THE APPLICATION OF FUZZY LOGIC ON SHORT TERM TRAFFIC PREDICTION FOR AUTOMATIC TOLL GATE CONTROL

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abstract : In this research, fuzzy logic concept is applied to develop a model of short term traffic prediction. The model combines the observed present and previous traffic volume with the historical traffic pattern as a base for prediction. Hourly traffic volume is used as a control period and historical data is utilized to build rules in Fuzzy Associative Memory. Two deffuzzification methods are implemented to obtain the best prediction model. In validating the model, Root Mean Square, Mean absolute Percentage and Quality Comparison are used as evaluation criteria. The evaluation shows that the predicted traffic resulted from the model developed with fuzzy logic has better outcome with higher accuracy.

1. INTRODUCTION

Toll Plazas of freeway constitute potential bottlenecks, and the congestion they bring out can be serious enough to warrant the consideration of alternative plaza designs and operating strategies. This congestion often occurs on weekends and holidays due to huge traffic volumes. This situation leads the toll operator to improve their service, especially in reducing waiting time due to long queue by effectively managing the toll gates.
At this time the toll gates are equipped with automatic traffic counter to obtain the number of vehicles in real time. Unfortunately, the use of this facility is limited only to secure the toll revenue. In order to meet the toll user satisfaction and to develop toll system toward an Integrated Traffic Systems with IVHS technology, an efficient and reliable facility for operational management is absolutely compulsory.

In the conventional way, the toll operators determine the number of toll gate that will be opened for a specific period based on historic traffic volume.

One of the potential solutions is to implement automatic control toll gate systems. This system can help the operator to manage the number of toll gate in an easy manner. At operational level, this automatic control toll gate system, should be supported by an efficient and effective traffic prediction method that can predict traffic volume accurately and in real time manner for a specific period.

The work reported in this paper describes a method to predict short term traffic volume by using fuzzy logic method which is first part of the research.

2. METHOD OF TRAFFIC PREDICTION

Traffic prediction is one of the most important aspects for highway operation, such as, ramp control metering, toll gate operation etc. There are several conventional methods which have been used in practice. First, method that uses traffic data directly from traffic counter, where some constraints have been identified with this method. Second, method that uses traffic pattern variation or historical average. In this method, statistically, traffic volume is expressed in a specific pattern based on time zone in a day or days in a week. A large deviation in prediction is often obtained by using this method due to uncertain traffic fluctuation for same period. Third, Urban Traffic Control System (UTCS) method which uses traffic pattern variation as a basis of prediction. The formula used in UTCS are as follows :

$$Nf_n = Nm_n + \gamma\left(Nm_{n-1} - Nr_{n-1}\right) + \sum_{s=0}^{n-1} \alpha^s\left(Nr_{n-s-1} - Nm_{n-s-1}\right) +$$

$$\gamma(1-\alpha)\sum_{s=0}^{n-2} \alpha^s\left(Nr_{n-s-2} - Nm_{n-s-2}\right) \qquad (1)$$

where,

Nf_n = predicted traffic volume at instant n
Nm_n = historical traffic volume at instant n
Nr_n = measured traffic volume at instant n
α = traffic constant
γ = adjustment coefficient
s = number of prediction conducted
n = prediction period

The above model is based on the difference between predicted and historical traffic volume. Combinations of α and γ affect the performance of the system and they are very specific for each case.

3. FUZZY CONCEPTS

A feature of crisp logic or conventional logic is typically the “black or white” reasoning; that is, either a fact holds true or it does not, and nothing else. In science, this way of thinking is unavoidable. However, information given by human, in most practical cases, is not as precise as it should be. It seems more reasonable to assign a transition buffer from complete exclusion to absolute inclusion. These problems lead us to what is now called fuzzy logic (Zadeh, 1987).

Fuzzy logic systems base their decisions or inputs in the form of linguistic variables derived from membership functions. These membership functions are formulae used to determine fuzzy set to which a value belongs and the degree of membership in that set. The variables are then matched with the preconditions of IF-THEN rules (fuzzy-logic rules), and the response of each rule is obtained through fuzzy implication. To perform compositional rule of inference, the response of each rule is weighted according to the confidence or degree of memberships of its inputs. The centroid of the responses is then calculated to generate the appropriate output.

