A Simulation-based Fuzzy Model for Traffic Signal Control

YASER E. HAWAS, Ph.D.
Professor, CEE Department
Director
Roadway, Transportation and Traffic Safety Research Center (RTTSRC)
UAE University
Al-Ain, P.O. Box 17777, UAE
E.mail: y.hawas@uaeu.ac.ae

ABSTRACT

Fuzzy logic has been recognized in the literature as an effective methodology for real-time signal control. The majority of the fuzzy controllers in the literature depend on simple logic that particularly depends on raw data of a single detector. Their input variables 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 in this paper 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 mathematical formulation of these traffic measures is presented. The fuzzy logic structure is addressed in details. A simulation model is devised to test the effectiveness of the FLM. The results are presented and discussed in details.

Key-Words: Traffic control, fuzzy logic model, real-time, detectors, traffic measures, simulation.

1 Introduction

The majority of the fuzzy logic controllers in the literature depend on raw counting detector data, with very few attempts (such as [1], [2] and [3]) 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 [1]. Mirchandani and Head (2001) introduced a real-time traffic control system that predicts some traffic measures such as travel time, queue spillbacks, and turning probabilities to enable pro-active control in [2]. Wen (2007) proposed 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 in [3].

In summary, the limitations of the reported fuzzy systems for traffic control in the literature are identified that (1) No consideration for the effect of the traffic stream composition (small cars, vans, trucks, buses, etc) (2) no consideration for the traffic congestion downstream the signal approaches, 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 (3) no consideration for the actual or the predicted queue on the approaches, as it
cannot be detected by the typical loop
detectors (4) no consideration for the
variability in the approach speeds and (5)
the majority of the fuzzy logic models in the
literature employ a sort of trading-off
concept the benefit of “extending” versus
“terminating” the current green times. Few
logics were recently introduced to assess the
phase sequencing or phase skipping.

A more effective controller is sought 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.

2 Overview of Fuzzy Logic
System

The FLM discussed in this paper assumes
the installation of two detectors for each
lane (one downstream, and one upstream).
This is the minimum requirement needed to
capture accurately the congestion status of
the approach.

The raw detectors’ readings are processed
by some traffic status estimator tool,
transferred into traffic measures (or
“knowledge”), which are then used as input
to the FLM. The knowledge here refers to
the estimated traffic measures beyond the
raw detector counts. The introduced FLM
utilizes the estimates of the following traffic
measures for each phase: Traffic counts on
link (approach) in PCU, Queue length
(count) on link (approach) in PCU, Truck
percentage, Average link speed and
downstream link blockage index; an index
(1-100) to indicate the congestion status of
the downstream link (100% indicating a
fully blocked downstream link)

The devised fuzzy controller is assessed
using a mesoscopic simulation model
(developed as an 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 logic receives traffic
measures from the simulator, and assigns
back green splits for the next time interval,
etc. The calibration of the FLM is done via
systematic sensitivity analysis of the
inference engine structure as will be
explained later. The details of this
simulation model will also be discussed in
more details later in this paper.

3 Formulation of traffic
status estimator

Hawas (2002) utilized a microscopic
simulation-based calibration approach to
derive the following speed-density
relationships: [4]

\[ v = a + b \frac{k^{1.5}}{k^{1.5}} + c \frac{k^{0.5}}{k^{0.5}} \]

Where \( k \) is the average density in
veh/km.lane and \( v \) is the average speed in
km/h. The value of the parameter, \( a \), is the
free-flow speed. The parameters \( b \) and \( c \) are
typically negative. As the value of the free-
flow speed increases, the parameters \( b \) and \( c \)
decrease.

