A Traffic Signal Controller for an Isolated Intersection using Fuzzy Logic Model

Nada B. AlNaser[1] and Yaser E. Hawas[1,2]

[1]*Roadway, Transportation, and Traffic Safety Research Center (RTTSRC), United Arab Emirates University, Al Ain, U.A.E.*

[2]*Department of Civil and Environmental Engineering, College of Engineering, United Arab Emirates University, Al Ain, U.A.E.*

Keywords: Signalized Intersection, Optimum Methods, Traffic Flows, Fuzzy Logic Model.

Abstract: With the revolution of the new technologies and intelligent transportation systems (ITS) as one category of the artificial intelligent (AI) models, fuzzy logic models (FLMs) were considered as one of the promising methods applied in signalized intersections. In general, results show significant improvements on the efficiency of the traffic networks and intersections. This paper presents a new method of developing an optimal real-time traffic signal controller using the fuzzy logic technique/method (FLM), taking into consideration all various incoming traffic flows. The developed FLM was designed for an isolated intersection with four legs, split phasing, and three different movements (through, right, and left). This research aims at developing an FLM that replicate the control settings of optimized methods. Calibration and validation tests were conducted to ensure accuracy and efficiency of the developed model. Results show that the developed FLM outputs are close to those obtained from optimum methods for traffic signal control systems.

1 INTRODUCTION

The main purpose of traffic engineering is to improve vehicles' movement and traffic safety (Roess, Prassas and Mcshane, 2004). The improvement of the traffic control systems is continues, wherein scholars keep on modifying existing controller, and integrating new ones. Sydney Coordinated Adaptive Traffic System (SCATS), Split Cycle and Offset Optimization Technique (SCOOT), and Fuzzy Signal Control (FUSICO), are of the most well-known and recent applied traffic signal control systems. For example, Sydney Coordinated Adaptive Traffic System (SCATS) shows a reduction in the delay time in cases of low traffic flows (Wolshon and Taylor, 1999). Another type of traffic signal controller is the adaptive traffic signal controller which uses the Approximate Dynamic Programming (ADP), where it shows an improvement of traffic efficiency by reducing vehicle delay time as compared to fixed-time traffic control systems (Cai, Wong and Heydecker, 2009).

Now-a-days, Intelligent Transportation Systems (ITS) as part of Artificial Intelligent (AI) are considered as a promising method in multiple areas of traffic and transportation engineering and management. Such Intelligent Transport Systems (ITS) are mainly applied to improve traffic operation system by enhancing the controller decision-making (Miles and Walker, 2006).

Fuzzy logic systems are considered as one of the applied methods in artificial intelligent systems, which is used to convert human-experience into practical systems (Štencl and Lendel, 2012). Fuzzy sets were presented initially by Lotfi Zadeh in 1965 (Ross, 2004). Applications of the FLM in transportation engineering was presented, describing the four components of FLM namely; fuzzification, fuzzy logic rules, inference engine, and defuzzification (Teodorovic, 1999).

Many of the developed FLM rules can be classified as 'pure fuzzy' models, in which input-output relationships were based on human-knowledge and experience (i.e. developed system for traffic signal controller for an isolated intersection (Pranevičius and Kraujalis, 2012)).

In other models, a genetic algorithm (GA) showed an improvement in the performance of a developed model, in which (GA) was designed and applied for optimizing the membership function and the fuzzy

AlNaser, N. and Hawas, Y.
A Traffic Signal Controller for an Isolated Intersection using Fuzzy Logic Model.
DOI: 10.5220/0007709603960403
In *Proceedings of the 5th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2019)*, pages 396-403
ISBN: 978-989-758-374-2

rules of traffic signal controllers, (Qiao, Yang and Gao, 2011).

Moreover, 'Neuro-Fuzzy, NF' systems or 'Adaptive Neuro-Fuzzy Inference System (ANFIS)' were also applied, and good results were achieved by reducing the average vehicle delay at signalized intersection (Iqbal et al., 2012), and (Seesara and Gadit, 2015).