At present, there is no systematic procedure for the design of fuzzy logic systems (Hsiao et.al., 1994). Conventional approaches have sought to subjectively define membership functions and rules by studying existing systems and then testing the design for proper output. The membership functions and/or rules are then adjusted when the design fails its test. In general, the development of fuzzy system can be divided further into three stages, namely, fuzzification, fuzzy inference and defuzzification (Chang and Wang, 1994), as shown in Figure 1.

3.1 Fuzzification

The fuzzification is a mapping from the crisp inputs into fuzzy subsets. The fuzzier decides the corresponding degrees of membership functions from the crisp inputs. The resulting fuzzy values are then fed into the fuzzy inference engine.

3.2 Fuzzy inference

The inference compositional rule is mostly adopted in the fuzzy inference (Zimmerman, 1991). The fuzzy rule base contains a set of IF-THEN fuzzy rules. The output is obtained from the data input and fuzzy relation.

3.3 Defuzzification

The defuzzification process generates crisp outputs from the fuzzy results. Output membership functions may be discrete or continuous. The weighted average defuzzification is mostly used for discrete membership functions. The commonly used continuous defuzzification strategies are centroid of area and mean of maximum.

4. DEVELOPMENT OF TRAFFIC PREDICTION SYSTEM.

There are three stages conducted in the development of the proposed system ;

4.1 Traffic Prediction Method.

The approach used in predicting traffic with fuzzy logic is to compare traffic volume obtained directly from traffic counter and the traffic pattern obtained from historical data. Diagramatically, Figure 2 represents the concept of the developed model in this research.

