A FUZZY LOGIC MODEL FOR NETWORK SIGNAL CONTROL AND TRANSIT PREEMPTION

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Abstract: The majority of the fuzzy controllers for traffic signal control in the literature operate using raw data from single point detectors installed on the intersection's various approaches. The input variables to the fuzzy logic controllers are usually simple estimates of traffic measures such as flow, speed or occupancy, estimated from such single detector readings. A room for improvement is sought herein by developing a fuzzy logic model (FLM) that could be integrated with smarter "processing" tools to estimate several traffic measures from multiple detectors on each approach. The estimates obtained from this processing tool are integrated as input knowledge into the FLM. The devised FLM structure is presented. A mesoscopic simulation model is devised to test the effectiveness of the FLM. The premise of the presented FLM is that it accounts for the network congestion downstream the individual traffic signals. This makes the FLM applicable for network rather than isolated type of signal control. Furthermore, the FLM accounts for transit pre-emption control as warranted. Several simulation-based experiments are presented including the basic FLM for isolated signal control, the FLM control enabling downstream congestion effect, and the one enabling transit pre-emption. The results are presented and discussed in details.

1 INTRODUCTION

Fuzzy logic models and artificial intelligence methodologies were reported to have promising capabilities to deal with highway traffic network problems. Some fuzzy logic applications for traffic modeling and control were developed using some intuitive approaches based on capturing the knowledge of the operators or experts (Sugeno and Nishida, 1985). More applications were developed using heuristic design rules or on-line adaptation of initially intuited rules (Zimmermann, 1996). Several FLM applications for traffic signal control were discussed in (Niittymaki and Pursula, 2000). A multi-level FLM coupled with a reasoning approach was used in (Niittymaki and Turunen, 2003). Multiple upstream detectors were used to measure flows and estimate queues. The traffic flows are used to estimate the approaches' traffic intensities, which are then used to decide on extension or termination of the current phase green using a two-stage FLM (Triba et al., 1999).

Fuzzy logic has been occasionally criticized because the membership functions and the knowledge base (rules) are conventionally set intuitively using reasoning arguments of huge data sets or trail-and-errors. As such, optimal performance is not guaranteed. To overcome these deficiencies, the neuro-fuzzy logic approach (integrated fuzzy logic and neural nets) had emerged in literature as a promising approach in controlling complex systems by utilizing the training capabilities of the neural nets (Hawas, 2007). Among the initial attempts for neuro-fuzzy logic applications for traffic signal control is the work reported in (Henry et al., 1998). The use of neural nets in learning [through simulation data] the best detector location as it relates to the signal delay is discussed in (Bingham, 2001). A set of simplified simulation experiments were developed to assess the performance and to illustrate the training of the FLM.

Simulation is recognized in literature as the tool to assess the effectiveness of the devised fuzzy logic models (Chou and Teng, 2003); (Kosonen, 2003); (Murat and Gedizlioglu, 2005). Simulation was also adopted together with multi-agent control scheme, and fuzzy inference (Kosonen, 2003). Each signal operates individually as an agent, negotiating with other agents (signals) about the control strategy

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(Kosonen, 2003).

The majority of the fuzzy logic controllers in the literature depend on raw counting detector data, with very few attempts (Palacharla and Nelson, 1999); (Mirchandani and Head, 2001); (Wen, 2007) made to transfer such data into other traffic measures that could be used to enhance the control intuition and/or effectiveness. Fuzzy logic and neural nets were utilized to estimate the link travel time (Palacharla and Nelson, 1999). A real-time traffic control system that predicts traffic measures [such as travel time, queue spillbacks, and turning probabilities to enable pro-active control] was introduced in (Mirchandani and Head, 2001). A framework for dynamic traffic light control coupled with a simulation model [to analyze the inter-arrival and inter-departure times to estimate the essential traffic measures needed for the control logic] was introduced in (Wen, 2007).

In summary, the limitations of the fuzzy systems for traffic control include the little consideration to the effect of the traffic stream composition (small cars, vans, trucks, buses, etc). Literally there is no consideration for transit vehicles preemptions. Among the limitations also is that the traffic congestion in the downstream of the signal approaches is not accounted for, and as such green time might not be effectively allocated to a phase (based on its upstream detector counts) in situations where the downstream approaches are exhibiting extreme congestion or blockage. Furthermore, little was reported on how the actual or the predicted queue on the approaches can be accurately estimated, as it cannot be detected by the typical single loop detector arrangement.