These FLM for traffic signal controllers were either limited to network parameters (i.e. geometry and number of lanes) or to input-output relationship in the rule block of the FLM controller (i.e. pure fuzzy). This paper presents the development of an FLM controller for a real-time traffic signal controller that can emulate the well-known optimization methods, taking into consideration various incoming traffic flows. Achieving this objective entails: 1) developing a fuzzy logic model, FLM, for a real-time signal control for a defined intersection, and calibrating it using various traffic flows and configurations that would be initially developed using a simulation environment, 2) developing an inference engine ('IF-THEN' logic) of the FLM, 3) testing the developed FLM controller by comparing its output to the output of optimal signal control settings, 4) validating the developed FLM controller using different set of input data (traffic flow combinations).

2 METHODOLOGY AND MODEL DEVELOPMENT

Various techniques and methods are applied for controlling traffic signal systems. In this research, the following sequence of procedures was applied to achieve the defined objective including; design of experiments, development and modelling an isolated intersection using a simulation software, extracting required data from the simulation model that would be used for FLM development (in the fuzzification process, and in the membership function development), FLM model calibration and verification, and finally conclusions and recommendations.

Throughout the literature, a common observation was that many of the developed FLMs were not verified against a well-known signal control optimization method, while in this research, the developed FLM controller was designed using the well-known traffic simulation and analysis model (SYNCHRO), in which the Highway Capacity Manual (HCM) formulae are applied for traffic signal optimization and green time estimations.

As for a base model, an isolated intersection was designed with four approaches (East, West, North, and South). For all operational scenarios, various assumptions were applied regarding control type, geometry, and traffic parameters. This includes; a pre-timed signalized intersection with protected left turn movement and split phasing operation, three shared lanes for each approach (East, West, North, and South) with a length of 500 m and speed of 60 km/h, saturation flow rate of 1900 veh/h/lane. The selected phases were same as the approaches, where each phase would serve a full approach. The percentage distributions of the approach traffic movements for the right, through, and left were 30%, 60%, and 10%, respectively. Also, a peak hour factor (PHF) of 0.92 was used, and 2% as the percentage of heavy vehicles.

The developed FLM is designed to work as a real-time traffic controller which has accessibility to raw field data of each approach, i ($i \in [1, 4]$). This data includes approach real-time traffic flow, v_i, and 95% of approach queue length, Q_i.

Based on these field data, green weight for each phase or approach, GW_i, would be estimated by applying the proposed FLM. The green time allocation for a particular phase, GT_i, could then be determined based on the estimated green weight of that phase, GW_i.

Out of the total cycle time, C, the higher the green weight, GW, the higher the allocated portion of green time, GT, for a specified phase, i.

The developed FLM was calibrated to determine the green weights, GW, that can be obtained using pure optimization methods such as the Highway Capacity Manual (HCM) optimization method.

In order to calibrate the rule base functions of the designed FLM, the following procedures were followed;

1. input variable, v_i, fuzzification,
2. verification of the developed membership function of v_i,
3. design of experiment to ensure covering wide range of approach traffic flows from free flow to grid locks,
4. output determination,
5. fuzzification of output variables, Q_i, GW_i, and C,
6. definition of Input-output relationship,
7. FLM development and calibration, and
8. validation of the developed FLM.

2.1 Input Variable, v_i, Fuzzification

In designing traffic models, field data collection is usually considered as the main input to the designed model. Herein, due to some limitations in the human resources, tools, and time, input data was obtained from a well-known optimization/simulation environment (SYNCHRO). Various traffic flow combinations, for the four approaches (East, West, North, and South), were considered.

The minimum and maximum traffic flow values were determined based on the level(s) of service (LOS) which was presented in Transportation Research Board (TRB), Circular 212 (Transportation Research Board, 1980). Moreover, the v/c ratio was recommended for use in the Canadian Capacity Guide (CCG) for Signalized Intersections (Teply et al., 2008), in which the level of service [LOS] is related to the value of the volume to capacity ratio, v/c. For example; if the v/c ratio is (less than 0.60), then the intersection LOS is defined as [A]. Similarly, LOS [B] represents a v/c ratio range of (0.60 to 0.69), LOS [C] represents a v/cratio range of (0.70 to 0.79), LOS [D] represents a v/cratio range of (0.80 to 0.89), LOS [E] represents a v/c ratio range of (0.90 to 0.99), and finally, the LOS [F] represents a v/c (greater than or equal to 1.00).

