evacuating corridors. The network consisted of a dense inner evacuation area and a less dense outer safe area. This network included 41 intersections (25 within the evacuation area and 16 in the safe area), eight evacuation origin zones, and 20 evacuation destination zones. Figure 1 depicts the evacuation network. The evacuation intersections are labeled 1-25 and are shaded gray. The outer intersections are labeled 26-41. The origin zones, labeled O1-O8 and the destination zones, labeled D1-D20 are also displayed. The network is symmetric in both the North-South and East-West directions. Within the figure, callouts identify the location of the critical intersections to be evaluated (Center, Inside, Corner, Edge). These four intersections were systematically replaced with the unconventional control strategies and evaluated based on delay time.

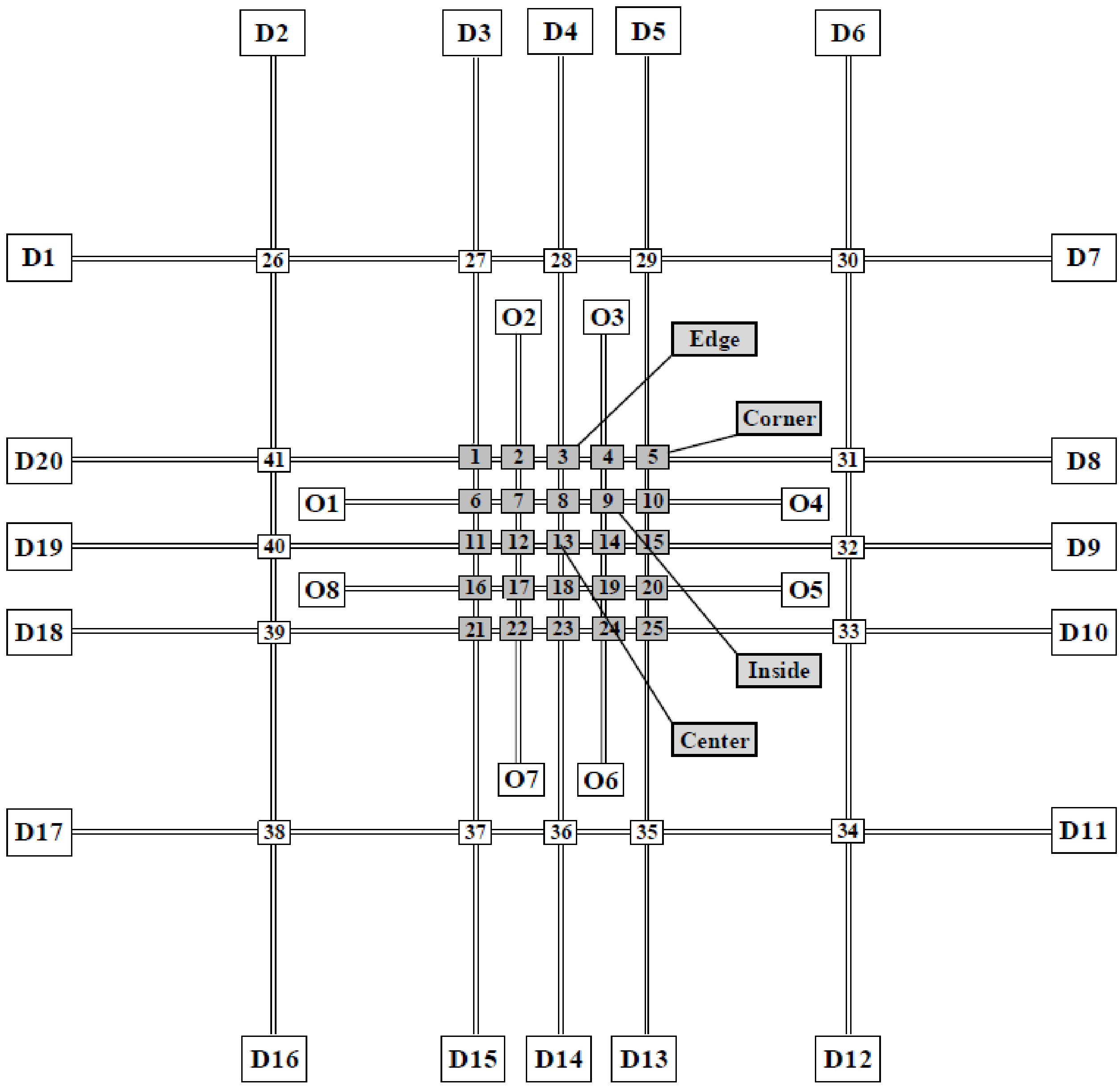

Figure 3: Evacuation Network (Intersections, Origins, & Destinations)

All the roads within the network are four lane (two lanes in each direction) and each intersection is signalized with four approach directions or legs. The speed limit of each road is 35 mph. Intersections within the evacuation area (1-25) have a shared through and right turn lane, a through lane, and