The majority of the fuzzy logic controllers in the literature are reactive to the raw detector data (counts) on the signal approaches. For instance, almost all the reported controllers depend on point detector "vehicular" counts with no considerations for vehicular types. Treating all types of vehicles equally might not result in fair treatment of all phases, if the traffic stream composition is varying among the phases. An approach with high percentage of heavy vehicles or busses should not be treated as equal as another approach with similar flows of small cars only. A better treatment is to account for the passenger car units flow instead of the vehicular flow. Alternatively, one could also devise a controller to preempt the public busses.

Furthermore, the raw vehicular counts do not explicitly capture the congestion status along the approaches. Incorporating additional variables such as concentration, actual approach speed, or queue length would result in a better logic. As a rule of thumb, a single point detector on each approach is not enough to capture the congestion status of the approach. Furthermore, a logic that depends on one traffic measure (such as flow) could employ erroneous decisions.

A more effective controller is sought herein by integrating the envisaged FLM to a processing tool of the raw data. This tool is intended to process the raw data into knowledge to develop smarter logic. The knowledge processing tool would utilize the detector counts to estimate some input variables to the FLM. In this paper, a fuzzy signal controller that incorporates "knowledge" in the decision making process and not merely raw detector data is developed. "Knowledge" term refers to any traffic measures estimated from raw data.

2 OVERVIEW OF FUZZY LOGIC SYSTEM

The developed FLM system requires the installation of two detectors for each lane (one downstream, and one upstream). This is the minimum requirement needed to accurately capture the congestion status of the approach. Additional detectors might be installed to increase the accuracy of estimating some traffic measures such as queue length, but this may be argued to be cost ineffective. For simplicity in presentation, we assume that the FLM is operating a four-phase signal; each approach is assigned a separate phase.

The logic depends on the (passenger car units) PCU estimates on each approach. This takes into account the traffic stream composition and the turning movement percentages (captured by the detectors). The field detectors' readings are processed further by some traffic status estimator tool, that transfer such field measures into complex traffic measures (or "knowledge"), which are then used as inputs to the FLM. The knowledge here refers to the estimated traffic measures beyond the field detector counts. The introduced FLM utilizes the estimates of the following traffic measures for each phase's approach:

- Traffic counts on approach in PCU
- Queue length (count) on approach in PCU
- Truck percentage
- Average approach speed
- Downstream link blockage index; an index (1-100) to indicate the congestion status of the downstream link (100% indicating a fully blocked downstream link)

• A transit indicator status (ON/OFF) or (1/0) when a transit vehicle is expected to reach/not to reach the queue to be served by the phase.

The above measures are utilized with other fixed indicators for each phase (such as link length and number of lanes) to estimate the so-called *green weight* for each phase, which is subsequently used in estimating the green splits for all the intersection traffic signal phases.

The devised fuzzy controller is assessed using a mesoscopic simulation model (developed as a Visual Basic Application VBA embedded EXCEL macro), which can be then easily integrated with any fuzzy logic controller. The FLM is integrated with the simulation model via a two-way communication protocol coded as a wrapper module macro in EXCEL. The DLL representing the FLM is linked to the simulator and receives inputs on the traffic measures (representing the field detectors data). The DLL estimates the traffic signal phase green splits for the next time interval, etc. The estimated green splits are then used by the simulator to simulate the next time cycle. The calibration of the FLM is done via systematic sensitivity analysis as will be discussed later.

3 SIGNAL CONTROL FUZZY LOGIC STRUCTURE

Figure 1 shows the fuzzy system structure including input variables, rule blocks and output variables. The connecting lines symbolize the data flow among the various rule blocks. As shown, the system comprises four rule blocks denoted by RB1, RB2, RB3 and RB4. The first rule block (RB1) has four inputs; the incoming approach's average speed (km/hr), the vehicular flow (veh/hr/lane), the length (m), and the number of lanes. The second rule block (RB2) has three input variables; traffic count on approach (pcu), queue count on approach (pcu), and the truck percentage. The time varying input variables are calculated using the traffic status estimators (Hawas, 2010). The third rule block (RB3) has two intermediate inputs; the output variables of the first and second rule blocks. These are denoted by the green weight I and II. The output of the third rule block is denoted by the total green weight, which represents the sum of these input variables (green weight I and green weight II).