Herein, using the assumed values for the lane saturation flow rate, s_i, as 1900 (veh/h/lane) for urban intersections, and the number of lanes, n (3 lanes), the total approach saturation flow, s (veh/h) was calculated by multiplying the lane saturation flow rate, s_i, by the number of lanes, n. This calculated value of the approach saturation flow, s, was determined as 5700 (veh/h).

Assuming equal number of lane groups, and that for the lane group; the saturation flow rate and the approach capacity are equal (5700 pcu/h).

Moreover, due to lane group turning movements consideration (turning movements of 30% right and 10% left), a reduction factor in estimating the approach traffic flow was considered and assumed to be 35%. This value was determined by conducting several simulation runs and experiments. From these experiments, it was found that the assumed reduction factor (35%) gives similar results and estimates of the total intersection v/c ratio using SYNCHRO simulation software.

Based on these findings, the approach traffic flow, v_i, was modified and estimated using following equation;

$$\text{Traffic flow for lane group (approach)}, \mathrm{v_i} \left(\frac{\mathrm{veh}}{\mathrm{h}}\right) = (1-0.35) \times \text{ Intersection v/c} \times \frac{5700(\frac{\mathrm{veh}}{\mathrm{h}})}{4} \qquad (1)$$

By determining various approach traffic flows, v_i, using equation (1) and with correspondence to the different v/c ratios presented in TRB, Circular 212 (Transportation Research Board, 1980), the main input of the proposed FLM, v_i, was determined.

The membership function of the input variable, v_i, was assumed to be distributed into five fuzzy terms (*low*, *medium*, *medium high*, *high and very high*), as shown in Figure 1.

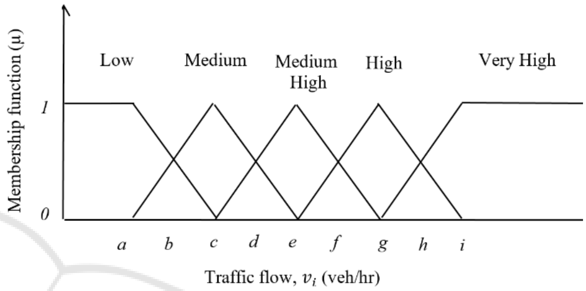

Figure 1: Fuzzification of Input Variable, Traffic Flow, v_i, (The Membership Function).

The traffic flow fuzzy terms of the membership function were defined based on the level of service, LOS, and the corresponding v/c ratio (Transportation Research Board, 1980). For example, the "*Low*" fuzzy term of traffic flow refers to LOS of "A & B", the "*Medium*" fuzzy term of traffic flow refers to LOS of "C", "*Medium High*" refers to LOS of "D", "*High*" refers to LOS of "E", and "*Very High*" fuzzy term of traffic flow refers to LOS of "F".

Using this definition and referring to the v/c ratio, the values of a, c, e, g, and i were determined in terms of (veh/h) as; 324, 695, 787, 880, and 1112, respectively.

In order to ensure covering all different combinations of traffic flows, a total of 289 combinations of approach traffic flow, v_i, were carefully selected covering traffic flow ranges from "*low*" to "*very high*".

2.2 Verification of the Developed Membership Function of Input Variable, v_i,

In order to ensure the validity of the fuzzification process to different v/c ratios, a well-known simulation environment (SYNCHRO) was used to randomly run selected values of v_i. The ICU-LOS as well as the estimated v/c ratio were recorded and compared with the TRB, Circular 212 (Transportation Research Board, 1980). Comparison results shows similarity in these parameter (LOS, and the v/c ratio) as shown in Table 1 below.

Table 1: LOS Comparison between the TRB- Circular 212, and SYNCHRO.

Tested $\boldsymbol{v/c}$	LOS- TRB- Circular 212 (Transportation Research Board, 1980)	ICU LOS (SYNCHRO)
0.3	A	A
0.65	B	B
0.75	C	C
0.85	D	D
0.92	E	E
0.95	E	E
0.99	E	E
1.1	F	F
1.2	F	G
1.4	F	H

2.3 Design of Experiment

After conducting the verification test, a simulation model of a signalized intersection with four legs was developed using the SYNCHRO simulation software, with optimized settings.

