Adaptive Freeway Ramp Metering and Variable Speed Limit Control: A Genetic-Fuzzy Approach

***Abstract*—This paper deals with the problem of ramp metering along with speed limit control of the freeway networks in order to reduce the peak hour congestion. An adaptive fuzzy control is proposed to solve the problem. To calibrate the fuzzy controller, genetic algorithm is used to tune the fuzzy sets parameters so that the total time spent in the network remains minimum. A macroscopic traffic model is used for tuning the controller in an adaptive scheme and for presenting the simulation results. The proposed method is tested in a stretch of a freeway network. To evaluate the efficiency of the method, the test results are examined and compared with traditional ALINEA controller and genetic-fuzzy ramp metering only case. The paper concludes that the proposed adaptive genetic-fuzzy control is expected to enhance the

Digital Object Identifier 10.1109/MITS.2009.932718

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performance of the freeway traffic network control while keeping the computational simplicity of the problem.

Index Terms – Ramp metering, variable speed limit control, fuzzy control, genetic algorithm.

I. Introduction

The expansion of car-ownership in many countries all over the world has led to daily occurrence of congestion in urban networks. The significant proportions of urban roads are freeways which carry a huge traffic volume every day. The freeway traffic management system is intended to reduce the congestion and its negative impacts such as safety problems, pollution and worsening the quality of life by using an appropriate traffic management and control. Several methods have been developed to improve the performance of freeway networks. Among them control strategies such as ramp metering, speed limits, and route recommendation are recognized as the most effective ways to relieve freeway traffic congestion.

Ramp metering is the most widely used type of freeway traffic control. The set-up consists of a traffic light placed at the entrance of the freeway. During the green phase only one vehicle is allowed to enter the freeway. Therefore, ramp metering is expected to prevent traffic breakdown by adjusting the metering rate such that the traffic density of the main flow remains below the critical value. Many algorithms have been applied so far to adjust the metering rate, some of them are mostly empirical, and others are based on the optimization algorithm. The fixed-time ramp metering [1], the demand-capacity strategy [2] and ALINEA [3] are very popular among other traditional strategies. On the other side, Model Predictive Control (MPC) [4] and nonlinear optimal ramp metering method proposed by [5] Kotsialos et al. (2002) are presented in the literature as an advance optimization based methods. A more detailed overview of ramp metering is reported in [6].

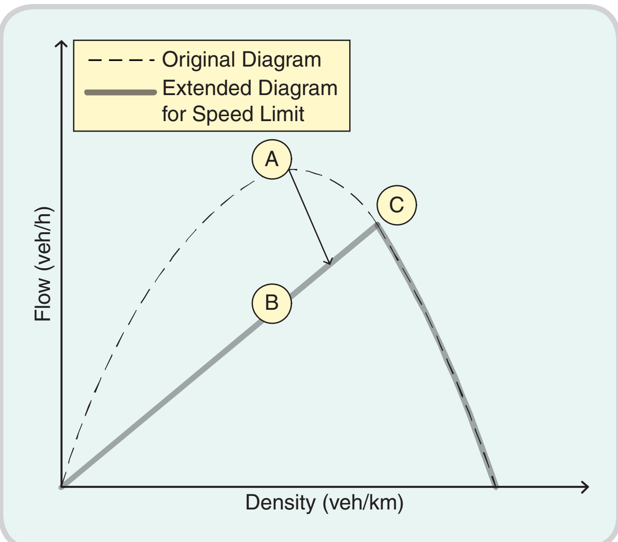

FIG 1 Speed limits change the flow state from A to somewhere between B and C.

Beside the ramp metering, the variable speed limits are recently considered as a tool for traffic breakdown prevention apart from their traditional application for traffic homogenization. In this case the speed limits lower than the critical speed (the speed corresponding to the maximum flow) is used. As propose in [4], the speed limits can complement the ramp meter when the traffic is highly congested.

Fuzzy logic algorithms appear to be suitable for traffic control application, because they can handle systematically inaccurate information e.g. inexact traffic model and sensor noisy measurements. Moreover, they are relatively simple for implementation in practice. The application of fuzzy control in freeway ramp metering control is reported in [7] and [8].

In this paper we use fuzzy control to deal with the problem of coordinated ramp metering and variable speed limit control which has the potential of reducing the traffic congestion in freeway with reasonable computational effort. The genetic algorithm is used to adaptively tune the fuzzy sets parameters using a macroscopic traffic model.