The fourth rule block (RB4) has three inputs; the total green weight (the output of the third rule block), the downstream blockage index, and the transit vehicle indicator (a binary variable: 1 if a transit vehicle is to be served during the current cycle and 0 otherwise). The overall system output is denoted by the "final weight" and it represents the estimated weight given to the traffic light phase that serves the approach under consideration.

The two rule blocks RB1 and RB2 complete each other in estimating the green weight. With reference to Figure 2, RB3 acts as "addition" rule block (adding the initial weights estimated by the RB1 and RB2). The result of such addition (output of RB3) is then combined with the effect of the downstream blockage [if activated] and the transit vehicle pre-emption [if activated] in RB4. The multiple rule block structure of the FLM is widely recommended in literature as it simplifies the sensitivity analysis, the calibration process of the fuzzy memberships, and the identification of the most significant contributing factors.

The results of the fuzzy-logic *inference* process are *linguistic* terms describing the output variable (e.g. *Low Final-Weight*, *Medium Final-Weight, etc)*. Each linguistic term covers a specific range of numerical values. The defuzzification process is responsible for converting the linguistic terms to numerical crisp values (of this particular range).

The crisp value obtained by the defuzzification process represents the system's estimate of the approach (phase) green weight. The weight is a real number representing the "importance" of serving this particular traffic light phase; the higher the weight, the more the green to assign to this phase.

The green split, $g_{i,\phi}$ of any phase ϕ and intersection *i* is estimated using a proportion formula that entails the *weight* of the phase, W_φ as follows:

$$g_{i,\phi} = G_i * \frac{W_\phi}{\sum_{\phi=1}^{\Phi} W_\phi} \quad (1)$$

Where:

$g_{i,\phi}$: Actual green time of phase ϕ at intersection *i*

Φ : Total number of phases

G_i : Total actual green time at intersection *i*

W_ϕ : Estimated weight by the FLM for phase ϕ

4 EXPERIMENTAL ANALYSES AND RESULTS

To assess the effectiveness of the FLM, several

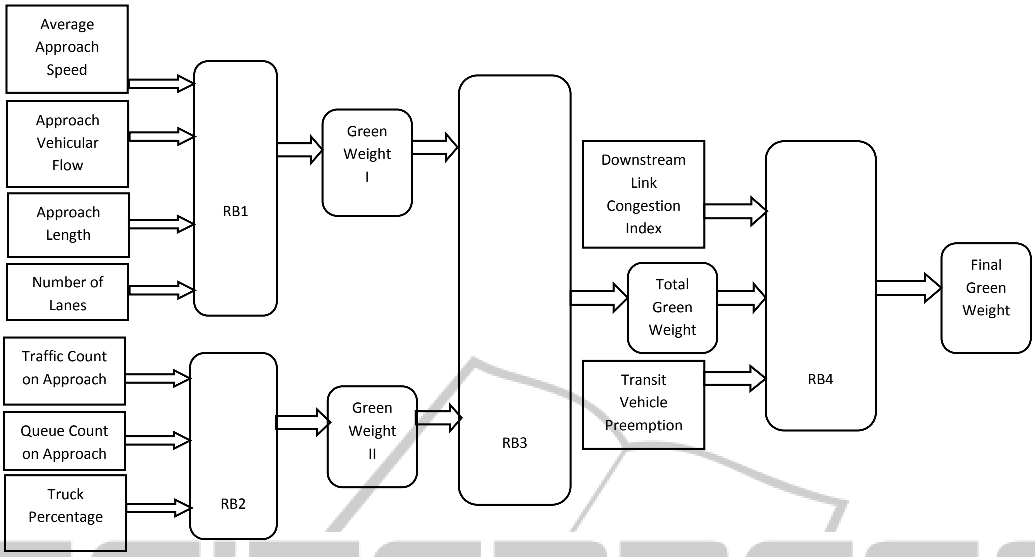


Figure1: Traffic signal control FLM structure, and rule blocks.

simulation-based scenarios were developed. A single four-leg intersection is tested with different traffic and geometric characteristics representing the different scenarios. Different approach variables were used to introduce variability in approach flow, length, number of lanes, free-flow speed, and truck percentages. Each approach is assumed to be served by a separate phase. Herein, we provide only a sample of these scenarios as well as their results. Each scenario is tested using a duration time of 1800 seconds to generate vehicles and 2000 seconds to clear the network. All scenarios were also tested using a fixed cycle time of 100 seconds.