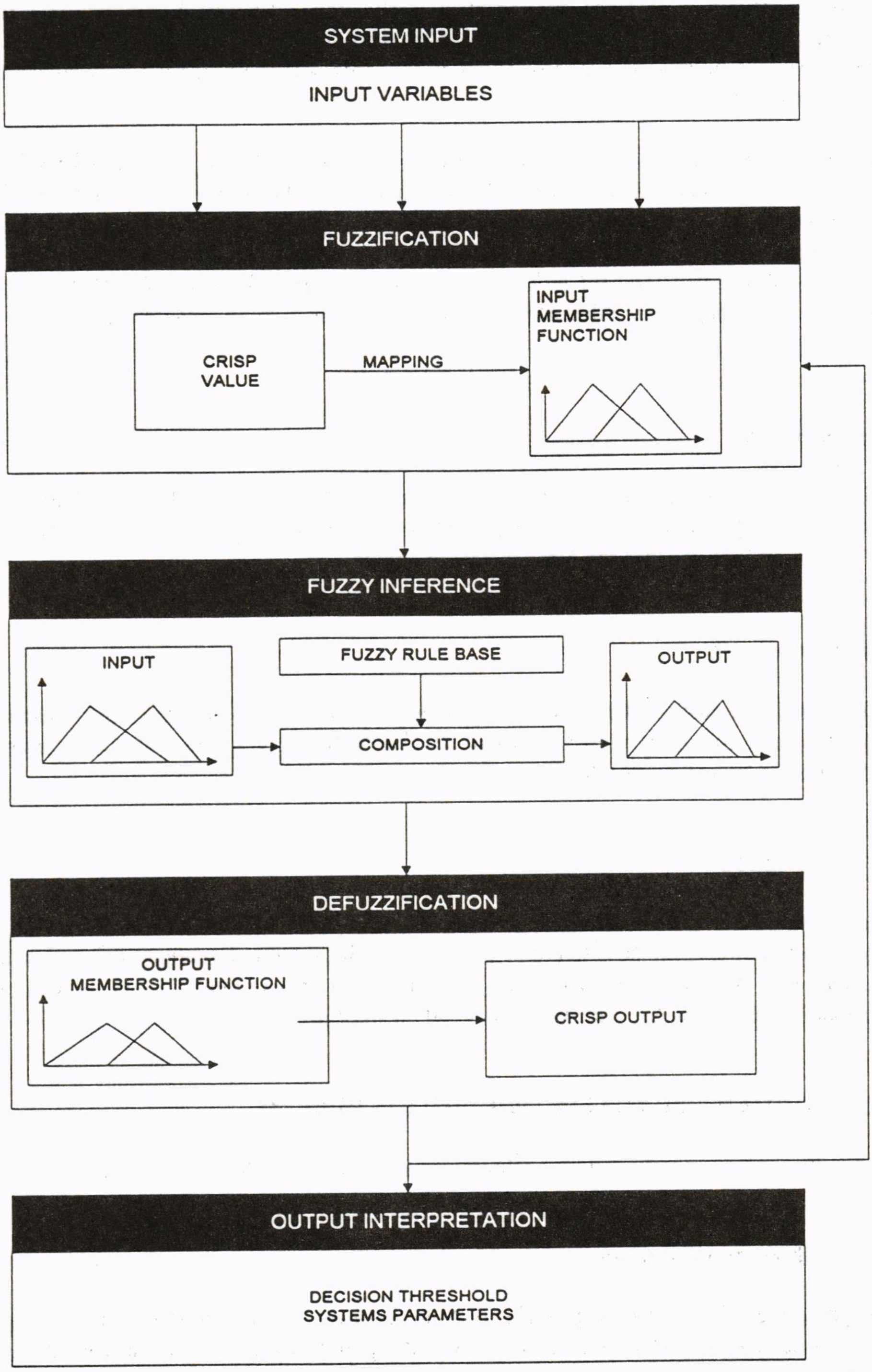

Figure 1. System Development Process.

Using historical traffic pattern as a basis, a coefficient variation, J, is calculated by comparing measured traffic volume of preceding hour for a specific period, $Nr_{(n-1)}$, (hourly basis is used as a control period) with historical data for the same period, $Nm_{(n-1)}$. The coefficient variation, J, is calculated with the following formulae (Iokibe et.al., 1993) :

$$J = \frac{Nr_{(n-1)}}{Nm_{(n-1)}} \qquad (2)$$

where,

J = Coefficient Variation
$Nr_{(n-1)}$ = Measured traffic volume of preceding hour
$Nm_{(n-1)}$ = Historical Traffic pattern at same period

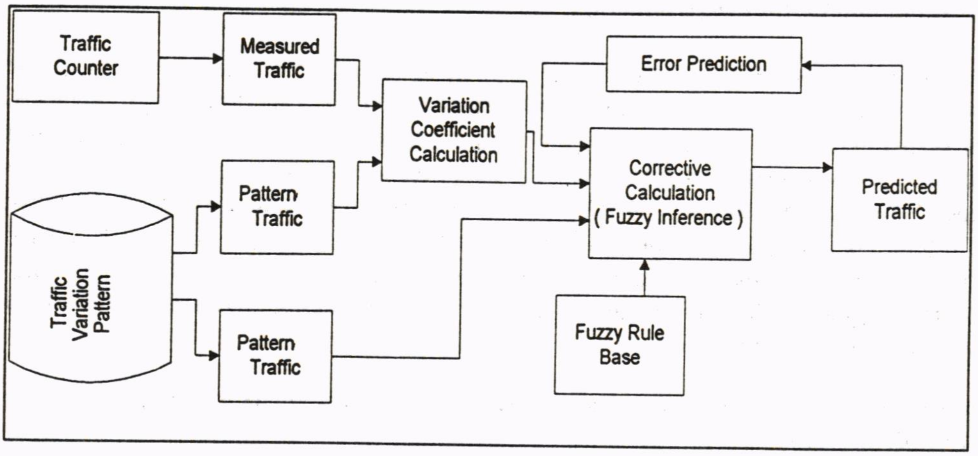

Figure.2. Flow of the Development of Traffic Prediction System (Iokibe et.al, 1993).