This paper is organized as follows. In Section II, the problem description is presented. In Section III, the basics of the fuzzy controller used in this study are introduced. In Section IV, the traffic flow model is introduced. The tuning process is explained in section V. The proposed method is applied to a benchmark problem in section VI. Finally, the conclusions are stated in Section VII.

II. Problem Description

We consider the problem of finding the best control settings for a group of controllers in a traffic network consisting of a ramp meters and variable speed limit signs. The control objective is to minimize the Total Time Spent (TTS). Ramp metering is the most widely used freeway traffic control method around the world. However, this approach is not so effective when the traffic demand is too high that ramp meter cannot relief the congestion by itself especially in situation where the capacity of ramp is limited which is the case in most of the practical applications. Adjusting speed limit through variable speed limit signs could partially address this issue and improve the effectiveness of the ramp metering system, as shown in [4]. The speed control changes the shape of the fundamental diagram (Fig. 1: reproduced from [4]). The speed limiters located just before the on-ramp segment can help reduce the outflow of the controlled segments, so that there will be some space left to accommodate the traffic from the on-ramp. Consequently, the density in the on-ramp area remains near the capacity, the outflow remains high and the breakdown could be prevented. Therefore, a combination of ramp metering and variable speed limit control has the potential to achieve better performance. Moreover, with different controllers working together, coordination among the controllers is essential to achieve a good performance.

The nonlinear and non-stationary behavior of traffic makes the modeling procedure extremely difficult. Therefore, many traditional models force the non-linear system into linear context with precision loss [7]. In addition, modern optimal control techniques have the complexity problem for implementing in real world applications. Meanwhile, fuzzy logic algorithms appear to be suitable for the real-world traffic problems because they can regulate nonlinear, stochastic and time delayed systems (like traffic systems), while keeping robustness and computational simplicity. Because of these promising features of fuzzy controller, we consider the application of this type of control in the problem of freeway ramp metering and speed limit control.

III. Fuzzy Ramp Metering and Variable Speed Limits

Fuzzy control is a successful alternative to the control problem of challenging systems, since it provides a systematic heuristic approach in constructing a nonlinear controller. In fuzzy control the rule base logic presents linguistic knowledge and human expertise for fuzzy sets; therefore, the practical experiences of operators can be systematically included. Because rules can be easily defined, changed and removed, they can be easily developed and modified. Furthermore, fuzzy controller inherently allows smooth transition of control signals that is an important feature. These valuable features have caught the attention of researcher in traffic control area to use fuzzy control.

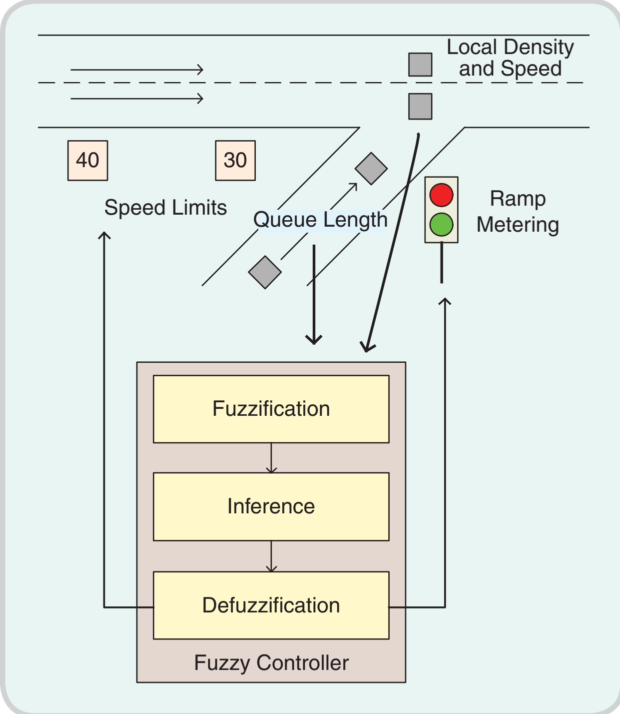

FIG 2 Fuzzy ramp metering and variable speed limit control.

To develop a fuzzy controller for ramp metering and variable speed limits, some input information that corresponds to the traffic conditions of controlled area is needed.