The minimum number of phases to serve a four-leg intersection varies based on the traffic volumes and type of the left turning phases (protected, permitted). For instance, if a four-leg intersection is to be served with the left turning volumes permitted, then a two-phase cycle would be needed. A four-phase signal would be needed if left turning volumes are to be served in a protected mode. In this paper, a 4-phase signal setting was used for simplicity, and to account for the fact that any potential left turning vehicles along the approach would have to be served in a protected mode.

The FLM applies to any number of phases and signal configuration (e.g. two, three, four phase signals). For instance, for a 4-leg two-phase signal (combining the through movements on opposing approaches), the FLM runs similarly on all four approaches; estimating a green weight for each. Then, the critical approach (of each phase) is identified as the one having higher green weight. In the implementation of the green splits, the critical approach green weight would be considered in estimating the phase green times. The green time of any phase (combining various movements) is determined in accordance to the most critical movement served by the phase. The logic allows for phase skipping if the phase's green weight is lesser than a pre-specified threshold value (if warranted). If a phase is skipped, the following phase in the (fixed) sequence is activated.

The inference engine of the 4th rule block was developed using sensitivity analysis. Initially, a correlation coefficient of 1.0 was assumed between the total green weight and the final green weight, a negative correlation (of -1.0) between the downstream congestion index and the final green weight, and a positive correlation of (1.0) between the final green weight and the transit vehicle preemption. The four experimental scenarios (in Table 1) were run and the average vehicle travel and delay times were estimated. The correlation coefficients were then slightly adjusted and again the average travel and delay times were estimated. The process of readjusting the correlation coefficients and the estimation of the travel and delay times were repeated until the system converges to minimal travel and delay times. The correlation coefficients corresponding to the minimal travel and delay times are 0.9, -0.8 and 0.75 for the total green weight, the downstream congestion index and the transit vehicle preemption, respectively.

The "base" Scenario (I) represents a medium congested network, assumes no downstream congestion and no transit preemption. The other three scenarios are similar to scenario I (in terms of the speed, the vehicular flow, the link length, the number of lanes and the truck percentage), but they differ in the downstream congestion values and/or the transit preemption.

Several other scenarios were previously tested and reported in Hawas (2010) using the isolated signal FLM. The reported scenarios accounted only for variations in the input variables of RB1 and RB2. They also accounted for scenarios with and without "knowledge estimator" activated. No consideration was given in Hawas (2010) to the downstream congestion effect or to the transit vehicle preemption influence [the inputs to RB4]. This paper extends on the work presented earlier in Hawas (2010) by accounting for the downstream congestion and the transit preemption.

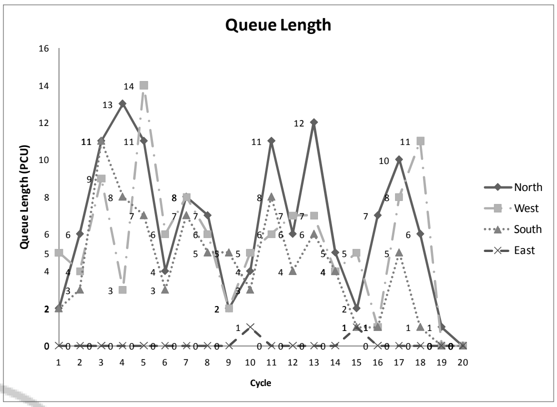
The analysis presented in this paper focuses on illustrating how the resulting FLM green times are influenced by the downstream congestion index and the transit vehicle preemption variables. That is, how will the green times patterns correspond to various patterns of network congestion and transit preemption scenarios.

Figure 2 illustrates the results of scenario I. Figures 2A and 2B shows the estimated queue length and the traffic count on each approach (estimated by the knowledge estimator). Because of the identical traffic conditions on all approaches (speed, traffic volume, link length, number of lanes, truck percentage), the approaches exhibit similar queue length and traffic count patterns. The resulting green times (of the FLM) are equal among the various phases as shown in Figure 2C.