Simultaneously, the coefficient variation and prediction error are corrected with the current traffic pattern from the historical data, in order to obtain the predicted traffic. Coefficient variation determines the magnitude of measured traffic influence to the predicted traffic for the same control period. Further, during inference process, the coefficient variation, J, and the current traffic pattern from the historical data, $Nm_{(n)}$, are fuzzified to obtain the predicted traffic, $Nf_{(n)}$. In order to minimize prediction error and dependency on the historical traffic pattern, an updating technique to the predicted traffic is used. The mathematical formulation of this technique is given as :

$$Nf_{(n)corrected} = Nf_{(n)predicted} + \Delta N_{required} \qquad (3)$$

where,

$Nf_{(n)corrected}$ = Predicted traffic after correction
$Nf_{(n)predicted}$ = Predicted traffic
$\Delta N_{required}$ = the required change

By Fuzzy logic, $Nf_{(n)}$ is obtained from the result of inference process with an additional input, that is, prediction error from preceding control period, ε_p, which is given as :

$$\varepsilon_p = \frac{1}{s}\sum_{n=1}^{s}\frac{Nf_{(n-1)} - Nr_{(n-1)}}{Nr_{(n-1)}} \tag{4}$$

where,

ε_p = mean prediction error of preceding period
$Nf_{(n-1)}$ = predicted traffic of preceding period
$Nr_{(n-1)}$ = measured traffic of preceding period
s = number of predictions conducted.

4.2 Input and Output Determination

In one domain, for input or output, usually consists of several fuzzy subsets. In this case the input/output domain consists of control fuzzy set and state fuzzy set. Referring to Figure 2, there are three inputs, namely, J, $Nm_{(n)}$ and ε_p, and one output $Nf_{(n)}$. For input J, the control fuzzy set is divided into five subsets and the state fuzzy set has a range of 0.0 to 2.0. For input $Nm_{(n)}$, control fuzzy set is divided into six subsets and the state fuzzy set has a range of 0.0 to 3,600 vehicles per hour. In similar way for input ε_p, control fuzzy set is divided into five subsets and the state fuzzy set has a range of -0.1 to 0.1. While for output $Nf_{(n)}$, control fuzzy set is divided into six subsets and the state fuzzy set has a range of 0.0 to 3,600 vehicles per hour.

Based on experience, the following guidance is used to determine membership function curve (Earl, 1992) :

- Membership function for each control fuzzy set is overlapped
- The overlapped area has range of 10% to 50%
- The number of overlapped points is smaller than 1 (one)
- The shape of control fuzzy set is triangular or trapezoidal

Based on the above guidance, the control fuzzy sets are determined as shown in Table 1 and Figure 4,5, 6 and 7 show the J, Nm, ε_p and N_f membership functions respectively.

Table 1. Fuzzy Set Values

Fuzzy Variables			
Coefficient Variation (J)	Traffic Pattern (N_m)	Prediction Error (ε_p)	Traffic Prediction (N_f)
Very Small (ZE)	Free-flow (ZE)	Negative Large (NB)	Free-flow (ZE)
Small (S)	Very Light (SS)	Negative Small (NS)	Very Light (SS)
Equal (M)	Light (SB)	Zero (ZE)	Light (SB)
Large (B)	Moderate (M)	Positive Small (PS)	Moderate (M)
Very Large (BB)	Heavy (BS)	Positive Large (PB)	Heavy (BS)
	Very Heavy (BB)		Very Heavy (BB)