a left-hand turn pocket on the major East-West approach. These inner intersections are spaced 0.5 miles apart and are shown in Figure 4. The outer intersections (26-41) consist of one shared through and right lane, and one left turn lane for all approach legs. The outer intersections are spaced further apart, ranging between 1.0 and 2.0 miles apart. The outer intersection's geometry is shown in Figure 5.

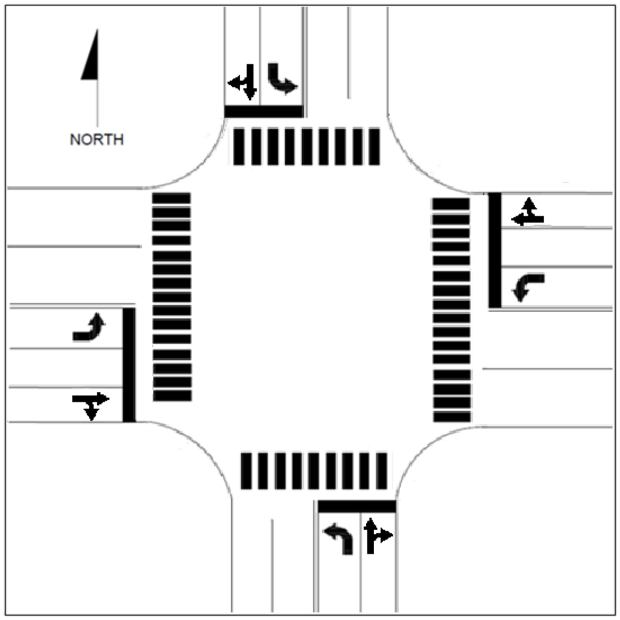

Figure 4: Inner Intersections (1-25)

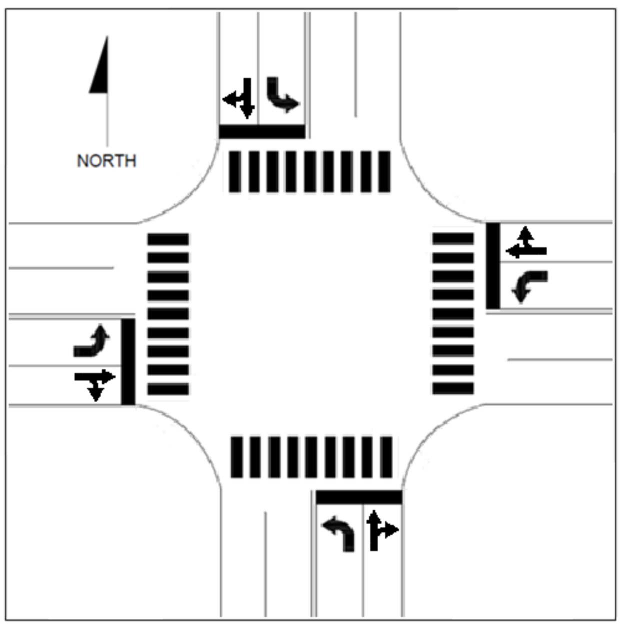

Figure 5: Outer Intersections (26-41)

5.1 EVACUATION SCENARIOS

Six evacuation demand scenarios were adapted from [16] to evaluate the intersection control strategies. Each scenario assumes the dense urban area containing intersections 1-25, requires an immediate no-notice evacuation. Evacuation origins are modeled as parking lots located at origin zones O1-O8. Evacuation destinations are modeled as parking lots located at destination zones D1-D20. The demand loading time for each scenario is 1 hour and evacuees are routed using VISSIM's dynamic traffic assignment method based on stochastic user equilibrium [22]. This traffic assignment method has been used in several previous evacuation studies [16]; [17]; [18]; and [19].