A simulation of 289 experimental scenarios covering various levels and combinations of traffic flows among the four approaches (East, West, North, and South) was conducted. These scenarios were carefully selected and simulated as a representation of field data collection, covering all levels of approach traffic flow.

The 289 scenarios were selected to cover all possible LOS's. Initially, only four different levels of fuzzy sets ("*low*", "*medium*", "*medium to high*", and "*high*") were considered for the traffic flow of each approach, where the "high" fuzzy term represents the LOS of "E & F". This resulted in 256 scenarios ($4^4 = 256$). However, in order to differentiate the totally blocked approach traffic flow (LOS "F"), a fifth level term ("*very high*") was considered, and additional 33 different experimental scenarios were considered for simulation.

2.4 Output Determination

For each of the 289 simulation-scenario, and using the traffic simulation software, SYNCHRO, three main outputs (Q_i, GT_i, and C) were obtained and recorded.

A new variable, approach green weight, GW_i, was estimated as the proportion of the approach green time, GT_i, out of the total intersection green time, G.

Figure 2 below represents the rule block (RB) of the fuzzy logic model structure.

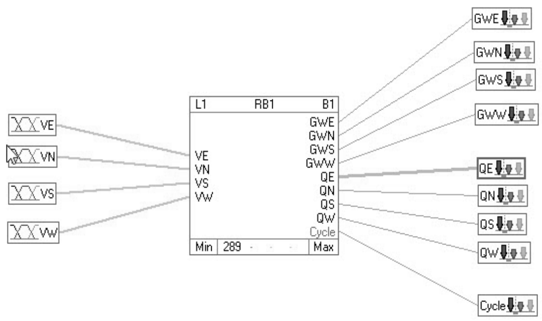

Figure 2: Rule Block (RB) of the fuzzy logic model (FLM).

2.5 Fuzzification of Output Variables, $\boldsymbol{Q_i}$, $\boldsymbol{GW_i}$, and $\boldsymbol{C}$

After conducting the 289 experimental runs, and recording the selected outputs for each experiment, the fuzzification of these outputs was done.

Fuzzification process was mainly done by determining the range of each output variable. The range of the output variable was determined by estimating the absolute difference between the maximum and minimum recorded values out of the 289 experiments. Table 2 shows the minimum and the maximum obtained-values of the output variables.

Table 2: Min and Max Output Values obtained from running the 289 SYNCHRO Simulation Runs.

	C (sec)	Q_i (m)	GT_i (sec)	GW_i
Min. of all approaches	80	24.3	16	0.170
Max. of all approaches	160	179.1	36	0.311

The range of each output variable was then divided into equal selected terms to determine the fuzzy sets for that variable. The membership function was then developed for each output variable as shown in Figure 3 and Figure 4. Where Figure 3 represents the membership function for the 95 percentile approach queue length, Q_i, and approach green weights, GW_i, while Figure 4 represents the membership function for the cycle length, C.

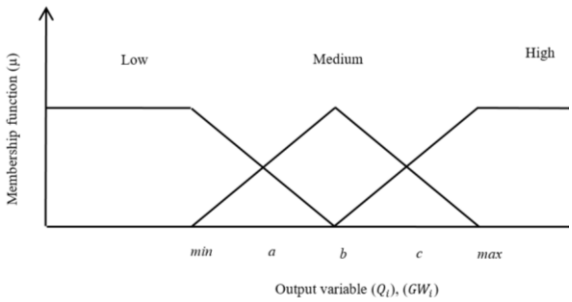

Figure 3: Fuzzification (Membership Function) for the 95 percentile approach queue length, Q_i, output variable, and approach green weight, GW_i.

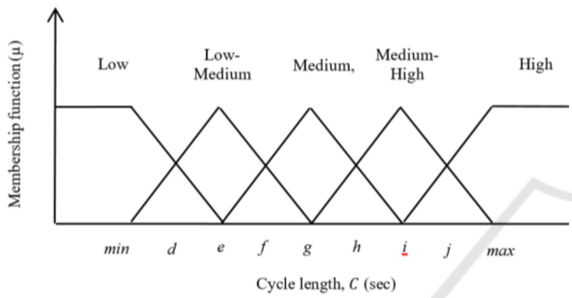

Figure 4: Fuzzification (Membership Function) of the cycle time, C output variable.