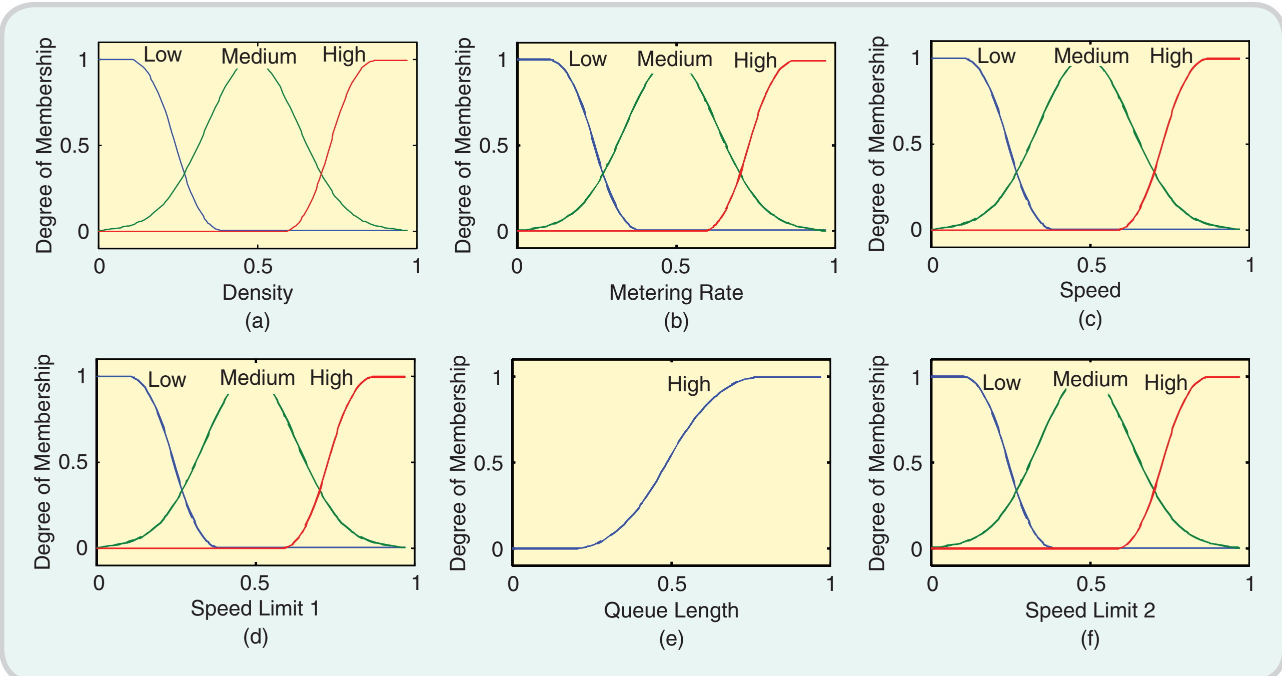

FIG 3 Initial normalized membership functions for inputs and outputs variables.