In general, there were two evacuation demands (medium and high) and three directional distributions, where evacuees were routed in a particular direction. This resulted in six unique evacuation scenarios (Scenario A – Scenario F). The medium demand scenario was developed to target a link volume to capacity ratio (v/c) of 0.8 to 0.9 and resulted in a total of 14,400 vehicles. The high demand scenario targeted a v/c ratio of 0.9-1.0 and resulted in a total evacuation demand of 19,200 vehicles.

Scenario A – This scenario evacuates a medium demand (14,400 vehicles) that is evenly distributed between destination zones D1-D20.

Scenario B – Evacuates a high demand (19,400 vehicles) and is also evenly distributed between the destination zones.

Scenario C – Uses a medium demand and assumes the evacuation threat is located to the North of the city, resulting in the closure of destinations located to the North (D2-D6). The evacuees are therefore, evenly distributed to the remaining 15 destination zones.

Scenario D – Uses a high demand but is otherwise identical to Scenario C.

Scenario E – Uses a medium demand and assumes the evacuation threat is located to the East of the city and as such, simulates a closure of destinations D7-D11. The evacuees are evenly routed to the remaining 15 destinations.

Scenario F – Uses a high demand but is otherwise identical to Scenario E.

5.2 ACTUATED CONTROL

The actuated signal control used for this research is a Ring Barrier Controller with lead-lead, protected/permissive left turn movements [16]. The signal cycle length is 86 seconds, the yellow time is four seconds, and the all-red time is three seconds. The actuated controller, as programmed in VISSIM 7.0, is shown in Figure 6. The actuated controller serves as the research control. It is assumed that this would be the default control method used during an evacuation. All other intersections in the network were programmed in the same fashion as displayed in Figure 6.