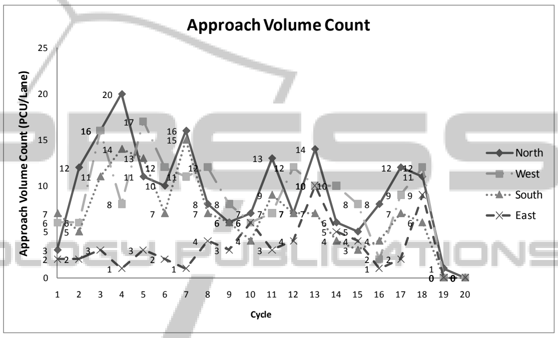
Table 1: Basic information of different tested scenarios.

Scenario*	Downstream congestion index	Transit vehicle pre-emption
I	10% or less on downstream links of all approaches	No transit preemption
II	10% or less on downstream links of all approaches	Transit preemption on NB approach only
III	80% or less on downstream link of NB approach	No transit preemption
IV	80% or less on downstream link of NB approach	Transit pre-emption on NB approach only

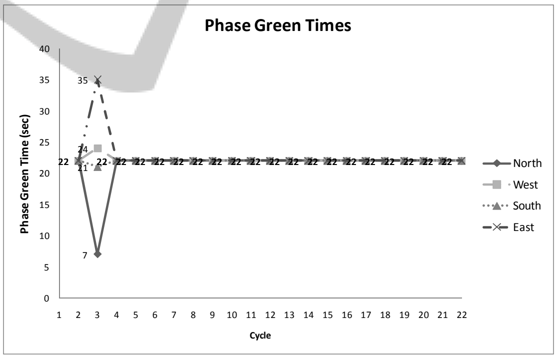
*All scenarios are set equal in link speed, link length, number of lanes, link vehicular flow, and truck percentage (60 km/hr speed, 500 veh/hr/lane vehicular flow, 500 m length, 2 lanes and 10% trucks).



(2A) Approach queue length (in PCU).



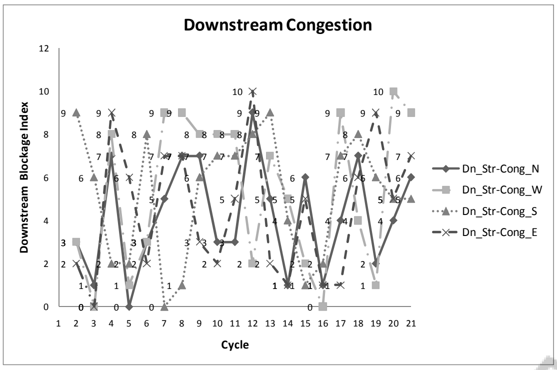
(2B) Approach volume count (PCU/lane).



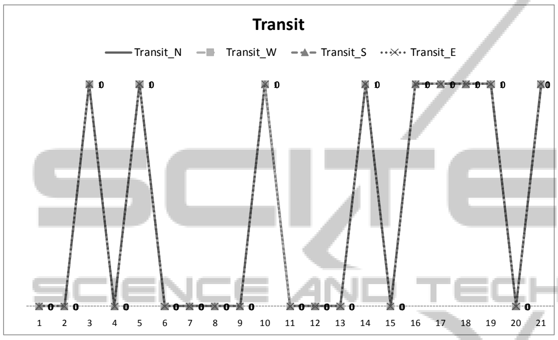
(2C) Phase green times (sec).

Figure 2: Results of experimental scenario I.

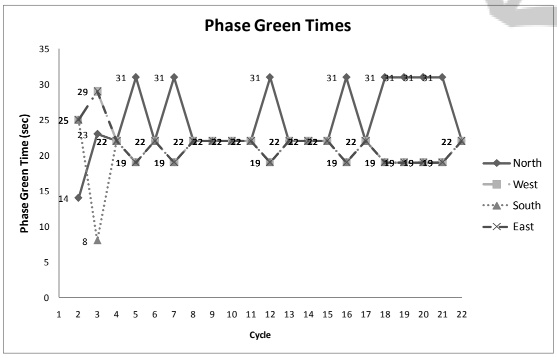
Scenario II is quite similar to scenario I. Slight congestion is exhibited on the downstream approaches (a congestion index of 10% or less) as shown in Figure 3A. The only difference (between the two scenarios) is that the transit vehicles incoming on the North bound (NB) approach are pre-empted (in scenario II). Figure 3B illustrates the cycles during which transit vehicles arrive at the intersection. The resulting FLM signal green times (in Figure 3C) are somehow identical for all the approaches except the NB. The resulting green time pattern of the NB approach (in Figure 3C) is consistent with the transit vehicle arrival pattern (Figure3B).