The values of a, b, and c shown in Figure 3 were estimated using equations (2), (3), and (4) respectively.

$$a = \min + \frac{1}{4}\ (\max - \ \min) \tag{2}$$

$$b = \ \min + \frac{2}{4}\ (\max - \ \min) \tag{3}$$

$$c = \min + \frac{3}{4}\ (\max - \ \min) \tag{4}$$

The obtained values of a, b, and c for the 95 percentile approach queue length, Q_i, were approximately; 63, 102, and 140 (m), respectively. For the Approach green weights, GW_i, the values of a, b, and c were; 0.205, 0.241, and 0.276, respectively. The fuzzification process of the 95 percentile approach queue length, as well as the approach green weights, GW_i, was done based on “IF-THEN” statements as explained below.

Based on Figure 3, the fuzzification formulae for the 95 percentile approach queue length output variable, Q_i, was integrated as the following equations (eqns. 5 to 9).

$$\text{If } \mathrm{Q_i} \ \le \ \mathrm{Q_{min}},\ \text{then } \mathrm{Q_i} \in \{\mathrm{L}\}, \mathrm{P_{Q_i}}(\mathrm{L}) = 1; \tag{5}$$

If $(\mathrm{Q_{min}} < \ \mathrm{Q_i} < \ \mathrm{Q_b})$, then

$$\mathrm{Q_i} \in \{\mathrm{L}, \mathrm{M}\}: \begin{cases} \mathrm{P_{Q_i}}(\mathrm{M}) = \left(\frac{\mathrm{Q_i} - \mathrm{Q_{min}}}{77.4}\right) \\ \mathrm{P_{Q_i}}(\mathrm{L}) = 1 - \mathrm{P_{Q_i}}(\mathrm{M}) \end{cases} \tag{6}$$

$$\text{If } \mathrm{Q_i} = \mathrm{Q_b},\ \text{ then } \mathrm{Q_i} \in \{\mathrm{M}\}, \mathrm{P_{Q_i}}(\mathrm{M}) = 1; \tag{7}$$

If $(\mathrm{Q_b} < \ \mathrm{Q_i} < \ \mathrm{Q_{max}})$, then

$$\mathrm{Q_i} \in \{\mathrm{M}, \mathrm{H}\}: \begin{cases} \mathrm{P_{Q_i}}(\mathrm{H}) = \left(\frac{\mathrm{Q_i} - \mathrm{Q_b}}{77.4}\right) \\ \mathrm{P_{Q_i}}(\mathrm{M}) = 1 - \mathrm{P_{Q_i}}(\mathrm{H}) \end{cases} \tag{8}$$

$$\text{If } \mathrm{Q_i} \ \ge \ \mathrm{Q_{max}},\ \text{ then } \mathrm{Q_i} \in \{\mathrm{H}\}, \mathrm{P_{Q_i}}(\mathrm{H}) = 1; \tag{9}$$

Similarly, the fuzzification formulae for the approach green weights output variable, GW_i, was integrated using the following equations (eqns. 10 to 14);

$$\text{If } \mathrm{GW_i} \ \le \ \mathrm{GW_{min}},\ \text{ then } \mathrm{GW_i} \in \{\mathrm{L}\}, \mathrm{P_{GW_i}}(\mathrm{L}) = 1; \tag{10}$$

If $(\mathrm{GW_{min}} < \mathrm{GW_i} < \mathrm{GW_b})$, then $\mathrm{GW_i} \in$

$$\{\mathrm{L}, \mathrm{M}\}: \begin{cases} \mathrm{P_{GW_i}}(\mathrm{M}) = \left(\frac{\mathrm{GW_i} - \mathrm{GW_{min}}}{0.07}\right) \\ \mathrm{P_{GW_i}}(\mathrm{L}) = 1 - \mathrm{P_{GW_i}}(\mathrm{M}) \end{cases} \tag{11}$$

$$\text{If } \mathrm{GW_i} = \mathrm{GW_b},\ \text{ then } \mathrm{GW_i} \in \{\mathrm{M}\}, \mathrm{P_{GW_i}}(\mathrm{M}) = 1; \tag{12}$$