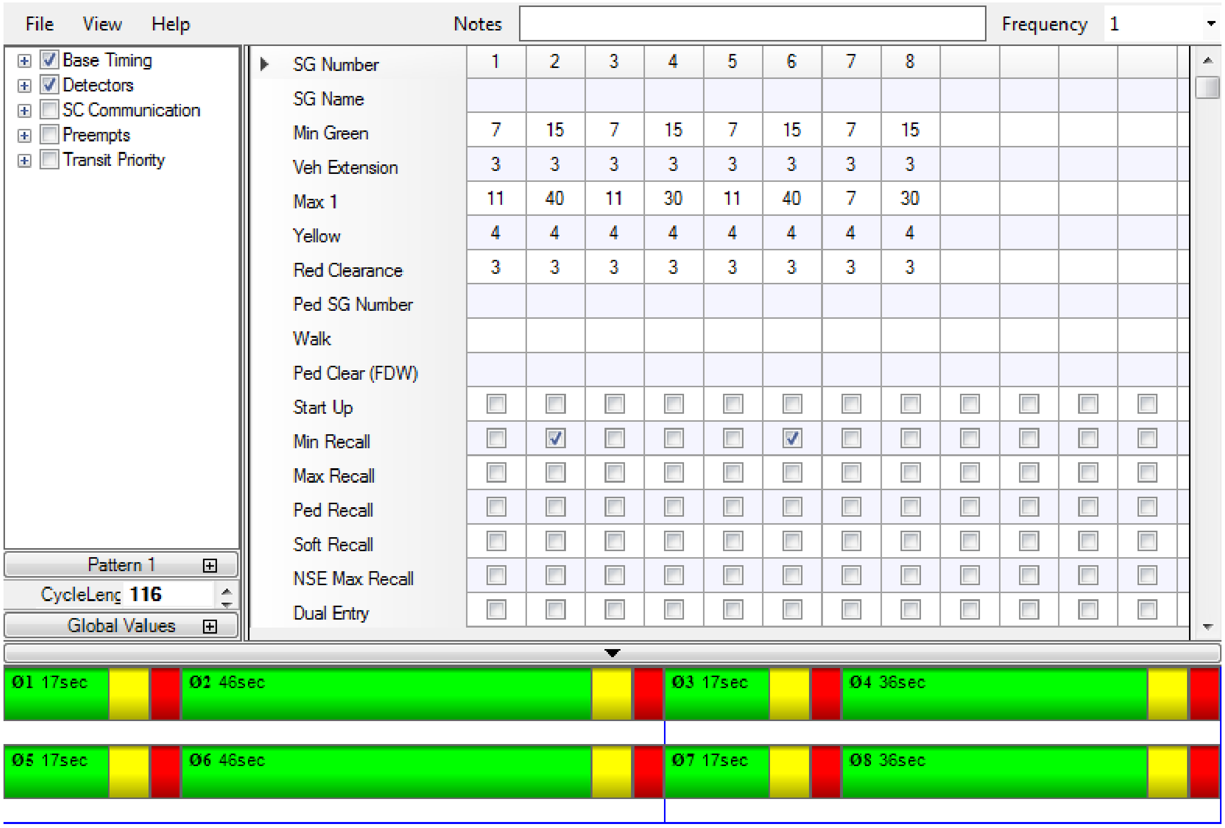

Figure 6: Actuated Controller Timing

5.3 CORRIDOR NETWORK RESULTS

Table 5 through Table 8 show the average simulated delay time for each scenario and control strategy. Also shown in these tables are the percent improvement (if any) which may be attributable to MTC. In general, as demand increased or became more concentrated in one direction, average delay time increased. This was an expected finding and indicates the evacuation network is near capacity. By increasing or concentrating evacuees in a single direction, queues build up near the evacuation destinations and propagates into the rest of the network, causing excessive delay. The table also indicates that changing the traffic control measure of a single, key intersection can have a significant effect on the overall average delay time (as much as 13%). This finding is consistent with the evacuation literature [16]; [20]; [21], however, the large variation between strategies, was profound. This shows that providing an improvement to even one intersection within a network can substantially improve evacuation performance. Another expected finding was that some unconventional control measures resulted in higher average delay time. This suggest that deploying a control strategy when unwarranted for the evacuation scenario can increase delay time within the network. To help prevent this, the following recommendations are proposed based on the findings of this research as a "rule-of-thumb" when implementing unconventional traffic control strategies:

Table 5: Center Intersection Delay Time

Center Intersection

Scenario:	Actuated:	MTC: (Minor)	MTC: (Major)
S-A	608	**563 (7.4%)**	587
S-B	970	**900 (7.22%)**	955
S-C	880	**856 (2.73%)**	**856 (2.73%)**
S-D	1404	**1230 (12.39%)**	1300
S-E	859	871	**840 (2.21%)**
S-F	1427	1409	**1335 (6.45%)**

Table 6: Inside Intersection Delay Time

Inside Intersection

Scenario:	Actuated:	MTC: (Minor)	MTC: (Major)
S-A	608	667	623
S-B	970	1110	**956 (1.44%)**
S-C	880	984	948
S-D	1404	1489	1454
S-E	859	915	906
S-F	1427	1512	**1425 (0.14%)**

Table 7: Corner Intersection Delay Time

Corner Intersection

Scenario:	Actuated:	MTC: (Minor)	MTC: (Major)
S-A	608	616	**603 (0.82%)**
S-B	970	985	**956 (1.44%)**
S-C	880	900	886
S-D	1404	1369	**1299 (7.48%)**
S-E	859	862	919
S-F	1427	**1386 (2.87%)**	1506

Table 8: Edge Intersection Delay Time

Edge Intersection			
Scenario:	**Actuated:**	**MTC: (Minor)**	**MTC: (Major)**
S-A	608	627	642
S-B	970	1015	993
S-C	880	**879 (0.11%)**	964
S-D	1404	1443	**1364 (2.85%)**
S-E	859	876	947
S-F	1427	1452	1593