(3A) Downstream approach congestion index.



(3B) Transit vehicles arrival pattern.

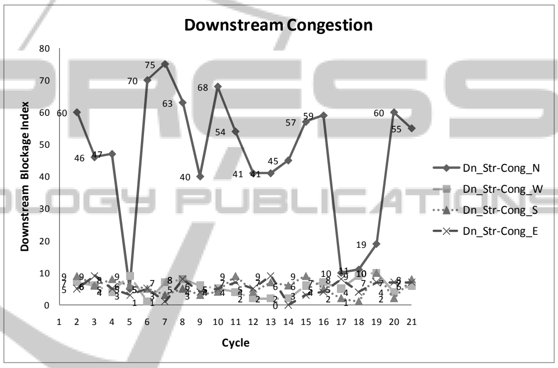


(3C) Phase green times (sec).

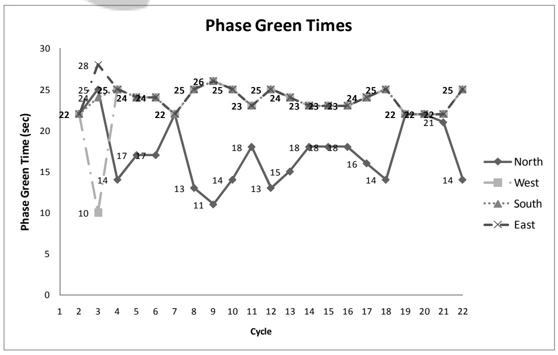
Figure 3: Results of experimental scenario II.

Scenario II represents the case of the FLM control system that is not only reactive to the traffic conditions along the incoming approaches, but also reactive to the incoming transit vehicles. Currently, all transit vehicles are pre-empted equally. That is, the FLM operates with a binary variable that activates the system's transit pre-emption logic, without providing any preferential treatment to various transit vehicles. The FLM shall be extended in further research to provide various levels of pre-emption based on the vehicle type, the transit vehicle's passenger occupancy and the distance between the transit vehicle and the approach's stop-line.

Scenario III is developed by introducing slight variations to scenario I. Similar to scenario I, slight congestion is exhibited on the downstream approaches of the intersection (a congestion index of 10% or less) as shown in Figure 3A. Only the downstream of the NB approach exhibits oscillating congestion (congestion index of 80% or less) as shown in Figure 4A. The transit pre-emption is activated. The resulting FLM signal green times (in Figure 4B) of the NB approach is lesser than that of the other approaches (although the traffic conditions are identical). The FLM (due to the congestion downstream the NB approach) allocates lesser green times to the NB phase. The higher the congestion index, the lesser the green times.



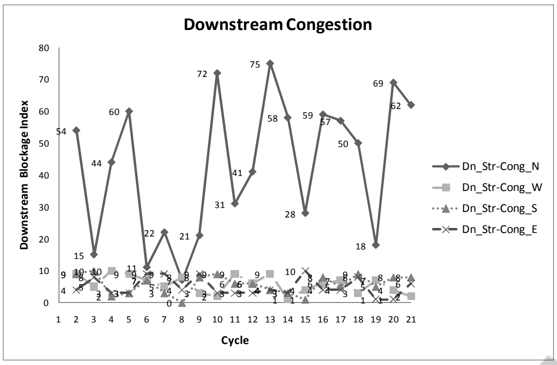
(4A) Downstream approach congestion index.



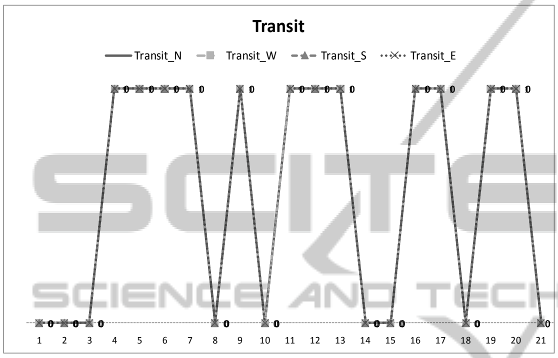
(4B) Phase green times (sec).