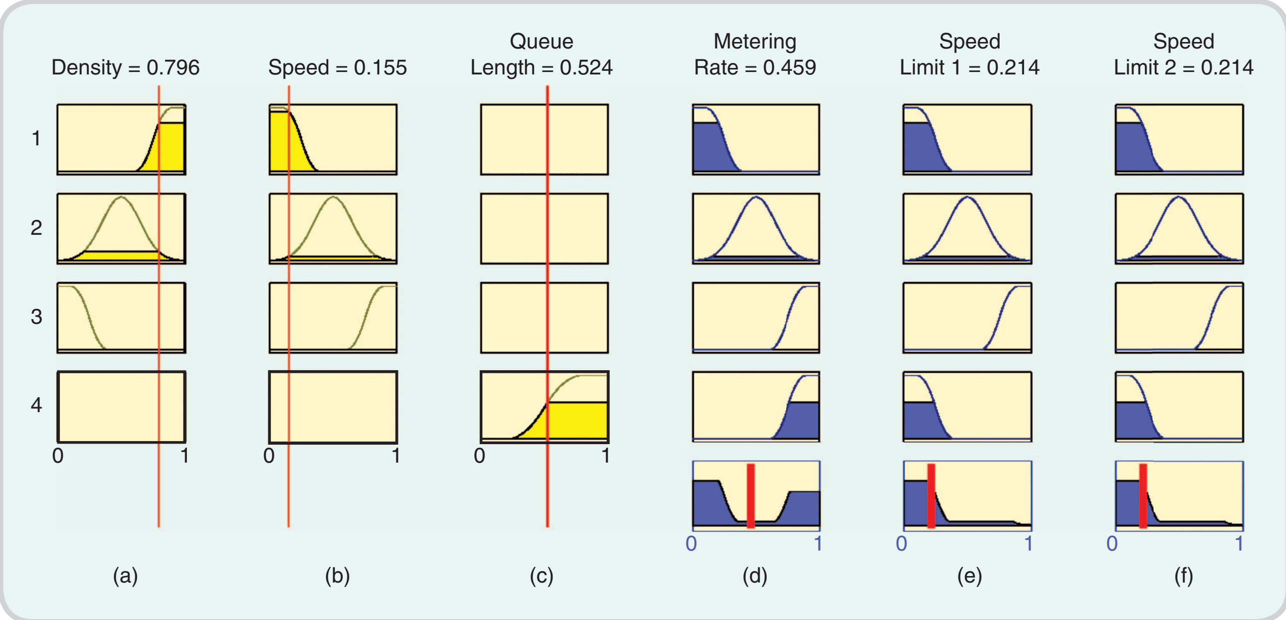

FIG 4 An example shows how input variables convert to output variable via the three fuzzy controller steps.

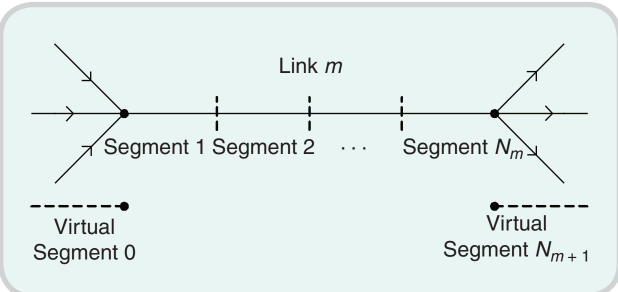

FIG 5 METANET model: link and node configuration.

In this paper, the local density and local speeds of mainstream flow at the vicinity of ramp plus the queue length of on-ramp are considered as the input data. The outputs of fuzzy controller are the metering rate and the two dynamic speed limits that are displayed on the freeway segments (Fig. 2). In the next part the three major components of a fuzzy controller are explained.

Table 1. Implemented rules for the fuzzy ramp metering and speed limit controller.

Antecedent	Consequent
If density is high and speed is low	Metering rate is low, speed limit 1 is low and speed limit 2 is low
If density is medium and speed is medium	Metering rate is medium, speed limit 1 is medium and speed limit 2 is medium
If density is low and speed is high	Metering rate is high, speed limit 1 is high and speed limit 2 is high
If queue length is high	Metering rate is high

A. Fuzzification

The first stage inside the controller block in Fig. 2 is fuzzification block which transforms crisp input values into grades of membership for linguistic terms of fuzzy sets. This procedure determines how well the particular input matches the conditions of the rules.

In our case, there are three measured inputs for the fuzzy on-ramp and dynamic speed controller which must be fuzzified. The local density and local speed are measured just where the on-ramp is located on the main road. Three different values "low", "medium" and "high" describe the density and speed variables and the queue length is described by the term "high". Also the output variables have to be fuzzified. The metering rate and two variable speed limits are the outputs which the terms "low", "medium" and "high" are assigned to. The Z-function, Gaussian distribution function and S-function are taken for membership function of "low", "medium" and "high" respectively. Fig. 3 shows the initial normalized membership function of each variable used in the structure of control.

B. Inference

The core of a fuzzy system is the part, which combines the facts obtained from the fuzzification with the rule base, and conducts the fuzzy reasoning process. The rules are based on expert opinions, operator experiences and system knowledge. Basically, these rules have the following format.

If <antecedent1> and/or <antecedent2 >...
Then <consequent1>, <consequent2>...

All rules are evaluated in parallel based on fuzzy set theory that describes interpretation of the logical operations such as the complement, intersection and unions of sets. For complementation, one minus the membership function has been chosen. AND and OR operations corresponds to the minimum and maximum functions respectively.

The consequent of a fuzzy rule assigns an entire fuzzy set to the outputs. This fuzzy set is represented by a membership function that is chosen to indicate the qualities of the consequent. Therefore each rule has a nonzero degree overlapping with other rules. To combine the inference results of these rules the aggregation method is used.

The rules for our controller were determined from expert knowledge and evaluation of simulation results. The rule-base for fuzzy ramp metering and variable speed limits is shown in Table 1.

A. Defuzzification

After the aggregation process, there is a fuzzy set for each output variable that needs to be converted into a single number (defuzzification process). For the defuzzification of both the ramp meter rate and the value of speed limiters, the center of gravity (COG) function is used.

Fig. 4 shows the procedure of how sample inputs convert to the outputs in fuzzy ramp metering and speed limit control through the three fuzzy steps (for more details about the fuzzy control refer to [9]).