Actuated Controller – The results suggest that an actuated controller performed well when intersection demand was moderate and more or less, evenly distributed among the four approach directions. In practice, actuated controllers are implemented without the supervision of a police officer as an authority figure. One of the most fundamental findings of this research was that actuated signal control can serve as a good default strategy as it provides a reasonable compromise between capacity and mobility. Allowing a reasonable level of service while not restricting moments through forced turnings. However, action should be taken when overwhelming demand from one or more directions causes queues to spillback and block driveways, entrance ramps, or other intersections. In this sense, actuated control can be thought of as the best intersection control strategy, until it becomes apparent the signal is incapable servicing the demand. Only then should authorities take action through the implementation of MTC or other tactics to address demand.

Manual Traffic Control – This intersection control strategy performed similar to an actuated controller, however, it was able to accommodate imbalanced demand to a greater extent. While both MTC and the actuated controller were able to handle diverse turning movements, only MTC can do so at exceedingly high volumes. Another important finding was that MTC outperformed all other intersection control strategies when downstream queues blocked the intersection. In other words, when congestion (from either a downstream bottleneck or intersection) propagates upstream and into the intersection, MTC should be deployed to alleviate the problem. However, for coordinated networks, the likelihood of this occurring decreases and therefore, limits the application of MTC to intersections immediately upstream of a bottleneck. However, there are also other intrinsic benefits to MTC, in that it puts "boots-on-the-ground" to observe conditions, respond to problems, and project the presence of authority during times of crisis. Its ultimate drawback however, is that it requires a police officer. During an emergency, police personnel are in high demand and the benefit gained by MTC must be weighed against competing priorities.

6.0 CONCLUSION

This research presented a methodology for simulating MTC which combined discrete choice modeling and traffic simulation to realistically represent the primary traffic control functions performed by police officers in the field. Using the method developed from this research, the MTC model can be adapted to simulate MTC at other intersections. With a relatively small sample size of officer observations and following the calibration procedure outlined in this paper, the MTC model can be adapted to simulate a wide range of intersection geometry and phasing to be tailored fitted to the modeler's needs.

The proposed approach to simulating MTC signifies a vast improvement over the state-of-the-practice, which uses a modified actuated controller to represent MTC (NRC, 2011). This research also recognizes that human-in-the-loop simulation is still the most accurate and realistic approach to simulating MTC. However, its limitations leave practitioners without a means of simulating multiple intersections simultaneously and autonomously at faster than real-time or the ability to conduct multiple simulation runs for statistical analysis [7]; [8].

From a choice modeling standpoint, the research findings suggested police officers in Baton Rouge, LA and Miami Gardens, FL, tended to direct traffic in a similar fashion; extending green time for high demand directions while attempting to avoid long gaps or waste in the traffic stream. This was expected and is quite consistent with the general concept of a traffic signal. The research also found that *Phase, Time* and *Gap* variables estimated by the various logit models had statistically similar values at a 95% confidence interval irrespective of the data collection day or location. While some level of similarity was expected, this degree of consistency was remarkable and indicates that when officers are placed in similar situation they are likely to make the same primary control decisions. This was important because it suggests that a properly trained and experienced police officer in Baton Rouge, LA would be just as effective directing traffic in Miami Gardens FL, and vice-versa.

From a simulation modeling standpoint, the manual traffic control model was shown to be statistically similar to the observed police controlled intersections with regard to phase length, standard deviation of phase length and intersection throughput. This was the goal of the calibration process and was an expected outcome. These results were validated on a separate dataset, which were also shown to be consistent. With this validity established, the model can be applied to simulate "what if" scenarios. Although the model cannot predict the precise effect of manual traffic control, it can be used to compute reliable estimates of its likely effect. Another application of the model would be to evaluate the effect of policy changes to manual traffic control. For example, if a policy was put in place that mandated a maximum cycle length of five minutes, the model could be modified to reflect this and estimate the likely impact on traffic.