If $(\mathrm{GW_b} < \ \mathrm{GW_i} < \ \mathrm{GW_{max}})$, then $\mathrm{GW_i} \in$

$$\{\mathrm{M}, \mathrm{H}\}: \begin{cases} \mathrm{P_{GW_i}}(\mathrm{H}) = \left(\frac{\mathrm{GW_i} - \mathrm{GW_b}}{0.07}\right) \\ \mathrm{P_{GW_i}}(\mathrm{M}) = 1 - \mathrm{P_{GW_i}}(\mathrm{H}) \end{cases} \tag{13}$$

$$\text{If } \mathrm{GW_i} \ \ge \ \mathrm{GW_{max}}, \text{then } \mathrm{GW_i} \in \{\mathrm{H}\}, \mathrm{P_{GW_i}}(\mathrm{H}) = 1; \tag{14}$$

Moreover, the domain of each fuzzy term {minimum, mid, and maximum} was defined as follows;

$\mathrm{Q_i}, \mathrm{GW_i}$ (Low):

$$\{0,\ \min, \min + \frac{2}{4}(\max - \ \min)\} \tag{15}$$

$\mathrm{Q_i}, \mathrm{GW_i}$ (Medium):

$$\{\min,\ \min + \frac{2}{4}(\max - \ \min), \max\} \tag{16}$$

$\mathrm{Q_i}, \mathrm{GW_i}$ (High):

$$\{\min + \frac{2}{4}(\max - \ \min), \max, \max+\} \tag{17}$$

With regards to the cycle length output variable, C, the values of d, e, f, g, h, i, and j were estimated based on simple mathematics, and found to be; 90, 100, 110, 120, 130, 140, and 150 (sec), respectively.

With reference to Figure 4, the fuzzification formulae for the cycle length output variable, C, was integrated as the following equations (eqns. 18 to 26).

$$\text{If } C \le C_{min},\ \text{then } C \in \{L\}, P_C(L) = 1; \tag{18}$$

$$\text{If } (C_{min} < C < C_e), \text{then } C \in \{L, (L{\sim}M)\}: \begin{cases} P_C(L{\sim}M) = \left(\frac{C - C_{min}}{20}\right) \\ P_C(L) = 1 - P_C(L{\sim}M) \end{cases} \tag{19}$$

$$\text{If } C = C_e,\ \text{then } C \in \{L{\sim}M\}, P_C(L{\sim}M) = 1; \tag{20}$$

$$\text{If } \left(C_e < C < C_g\right), \text{then } C \in \{(L{\sim}M), M\}: \begin{cases} P_C(M) = \left(\frac{C - C_e}{20}\right) \\ P_C(L{\sim}M) = 1 - P_C(M) \end{cases} \tag{21}$$

$$\text{If } C = C_g,\ \text{then } C \in \{M\}, P_C(M) = 1; \tag{22}$$

$$\text{If } \left(C_g < C < C_i\right), \text{then } C \in \{M, (M{\sim}H)\}: \begin{cases} P_C(M{\sim}H) = \left(\frac{C - C_g}{20}\right) \\ P_C(M) = 1 - P_C(M{\sim}H) \end{cases} \tag{23}$$

$$\text{If } C = C_i,\ \text{then } C \in \{M{\sim}H\}, P_C(M{\sim}H) = 1; \tag{24}$$

$$\text{If } (C_i < C < C_{max}), \text{then } C \in \{(M{\sim}H), H\}: \begin{cases} P_C(H) = \left(\frac{C - C_i}{20}\right) \\ P_C(M{\sim}H) = 1 - P_C(H) \end{cases} \tag{25}$$

$$\text{If } C \ge C_{max},\ \text{then } C \in \{H\}, P_C(H) = 1; \tag{26}$$

The range for each fuzzy term of the, C, variable {minimum, mid, and maximum} was defined as follows:

$$C\ (L): \{0, \min, \min + \tfrac{2}{8}(\max - \min\} \tag{27}$$

$$C\ (L{\sim}M): \{\min, \min + \tfrac{2}{8}(\max - \min), \min + \tfrac{4}{8}(\max - \min)\} \tag{28}$$

$$C\ (M): \{\min + \tfrac{2}{8}(\max - \min), \min + \tfrac{4}{8}(\max - \min), \min + \tfrac{6}{8}(\max - \min)\} \tag{29}$$

$$C\ (M{\sim}H): \{\min + \tfrac{4}{8}(\max - \min), \min + \tfrac{6}{8}(\max - \min), \max\} \tag{30}$$

$$C\ (H): \{\min + \tfrac{6}{8}(\max - \min), \max, \max +\} \tag{31}$$

2.6 Definition of the Input-Output Relationship

After running the 289 different experimental tests in SYNCHRO, and following the developed fuzzification process for the input variable as well as the output variables, the input-output relationship was formed.