In this paper the fuzzy control is implemented in Matlab using fuzzy toolbox [10].

IV. Macroscopic Traffic Flow Model

The traffic flow model adopted here is the destination independent METANET model (see [5] for more details) and an extension to the model for speed limits (see [4] for more details). This model is used in tuning procedure of controllers' parameters to finely adjust the fuzzy controller.

The METANET is a macroscopic traffic model that is discrete in both space and time. The model represents the network by a directed graph with the links corresponding to freeway stretches, as illustrated in Fig. 5. A freeway link (m) is divided into (N_m) segments (indicated by the index i) of length ($l_{m,i}$) and by the number of lanes (n_m). Each segment (i) of link (m) at the time instant $t = kT, k = 0, \ldots, K$ is macroscopically characterized by the *traffic density* $\rho_{m,i}(k)$ (veh/lane/km), the *mean speed* $v_{m,i}(k)$ (km/h) and the *traffic volume* $q_{m,i}(k)$ (veh/h). The time step used for simulation is denoted by T. The following equations describe the evolution of the network for each segment i of link m at each time step k. Each link has uniform characteristics i.e. no on-ramp or off-ramp and no major changes in geometry. The nodes of the graph are placed between links where the major changes, such as on-ramps and off-ramps in road geometry occur. Table 2 describes the notations related to the METANET model.

Table 2. Notation used in METANET model.

m, μ	Link index
i	Segment index
T	Simulation step size
k	Time step counter
$\rho_{m,i}(k)$	Density of segment i of freeway link m (veh/km/lane)
$v_{m,i}(k)$	Speed of segment i of freeway link m (km/h)
$q_{m,i}(k)$	Flow of segment i of freeway link m (veh/h)
N_m	Number of segments in link m
n_m	Number of lanes in link m
$l_{m,i}$	Length of segment i in link m (km)
τ	Time constant of the speed relaxation term (h)
κ	Speed anticipation term parameter (veh/km/lane)
υ	Speed anticipation term parameter (km^2/h)
a_m	Parameter of the fundamental diagram
$\rho_{\mathrm{crit},m}$	Critical density of link m (veh/km/lane)
$V(\rho_{m,i}(k))$	Speed of segment i of link m on a homogeneous freeway as a function of the density $\rho_{m,i}(k)$
$\rho_{\max,m}$	Maximum density (veh/km/lane) of link m
$v_{\mathrm{free},m}$	Free-flow speed of link m (km/h)
$w_o(k)$	Length of the queue on on-ramp o at the time step k (veh)
$q_o(k)$	Flow that enters into the freeway at time sep k (veh/h)
$d_o(k)$	Traffic demand at origin o at time step k (veh/h)
$r_o(k)$	Ramp metering rate of on-ramp o at time step k
Q_o	On-ramp capacity (veh/h)
δ	Speed drop term parameter caused by merging at an on-ramp
n	Node index
Q_n	Total flow that enters freeway node n (veh/h)
I_n	Set of link indexes that enter node n
O_n	Set of link indexes that leave node n
β_n^m	Fraction of the traffic that leaves node n via link m
$v_{\mathrm{control},m,i}$	Speed limit applied in segment i of link m (km/h)
α	Parameter expressing the disobedience of drivers with the displayed speed limits

The traffic stream models that capture the evolution of traffic on each segment at each time step are shown in (1)–(8) (Table 3). The node equations that represent the relation between the connected links are given in (9)–(12), (Table 4), which show how the traffic flow that enters a node is distributed to the emanating links.

V. Adaptive Tuning

Because the fuzzy controller with the predefined setting parameters cannot adequately cope with the disturbances (such as inconsistent traffic demand pattern) and changes in traffic system (weather condition, incidents or road maintenance), we use genetic algorithm to adaptively tune the fuzzy sets parameters based on a METANET model and predicting the performance of the system in a short horizon every five minutes. Fig. 6 shows the diagram of the control system along with the tuning section. In this structure the parameter of

Table 3. Link equations and description.