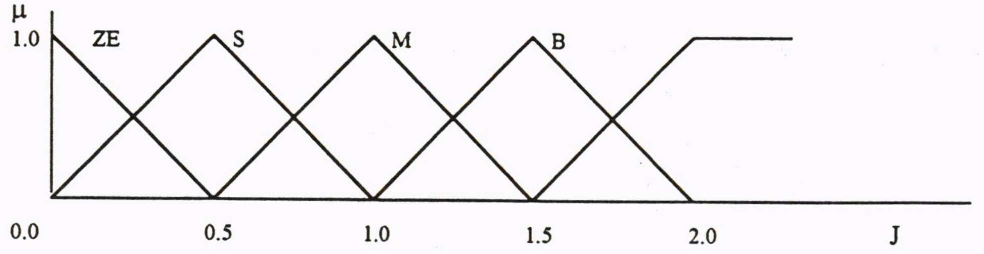

Figure 4. *J* Membership Functions

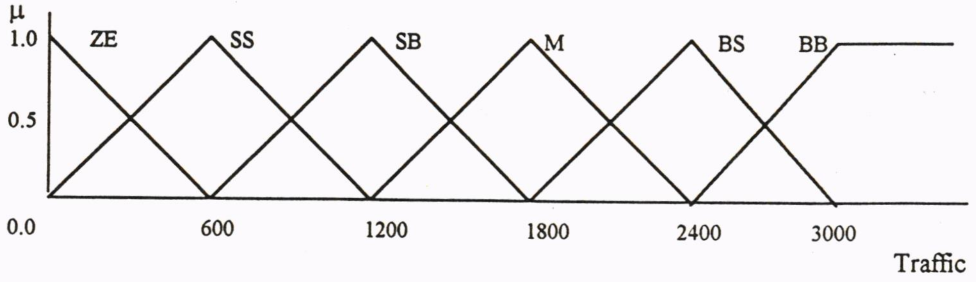

Figure 5. N_m Membership Functions

4.3 Rules Determination and Defuzzification Methods

4.3.1 Rules Determination

There is no systematic procedure to determine rules which maps input to output. Rules determination is based on the logic and experience of the designer and it is unique for each designer. For the purpose of this research, rules in the fuzzy associative memory (FAM) within the developed software have been tested by trial and error. This will be displayed at the initiation of the process, without a need to make a change. However, this does not hinder the possibility of changing the rules.

As mentioned in the previous discussion, there are three input variables, namely, J, N_m, ε_p, which, each of them is divided into 5, 6 and 5 control fuzzy sets, respectively. Consequently, there are 5x6x5 = 150 rules that should be developed to handle all possibilities of input combination, and then all these rules are stored in the FAM Bank.

In general, These fuzzy rules are developed with the following approaches :

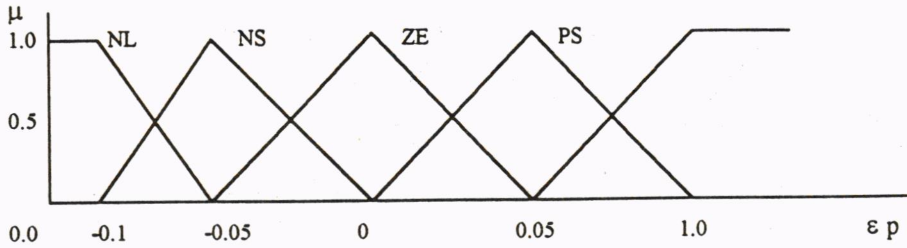

Figure 6. ε_p Membership Functions

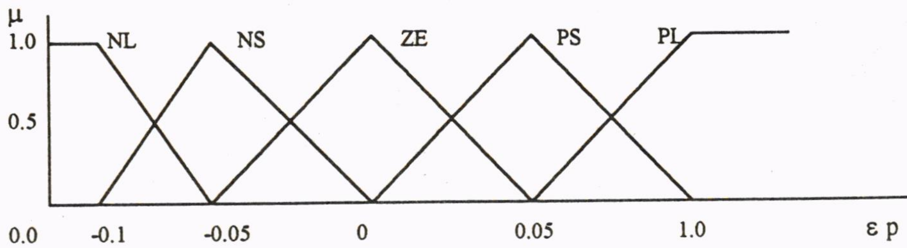

Figure 7. N_f Membership Functions

1. If J approaches 1.0, and if N_m is N, and if there is no ε_p, then N_f should be close to N without any correction.
2. If J approaches 1.0, and if N_m is N, and if there is ε_p, then N_f should be close to N with a correction.
3. If J less than 1.0, and if N_m is N, and if there is no ε_p, then N_f should be less than N without any correction.
4. If J less than 1.0, and if N_m is N, and if there is ε_p, then N_f should be less than N with a correction.
5. If J larger than 1.0, and if N_m is N, and if there is no ε_p, then N_f should be more than N without any correction.
6. If J larger than 1.0, and if N_m is N, and if there is ε_p, then N_f should be more than N with a correction.