Figure 4: Results of experimental scenario III.

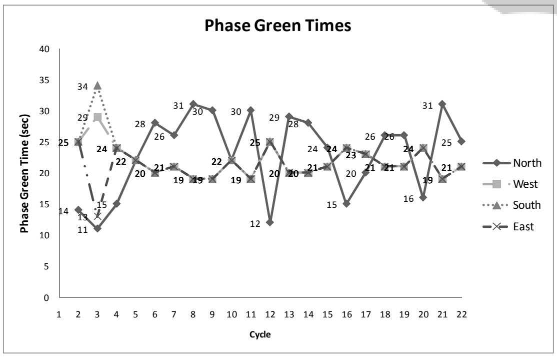
Scenario IV combines the congestion downstream the NB approach (Figure 5A) and the transit preemption on the NB approach (Figure 5B). The resulting NB green times as such oscillates to balance the two conflicting criteria; lesser green time due to the downstream congestion and the higher green time due to the transit preemption. The resulting green times of the various intersection phases is illustrated in Figure 5C.



(5A) Downstream approach congestion index.



(5B) Transit vehicles arrival pattern.



(5C) Phase green times (sec).

Figure 5: Results of experimental scenario IV.

5 CONCLUSIONS AND FUTURE RESEARCH

This paper presented a FLM that can be coupled with smart "processing" tools to estimate several traffic measures from multiple detectors on each approach. The estimates obtained from this processing tool are integrated as inputs into the FLM. The FLM explicitly accounts for the congestion on the links downstream the controlled intersection. As such, the FLM can be regarded as a semi-network control procedure. The FLM can also adjust the signal settings to provide transit preemptions. The presented FLM was tested with four scenarios to assess the sensitivity of the model to the downstream and the transit preemption variables.

The resulting green time patterns clearly illustrate the sensitivity of the FLM to the congestion and the transit preemption variables. More research is being undertaken to demonstrate the presented model effectiveness in real-life conditions. Also, comparative analysis of the presented FLM effectiveness vis-à-vis other real-time signal controllers shall be considered for future research.

Further appealing improvement to the system can be achieved by further processing of the raw data to have estimates of the expected approach delays. The green splits can be then adjusted to explicitly assign green weight based on expected delay estimates. This will be considered for the future upgrades of the FLM. More sophisticated knowledge can be formed by considering more than two detectors, and better accuracy can be sought through modifying the detector locations.

The presented FLM control system is not only reactive to the traffic conditions along the incoming approaches, but also reactive to the incoming transit vehicles and the downstream approaches congestion. Currently, all transit vehicles are pre-empted equally. That is, the FLM operates with a binary variable that activates the system's transit pre-emption logic, without providing any preferential treatment to various transit vehicles. The FLM shall be extended in further research to provide various levels of pre-emption based on the vehicle type, the transit vehicle's passenger occupancy and the distance between the transit vehicle and the approach's stop-line.

The downstream congestion is modelled herein through congestion index that quantifies the degree of downstream link occupancy. Future research shall include the coupling of the FLM with smart processors that can utilize the downstream approach's detector readings to provide better estimates of the downstream congestion status; the distribution of the vehicles, and extent of queues along the downstream links.

Moreover, the FLM shall be also restructured as a multi-level control system for incident detection, signal control and transit priority. These systems however if deployed individually may result in conflicting decisions and as such they need to be integrated to insure consistency of decisions leading to optimized traffic network performance. The multi-level FLM is envisaged to comprise three levels. The first level shall be responsible for detecting incidents in urban networks using field street detectors. The second level shall operate a heuristic based logic for real-time signal control with extended capabilities to operate special scenarios if incidents are detected, aiming at better traffic management during such incidents. The third level shall deploy several strategies for transit vehicles priority. The three levels shall operate in a closed loop fashion to insure consistency of decisions and better traffic management. The system shall be tested within a simulation-based environment under various operational conditions reflecting network congestion, incident situations, and transit demand patterns.

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