Assume \( V_{0i} \) represents the free flow speed of
the approach \( i \) (km/hr). The above speed
formula is adjusted to capture the traffic
composition, at any time \( t \). In other words,
the function accounts for passenger car units
instead of vehicular counts.

\[ v_i = (V_{0i} + b \frac{P_{i,t} * 1000}{L_i} p_1 +
+ c \frac{P_{i,t} * 1000}{L_i} p_2) / 3.6 \text{ (m/sec)} \] (1)

Where \( P_{i,t} \) is the number of passenger car
units on link \( i \), at time \( t \). \( L_i \) is the total length
lanes of link \( i \) (meters). \( b, c, p_1 \text{ and } p_2 \)
are the calibrated speed-density function
parameters [4]. For instance, for free flow
speed of 80 km/hr, the values of the \( b, c, p_1 \text{ and } p_2 \)
parameters are -0.00055, -2.5, 2.5
and 0.5, respectively.

\[ P_{i,t} = P_{i,t-1} + US_{i,c,t} + f_{T} \text{ * } US_{T,T,t} - DS_{i,c,t} -
- f_{T} \text{ * } DS_{i,T,t} \] (2)
Where \( US_{i,c,t} \) is the number of car hits on the upstream detectors of link \( i \) at time \( t \), \( US_{i,T,t} \) is the number of truck hits on the upstream detectors of link \( i \) at time \( t \), \( DS_{i,c,t} \) is the number of car hits on the downstream detectors of link \( i \) at time \( t \), \( DS_{i,T,t} \) is the number of truck hits on the downstream detectors of link \( i \) at time \( t \), and \( f_T \) is the truck factor (taken here as 3). Equation (2) is used to update the passenger car unit counts on any link \( i \) at time \( t \).

Similar to the above equation, the following equation (3) is used to update the total vehicular counts on any link \( i \) at time \( t \). Note here that the truck factor is simply dropped off equation 2 to form equation 3.

\[
N_{i,t} = N_{i,t-1} + US_{i,c,t} + US_{i,T,t} - DS_{i,c,t} - DS_{i,T,t}
\] (3)

For any vehicle \( h \) hitting the upstream detector of link \( i \) at time \( g \) (sec), the vehicle is estimated to reach a virtual queue downstream the link at time \( q_{h,i} \)

\[
q_{h,i} = g + l_i / v_i
\] (4)

Where \( l_i \) is the link length (meters).

The total numbers of vehicles in the virtual queue of link \( i \) at any time \( t \) is estimated as follows:

\[
Q_{i,t} = Q_{i,t-1} + A_{i,t-1} - S_{i,t-1}
\] (5)

Equation 5 states that the virtual queue of link \( i \) at time \( t \) is equal to that of the link at time \( t-1 \), plus the arrivals to the queue at time interval \( t-1 \), minus those served at time interval \( t-1 \).

\[
A_{i,t-1} = \sum_{h=1}^{H} \delta_h
\] (6)

\[
\delta_h = 1 \text{ if } q_{h,i} = t-1, \text{ and } 0 \text{ otherwise,}
\] (7)

\( H \) is the numbers of vehicles on link \( i \) at time \( t-1 \). Equations 6 and 7 are used to estimate the number of vehicular arrivals to the virtual queue of link \( i \) at time \( t-1 \). \( \delta_h \) is a binary number indicator of one if vehicle \( h \) reaches the virtual queue at time \( t-1 \), and zero otherwise.

\[
S_{i,t-1} = DS_{i,c,t-1} + f_T*DS_{i,T,t-1}
\] (8)

Equation 8 is used to estimate the number of vehicles on link \( i \) served at time \( t-1 \). It is equal to the sum of the downstream detectors hits by cars and trucks.

The “vehicular” virtual queue length (represented by equations 5 through 8) can also be represented in passenger car units with the set of equations 9 through 12.

\[
PQ_{i,t} = PQ_{i,t-1} + PA_{i,t-1} - PS_{i,t-1}
\] (9)

Equation 9 states that the virtual queue of link \( i \) at time \( t \) (in passenger car units) is equal to that of the link at time \( t-1 \), plus the passenger car arrivals to the queue at time interval \( t-1 \), minus those served at time interval \( t-1 \).

\[
PA_{i,t-1} = \sum_{h=1}^{H} \phi_h
\] (10)

\[
\phi_h = 1 \text{ if } q_{h,i} = t-1 \text{ and } h \text{ is a car, } f_T \text{ if } q_{h,i} = t-1 \text{ and } h \text{ is a truck, and } 0 \text{ otherwise (11)}
\]