One of the most common methods in defining the input-output relationship is 'Pure Fuzzy Logic' where input-output relationship is actually developed based on experience and experts' opinion.

In order to ensure replicating actual optimized real-time traffic control methods, the input-output relationship in this research was determined based on the 289 conducted tests in SYNCHRO. That is, for each simulation run, a new (if-then) rule was obtained and added to the rule block of the fuzzy logic.

By the end, a total of 289 if-then rules were coded for the membership function of the FLM rule block.

2.7 Fuzzy Logic Model Development and Calibration

The proposed fuzzy logic model was developed using a specialized software, FuzzyTECH. Input and output variables, as well as the rule block, were defined and integrated based on the designed FLM as discussed in this paper.

By developing the designed FLM, a calibration process was conducted to measure the difference between the developed FLM system and the HCM optimized methods (SYNCHRO). Where the same 289 scenarios, which were used in SYNCHRO simulation model, were again applied and imported in the developed FLM using the FuzzyTECH software.

The obtained results from the FLM were then compared with the SYNCHRO results using descriptive statistical methods. Both difference and percentage difference between the two model outputs' (FLM and SYNCHRO) were estimated. Mainly, the cycle time, C, and green times using the green weights' estimates, GW, of the FLM were used in the comparison for the calibration test.

The main criteria which was applied and followed in the calibration stage was that; the average percentage difference between the FLM output and SYNCHRO output should not exceed the confidence interval, which was considered here as 10.

The obtained results showed that the average percentage difference between the FLM and SYNCHRO for each of the cycle time, C, and green times, GT_i output parameters were 6% and 7.7%, respectively, which are lesser than the 10% (the considered confidence interval).

As the developed FLM was subjected to calibration test and passed the acceptance criteria (percentage difference between the FLM and SYNCHRO did not exceed the confidence-interval), the calibration test was finalized and ended.

2.8 Validation of the Developed Fuzzy Logic Model

Validation test is considered as a standard practice in developing new models, in which a new set of input data is used in the developed model for validation purpose.

In this research a validation test was conducted by comparing the output results obtained from both; the developed FLM and the simulation model (SYNCHRO), using a new set of input data (traffic flows).

The new set of input data was randomly selected, covering various levels of traffic flow (ranging from low to very high traffic flows). This data was then applied in the simulation model (SYNCHRO), with the similar parameters (geometric, traffic, and control), which were used initially in designing the model.

The main considered outputs from the validation test that would be considered in the assessment of the developed FLM were; the cycle time and green times for each of the four approaches. The acceptance criteria which was used in the validation test was similar to the one that was applied before in the calibration stage. That is; the absolute value of the average percentage difference between the FLM and SYNCHRO outputs should not exceed the confidence interval (a confidence interval of 10% was used).

After running the validation test, output data was recorded and analysed. Comparison among the results indicated that absolute percentage difference between the FLM and SYNCHRO outputs for each of the cycle time (%Δ C), and the approach green times (%Δ GT_i) were 3.5%, and 3.3%, respectively, which were lesser than the 10% (the selected confidence interval).

By completing this stage, it can be concluded that the developed FLM is valid and can replicate the optimized measures of traffic signal control models, such as SYNCHRO.

3 DISCUSSIONS AND CONCLUSIONS

In this study, a Fuzzy Logic Model, FLM, is developed to act as an optimized real-time traffic signal controller, for all traffic conditions from free flow to highly congested flow. It can be used as a base model to which other parameters could be added. For example, in urban areas, pedestrian traffic could significantly affect the control settings. The optimal can be easily modified to include pedestrian flow as input. The rule block can be adjusted to consider the pedestrian priority. Other factors might be considered as well, such as presence of priority or emergency vehicles, etc.