In general, the results of the research showed that MTC, when implemented properly can reduce average evacuee delay time, significantly. However, equally important to note is that MTC can have the opposite effect if not properly planned and executed. Among the research findings was that actuated controller should be used for moderate demand levels that is approximately balanced between the approach directions. Manual traffic control is costly in terms personnel resources but it is best suited for intersections immediately upstream of a bottleneck or for closely spaced, uncoordinated signalized intersections.

7.0 REFERENCES

1. Pretty, R. (1974). Police control of traffic: A study at a Brisban intersection. *Australian Road Research Board (ARRB) Conference*, 7, 83-95. Print.

2. Mahalel, D., Gur, Y., & Shiftan, Y. (1991). Manual versus automatic operation of traffic signals. *Transportation Research Part A: Policy and Practices*, *25A*(2/3), 121-127.

3. Ye, Z., Veneziano, D., & S. Lassacher. (2009). *Analysis of manual traffic control at all-way stop-controlled intersections during special events*. Paper presented at the Transportation Research Board 88th Annual Meeting Compendium of Papers. Washington D.C.: Transportation Research Board. Print.

4. Marsh, B. (1927). Traffic Control. *Annals of the American Academy of Political and Social Sciences*, p. 91

5. Eno, W. P. (1920). *The science of highway traffic regulation*. New York: Press of Byron Adams.

6. Schad, B.T. (1935). *Traffic control at signalized street Intersection*. (Doctoral Dissertation). University of Michigan, MI.

7. So, J., Lee, J., & Park, B. (2013). Evaluation of Manual Traffic-Signal Control under Oversaturated Conditions Using Hardware-in-the-Loop Simulation. *Journal of Transportation Engineering,* 1068-1075.

8. Ding, N., He, Q., Wu, C., 2014. Performance measures of manual multi-modal traffic signal control. Trans. Res. Rec.: J. Trans. Res. Board (submitted for publication).

9. Carson , J., & R. Bylsma. (2003). *NCHRP SYNTHESIS 309: Transportation Planning and Management for Special Events*. (1st ed.). Washington D.C.: Transportation Research Board, 1-19. Web. <http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_syn_309a.pdf>.

10. Nuclear Regulatory Commission (NRC). NUREG/CR-7002 SAND2010-0016P, Criteria for Development of Evacuation Time Estimate Studies, November 2011 (NRC, 2011)

11. Ben-Akiva, M., & Lerman, S. (1985). *Discrete choice analysis: Theory and application to travel demand*. Cambridge: The MIT Press.

12. VISSIM (2007). *VAP2.16 Interface User Manual*. PTV Planug Transport Verkehr AG.

13. Hosmer D.W. and Lemeshow S. (1980). A goodness-of-fit test for the multiple logistic regression model. *Communications in Statistics,* A10, 1043-1069.

14. Wilson, W. (2009). *Statistical methods*. San Diego, CA: Academic.

15. El-Metwally, M., and P. Murray-Tuite, *Selecting 4-leg intersections for crossing elimination in evacuations*. to appear in Transportation Research Record: Journal of the Transportation Research Board, 2015.

16. Liu, Y. and Z. Luo, *A bi-level model for planning signalized and uninterrupted flow intersections in an evacuation network*. Computer-Aided Civil and Infrastructure Engineering, 2012. **27**(10): p. 731-747.

17. Liu, Y., G. L. Chang, Y. Liu, and X. Lai, *Corridor-Based Emergency Evacuation System for Washington, D.C.: System Development and Case Study*. Transportation Research Record: Journal of the Transportation Research Board, 2008. **2041**(1): p. 58-67

18. Xie, C. and M.A. Turnquist, *Lane-based evacuation network optimization: An integrated Lagrangian relaxation and tabu search approach*. Transportation Research Part C: Emerging Technologies, 2011. **19**(1): p. 40-63

19. Parr, S., and E. Kaisar, *Critical intersection optimization during urban evacuation utilizing dynamic programming*. Journal of Transportation Safety and Security, 2011. **3**(1): p. 59-76.

20. Parr, S. A. (2014). Analysis and Modeling of Manual Traffic Control for Signalized Intersections.