Equations 10 and 11 are used to estimate the number of passenger car arrivals to the virtual queue of link \( i \) at time \( t-1 \). \( \phi_h \) is an integer of one if vehicle \( h \) is a car and reaches the virtual queue at time \( t-1 \), \( f_T \) (three) if vehicle \( h \) is a truck and reaches the virtual queue at time \( t-1 \), and zero otherwise.

\[
PS_{i,t-1} = DS_{i,c,t-1} + f_T*DS_{i,T,t-1}
\] (12)

Equation 12 is used to estimate the number of passenger cars on link \( i \) served at time \( t-1 \). It is equal to the sum of the downstream detectors hits by cars, plus those by trucks multiplied by the truck factors.

The above equations represent the recursive functions used to estimate the FLM’s input variables from the raw data of the two detectors sets downstream and upstream the various links. Here, we assume that each link is operated by a separate signal phase.

The vehicular flow on any link \( i \) at time \( t \), \( F_{i,t} \) is estimated from ratio of the vehicular hits on the upstream detectors (away from
the queues downstream the link) to the length of the time interval, \( dt \) as follows:

\[
F_{i,t} = \frac{(US_{i,c,t} + US_{i,T,t})}{dt} \quad (13)
\]

The link blockage, \( B_{i,t} \), is estimated as the length occupied by all the vehicles on link \( i \) at time \( t \) to the total lane length of the link, using equation (14)

\[
B_{i,t} = P_{i,t} \times \frac{l \times 100}{L_i} \quad (14)
\]

Where \( P_{i,t} \) is the total passenger units counts on link \( i \) at time \( t \) (estimated using equation 2), \( l \) is the average length of the passenger car unit, and \( L_i \) is the total lane length of link \( i \).

The truck percentage on link \( i \) at time \( t \) is estimated as the proportion of the truck count to the total vehicular count as shown in equation 15.

\[
T_{i,t} = T_{i,t-1} + US_{i,T,t} - DS_{i,T,t}, \quad T_{i,t,\%} = \frac{T_{i,t} \times 100}{N_{i,t}} \quad (15)
\]

Where \( T_{i,t} \) is the truck counts on link \( i \) at time \( t \), and \( T_{i,t,\%} \) is the truck percentage.

It should be noted here that the assigned green time to the link affects the number of vehicles served and as such all the above traffic measures. The estimated traffic measures (equations 1 through 15) represent the so-called knowledge input to the devised FLM as described hereafter. The fuzzy controller is used to estimate the green splits assigned to each link (phase). The controller is linked as a DLL via a visual basic wrapper with the i-SIM-S simulator for assessment. The details of the i-SIM-S simulator can be found in [5], [6] and [7].

The traffic status estimator (MTSSIMA model; [4]) is mesoscopic in nature and as such does not have the adequate capabilities to model detectors and as such cannot be used to carry on generate the detector data that would be needed for the testing of the fuzzy logic algorithm.

In this paper, vehicle movements are modeled individually, simulated individually in a microscopic car-following model, i-SIM-S ([5], [6] and [7]). I-SIM-S is used in this paper to simulate all studied scenarios, and generate detector data, which are then used by the “traffic status estimator” (with mesoscopic relationships of MTSSIMA) to estimate the inputs to the FLM.

The MTSSIMA formulae were used as part of the traffic status estimator module to estimate the input variables to the FLM, but not in simulating the vehicular movements or detector modeling in any of the conducted simulation-based experiments.

In real life, in applying the FLM in reality, one would not actually need a microscopic simulator (to generate detector data), but would actually use the readings of the field detectors. In such case, there will be no need for the microscopic modeling of detectors through I-SIM-S. Furthermore, in real life, one would actually need the “traffic status estimator” for processing the detectors readings and estimating inputs to the FLM.

**4 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. As shown, the system comprises four rule blocks denoted by PB1, PB2, PB3 and PB4. The two rule blocks RB1 and RB2 complete each other in estimating the green weight. With reference to Figure 1, 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 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 relatively wide range of numerical values. The Defuzzification process is responsible for converting the linguistic terms to numerical crisp values.