The approach traffic flow is considered as the main input for the developed FLM. The outputs are the cycle time, C, and the approach green time, GT_i. The membership of the FLM rule block (the Input-Output relationship) is developed based on data collected from a real-time traffic simulation software, SYNCHRO. Using such simulation software (that follows optimized methods e.g. HCM) ensures the accuracy of collected data in optimized settings. Moreover difficulties and deficiencies, faced during real-life data collection, in covering various combinations of different levels of traffic flow at a signalized intersection are overcome.

With regards to the developed FLM, the input variable, v_i, is based on the definition of LOS with correspondence to the v/c ratio, where. $v_i$is then fuzzified by characterizing the LOSs with five fuzzy terms.

A total of 289 different traffic scenarios are simulated in SYNCHRO and output data is recorded. The rule block of the proposed FLM is then defined based on the recorded data from SYNCHRO.

Calibration test is conducted, in which output results of both SYNCHRO and the developed FLM are similar, with a minor accepted difference (6% and 7.7%, as an average percentage difference for the cycle time, C, and green times, GT_i, respectively).

Further, a new set of input data is tested to ensure the validity of the developed FLM in replicating optimum traffic signal control settings. Results prove the validity of the proposed FLM, where the absolute percentage difference between the FLM and SYNCHRO outputs are 3.5%, and 3.3%, for %ΔC, and %ΔGT_i respectively.

Results show that using the developed FLM for controlling traffic signals with optimized conditions is promising as it proved its' ability to provide optimal solution for all different traffic flow combinations.

During all model development stages, including; the simulation, calibration, and the validation processes, some assumptions were used such as; geometry of the intersection, type of the traffic controller, etc. Future work might consider using different or additional parameters such as pedestrians.

ACKNOWLEDGEMENTS

This research has been partially funded by UAE University fund 31R030.

REFERENCES

Roess, R., Prassas, E., Mcshane, W., 2004. *Traffic Engineering*, Pearson Prentice Hall. New Jersey, 3rd edition.

Wolshon, B., Taylor, W., 1999. Analysis of intersection delay under real-time adaptive signal control. *Transportation Research Part C*, vol. 7, pg 53-72.

Cai, C., Wong, C., & Heydecker, B., 2009. Adaptive traffic signal control using approximate dynamic programming. *Transportation Research Part C*, vol. 17, pg 456–474.

Miles, J., Walker, A., 2006. The potential Application of Artificial Intelligence in Transport. *IEEE Proceedings Intelligent Transport Systems*, vol. 153, Issue 3, pg 183-198.

Štencl, M., Lendel, V., 2012. Application of selected artificial intelligence methods in terms of transport and intelligent transport systems. *Periodica Polytechnica Transportation Engineering*, vol. 40, No. 1, pp. 11-16.

Ross, T., 2004. *Fuzzy Logic with engineering applications*, John Wiley & Sons Inc. England, 2nd edition.

Teodorovic, D., 1999. Fuzzy logic systems for transportation engineering: the state of the art. *Transportation Research Part A*, vol. 33, pg 337-364.

Pranevičius, H., & Kraujalis, T., 2012. Knowledge based traffic signal control model for signalized intersection. *Transport*, vol. 27, no. 3, pg 263–267.

Qiao, J., Yang, N., & Gao, J., 2011. Two-Stage Fuzzy Logic Controller for Signalized Intersection. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 41, no.1, pg 178 - 184.

Iqbal, Md., Zahin, A., Islam, Z., Kaiser, M., 2012. Neuro-Fuzzy based adaptive traffic flow control system. *International Conference on Communications, Devices and Intelligent Systems (CODIS)*, pp. 349-352.

Seesara, S., Gadit, J., 2015. Smart Traffic Control Using Adaptive Neuro-Fuzzy Inference System (ANFIS). *International Journal of Advance Engineering and Research Development (IJAERD)*, vol. 2, issue 5, pg. 295-302.

Transportation Research Board, 1980. Interim Materials on Highway Capacity- Transportation Research Circular No. 212. Washington, D.C.

Teply, S., Allingham, D., Richardson, D., Stephenson, B., and Gough, J. (Editor), 2008. *Canadian capacity guide for signalized intersections*, Institute of Transportation Engineers, & Transportation Association of Canada, 3rd ed. ch.4, pp 99-100.