4.3.2 Selection of Defuzzification Method

In designing the system, Center of Gravity (Centroid) and Mean of Maximum (MOM) method are selected as defuzzification method. Since the membership function curves are symmetrical and the correlation-minimum inference technique is used, the Centroid formula can be simplified as follows ;

$$x = \frac{\sum m_i m_{oi}(x)}{\mu_{oi}} \tag{5}$$

where,

x = crisp value
m = control mean value
I = control area index
μ = degree of membership
o = ouput fuzzy set

While for MOM defuzzification method, crisp value can be obtained by searching the mean value of the largest activated control fuzzy set.

All the steps discussed above are coded in a software written in *Visual Basic* ver.3.0. Further the program is entitled "FUZTRAPSYS" and it works under *Windows* environment.

5. SYSTEM VALIDATION AND ANALYSIS

A trial on to the model is conducted to observe the performance of fuzzy logic application on the system and to see the effectiveness and reliability of the system itself. In slightly detailed level, the test is carried out to see the level of achievement of the system by utilizing measured traffic volume and different historical traffic pattern. Furthermore, the predicted traffic resulted from Centroid and MOM method, is compared with that of the Historical Average (HA) method and that of the UTCS-2 method. In the testing process, Root Mean Square Estimate (RMSE), Mean absolute Percentage Estimate (MAPE) and Quality Comparison (Q-ratio) are used as evaluation criteria ;

$$MAPE(\%) = \frac{1}{s}\sum_{t=1}^{s}\left|\frac{Nf_n - Nr_n}{Nr_n}\right| \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{s}\left(Nf_n - Nr_n\right)^2}{s}} \tag{7}$$

Q-ratio is used to measure the quality of historical data with the following rules :

- If measured values are larger than that of predicted ones, then ;

  Q = measured/predicted (8a)

- If predicted values are larger than that of measured ones, then ;

  Q = predicted/measured (8b)

The Q-ratio criteria are very important to the achievement of the system, because the inverse of this value determines the level of accuracy of the system.

In general, the level of achievement of the system in the trial, is affected by the influence of the historical traffic pattern to the measured traffic. The more the historical traffic pattern influences the measured traffic, the better the system is, or in other word, the error of traffic prediction is smaller compared with the actual traffic. This phenomena is valid for both conventional method and fuzzy logic based method.

As an example, Table 2 shows the result of the test, where the predicted traffic is compared with the historical data for selected work day and Table 3 shows the other test, where the predicted traffic is compared with the historical data for the same day as measured traffic (average value). It is seen that the average error prediction resulted from the Centroid method is smaller than that of conventional methods, consequently, the accuracy of prediction is higher. While the average error prediction resulted from MOM method shows inconsistency results compared with the conventional methods.

Table 2. Comparison of measured traffic with historical work-day traffic.

	Centroid	MOM	UTCS-2	H.A
MAPE	11.0002	21.4414	15.7951	22.2317
Q - Ratio	1.11873	1.28438	1.16355	1.26529
RMSE	280.849	452.077	500.413	551.899

Table 3. Comparison of measured traffic with historical traffic.
(same day as measured traffic)

	Centroid	MOM	UTCS-2	H.A
MAPE	10.9038	20.0978	15.6093	22.5246
Q - Ratio	1.11378	1.25924	1.15835	1.25973
RMSE	266.371	437.919	478.915	594.224

From the test result, it is seen that the developed system is able to predict traffic volume for the next hour, although the measured traffic has a significant deviation to the traffic pattern.

6. CONCLUSIONS

The following conclusions can be drawn :

- The developed system is able to predict traffic volume in hourly basis.
- The Centroid method shows that the accuracy of prediction is higher than that of conventional method.
- The Centroid method gives better results than the MOM method does.
- The use of historical traffic pattern of the same days with the measured traffic will gain a better result.

7. FURTHER RESEARCH.

The second stage of the research is now undergoing, where the time basis for prediction is slightly modified from hourly into 15 minute period, and furthermore, the second modul of the software which is concerned with the operational characteristic of toll Gate is still being developed by utilizing queueing properties. Once this stage is finished, the next stage will be incorporating both modules into one package.

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