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

The system is divided in several rule blocks to avoid the complexity of the system that may result in considering all input variables in one rule block. All variant input variables to the fuzzy system are calculated using the traffic status estimators as indicated earlier by equations 1 through 15.

The FLM estimates a green weight for each phase (as shown in figure 1). This weight is the crisp value obtained by the defuzzification process, and it is a real number representing the “importance” of this particular phase; the higher the weight, the more the green to assign to this phase.

The green split, $g_{i,\phi}$ of any phase $\phi$ is estimated in proportion to the weight of the phase, $W_\phi$ as follows:

$$G_i = C_i - \sum_{\phi=1}^{\Phi} (Y_\phi + AR_\phi)$$  \hspace{1cm} (16)

Where:

- $G_i$: Total actual green time at intersection $i$
- $C_i$: Preset cycle length of signal $i$
- $Y_\phi$: Amber (yellow) time interval of phase $\phi$
- $AR_\phi$: All-red time interval of phase $\phi$
- $\Phi$: Total number of phases
- $W_\phi$: Estimated weight by the FLM for phase $\phi$

$$g_{i,\phi} = G_i \ast \frac{W_\phi}{\sum_{\phi=1}^{\Phi} W_\phi}$$  \hspace{1cm} (17)

Where:

- $g_{i,\phi}$: Actual green time of phase $\phi$ at intersection $i$; estimated from equation (16)
- $W_\phi$: Estimated weight by the FLM for phase $\phi$

5 Simulation-based Analysis Tool

Figure 2 illustrates the simulation-based analysis tool used to assess the effectiveness of the devised FLM for signal control. The analysis tool comprises four main groups of modules; input modules, simulation modules, traffic status estimation modules, and fuzzy logic modules. The data flows among the various modules are illustrated in the figure.

5.1 Simulation Modules

In brief, the simulation module is a mesoscopic model based on macroscopic speed-density relationship indicated by equation 1. Hawas (2002) provides more details on the calibration of these macroscopic relationships in [4]. Vehicle movements along approaches, queues forming, and dissipation are modeled microscopically taken into consideration the phase green times estimated by the fuzzy logic modules (at the beginning of each “cycle” interval).

At each time interval, $t$ (default value is 1 second), the simulation module reports for each approach, and for each vehicle currently on such approach the following measures:

- ID: identification number of vehicles
- Type: type of the vehicle (C: car or T: truck)
• GT: time at which vehicle is generated (seconds)
• QT: time at which vehicle reaches queue (seconds)
• SS: signal status as vehicle reaches stop-line (G: green, R: Red or Y: yellow)
• Qn: order of vehicle in reaching stop-line queue
• ST: time at which vehicle is served (seconds)
• D: vehicle delay (seconds)

In addition, the status of each detector (on approach) is reported by a binary variable (on or off) to replicate the passage of any vehicle along such detector. The detector status is reported each time interval t.

6 Experimental Analyses and Results

To assess the effectiveness of the FLM, several simulation-based scenarios were introduced. A single four-leg intersection is tested with different traffic and geometric characteristics representing different scenarios. 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. In this paper, a 4-phase signal 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. 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.

Table 1 provides description of tested scenario variables. Values used in the “base” Scenario (I) are indicated in the table. This scenario represents a medium congested network. Variants of the base scenario were introduced to capture the effect of the variable changes on the effectiveness of the devised logic. Scenarios II, III, and IV examine the effect of approach vehicular flow.
The logic accounts for fixed phase sequence. In reality, it is mostly clockwise or counterclockwise. Even though the phase sequencing is fixed (to replicate the reality of phase sequencing in the majority of the fixed cycle controllers), the FLM has the ability of phase skipping if there is no demand on any of the phases. 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 simulation results (average vehicle delay) of the various scenarios were assessed using the HCM formulae for coordinated signal settings using Synchro 6 software. HCM (as shown in Figure 3) and the fuzzy-logic experimental model indicated an average vehicle delay of 42.3 and 40.7 seconds, respectively.

---

**Table 1: Summary of tested scenario variables.**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description and Variable Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>I (Base)</td>
<td>Approach Variable&lt;br&gt;Flow (veh/hr) 500 500 500 500&lt;br&gt;Truck Proportion 10 10 10 10&lt;br&gt;Number of Lanes 2 2 2 2&lt;br&gt;Length (m) 500 500 500 500&lt;br&gt;Free Flow Speed (km/hr) 80 80 80 80</td>
</tr>
<tr>
<td>II</td>
<td>Similar to Scenario I with uniform flow of 800 veh/hr</td>
</tr>
<tr>
<td>III</td>
<td>Similar to Scenario I with uniform flow of 200 veh/hr</td>
</tr>
<tr>
<td>IV</td>
<td>Similar to Scenario I with SB flow =1000 veh/hr</td>
</tr>
<tr>
<td>V</td>
<td>Similar to Scenario I with SB truck proportion = 30%</td>
</tr>
<tr>
<td>VI</td>
<td>Similar to Scenario I with SB number of lanes = 1</td>
</tr>
<tr>
<td>VII</td>
<td>Similar to Scenario I with SB approach length = 200 m</td>
</tr>
<tr>
<td>VIII</td>
<td>Similar to Scenario I with SB free flow speed = 60 km/hr</td>
</tr>
<tr>
<td>IX</td>
<td>Similar to Scenario I with SB free flow speed = 40 km/hr</td>
</tr>
</tbody>
</table>
It is to be noted that the system is applicable to “individual” isolated signal controllers, but taking into account the congestion status downstream the intersection.

Further testing and analyses were done to assess the added value of the traffic status estimator. Each of the nine scenarios in table 1 was tested twice; with rule block 2 (of Figure 1) activated, and deactivated. It should be noted that the 2nd rule block inputs are directly driven by the traffic status estimator.

The two systems (with and without the 2nd rule block activated) are referred to herein as WKE and WOKE, respectively. It was found that both systems provide more or less same network productivity expressed as the number of vehicles generated and served by the signal controller. The results of both systems are summarized in Figure 4.

Fig 4 indicates that with the activation of the traffic status estimator (WKE), the overall travel time is generally lesser than of the corresponding values of the (WOKE) system. The most significant difference is noticed with scenario IV, where on intersection approach is heavily congested as compared to the other approaches. In general, Fig.4 indicates better performance of the WKE system as compared to the WOKE one.

Also, the variability of green phase time against different scenarios clearly demonstrates the relationships among the queue length, speed and link counts on one hand, and the resulting green splits on the other hand. When variability are introduced to truck proportion, number of lanes and approach length respectively, it is found that as the truck proportion increases, the FLM assigns more green to the approach phase, as the number of lanes decreases, the FLM allocates more green to avoid long queues and congestion and the lesser the approach length, the shorter the green duration assigned to the approach phase. Results also indicate that the lesser the free flow speed, the higher the assigned green durations.
It should be noted that the green weight of the phase is not a function of the cycle time itself. Rather, it is a function of the input variables (which would indeed get affected by the cycle time and the green times). The FLM does not require any modification to operate on various cycle times as scenario IX was tested with three cycle times; 80, 100 and 120 seconds

7 Conclusions and Future Work

This paper presented a 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 inputs into the FLM. The relationship among the estimated “traffic status” and the FLM’s output variable (green weights) can be set intuitively to a great extent. The intuitive relationships among the input output variables were optimized via sensitivity analyses (testing the most appropriate levels of correlation among input and output variables to minimize overall travel time measures).

The mesoscopic relationships of the traffic status estimator and the I-SIM-S microscopic model were calibrated and verified using a mixed approach comprising the use of field data as well-as data generated by a benchmark well-validated simulator, NETSIM ([4] and [7]). It is legitimate as such to claim that the accuracy and validity of the simulation tools are essential to get accurate estimates of the FLM input variables, and as such effective signal control strategies.

The results presented herein are limited by the accuracy of the input variables, which is affected by the specific settings of the detectors along the approach. More sophisticated knowledge can be formed by considering more than two detectors, and better accuracy can be sought through modifying the detector locations.

References