$q_{m,i}(k) = \rho_{m,i}(k) v_{m,i}(k) n_m$	(1)	Flow-density-speed equation
$\rho_{m,i}(k+1) = \rho_{m,i}(k) + \frac{T}{l_{m,i} n_m}[q_{m,i-1}(k) - q_{m,i}(k)]$	(2)	Conservation of vehicles
$v_{m,i}(k+1) = v_{m,i}(k) + \underbrace{\frac{T}{\tau_m}\{V[\rho_{m,i}(k)] - v_{m,i}(k)\}}_{\text{Relaxation Term}} + \underbrace{\frac{T}{l_{m,i}} v_{m,i}(k)[v_{m,i-1}(k) - v_{m,i}(k)]}_{\text{Convection Term}} - \underbrace{\frac{\vartheta_m T}{\tau_m . l_{m,i}} \frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa_m}}_{\text{Anticipation Term}}$	(3)	Speed dynamic Relaxation term: drivers try to achieve desired speed $V(\rho)$. Convection term: Speed decrease or increase caused by inflow of vehicles. Anticipation term: the speed decrease (increase) as drivers experience the density increase (decrease) in downstream.
$V[\rho_{m,i}(k)] = v_{\text{free},m} \exp\left(-\frac{1}{a_m}\left(\frac{\rho_{m,i}(k)}{\rho_{\text{crit},m}}\right)^{a_m}\right)$	(4)	Speed-density relation (fundamental diagram)
$w_o(k+1) = w_o(k) + T(d_o(k) - q_o(k))$	(5)	Origins' queuing model
$q_o(k) = \min\left[d_o(k) + \frac{w_o(k)}{T}, Q_o . r_o(k), Q_o \frac{\rho_{\max,m} - \rho_{m,1}(k)}{\rho_{\max,m} - \rho_{\text{crit},m}}\right]$	(6)	Ramp outflow equation The outflow depends on the traffic condition in the main-stream and also on the metering rate, $r_o(k) \in [0,1]$
$V(\rho_{m,i}(k)) = \min \left\{ \begin{array}{c} v_{\text{free},m} \exp\left(-\frac{1}{a_m}\left(\frac{\rho_{m,i}(k)}{\rho_{crit,m}}\right)^{am}\right), \\ (1+\alpha) v_{\text{control},m,i}(k) \end{array} \right\}$	(7)	Speed limit model The desired speed is the minimum of the speed determined by (4) and the speed limit, which is displayed on the variable message sign (VMS).
$-\frac{\delta T q_o(k) v_{m,1}}{l_{m,i} n_m (\rho_{m,1}(k) + \kappa)}$	(8)	Speed drop caused by merging phenomena. If there is an on-ramp then the term must be added to (3)

Table 4. Node equation and descriptions.

$Q_n(k) = \sum_{\mu \in I_n} q_{\mu, N_\mu}(k)$	(9)	Total traffic flow enter node n
$q_{m,0}(k) = \beta_n^m(k) . Q_n(k)$	(10)	Traffic flow that leaves node n via link m
$\rho_{m,N_{m+1}}(k) = \frac{\sum_{\mu \in 0_n} \rho_{\mu,1}^2(k)}{\sum_{\mu \in 0_n} \rho_{\mu,1}(k)}$	(11)	Virtual downstream density, when node n has more than one leaving link
$v_{m,0}(k) = \frac{\sum_{\mu \in I_n} v_{\mu,N_\mu}(k) . q_{\mu,N_\mu}(k)}{\sum_{\mu \in I_n} q_{\mu,N_\mu}(k)}$	(12)	Virtual upstream speed, when node n has more than one entering link

METANET model can be changed over the time in order to accurately consider the characteristics of real traffic system if any unusual changes occur.

A. Genetic Algorithm

The origin of genetic algorithm was found in the studies for simulating the mechanism of the natural evolution and selection by John Holland. By adopting such concepts borrowed from nature, genetic algorithms are able to evolve optimal solutions to a large variety of problems. Genetic algorithm starts with an initial set of random solutions called population. Each individual in the population is called a chromosome, representing a solution to the problem. The evolution operation simulates the process of Darwinian evolution to create population from generation to generation by selection, crossover and mutation operations. The success of genetic algorithm is founded in its ability to keep existing parts of solution, which have a positive effect on the outcome [11].

The two parameters of Z-Shape, Gaussian and S-shape fuzzy set for inputs and outputs variables are changed by the genetic algorithm. Therefore, a total of 32 values for a controller are coded. To compromise between computation time and precision, the 30 individuals are selected.

After creating a new population the fitness value has to be calculated for each member in the population and then ranked based on the fitness value. The genetic algorithm selects 'parents' from the current population by using a selection probability. Then the reproduction of 'children' from the selected parents occurs by using recombination and mutation. The cycle of evaluation, selection and reproduction terminates when the convergence criteria is met.

In this paper the genetic algorithm toolbox implemented in Matlab is employed [12].

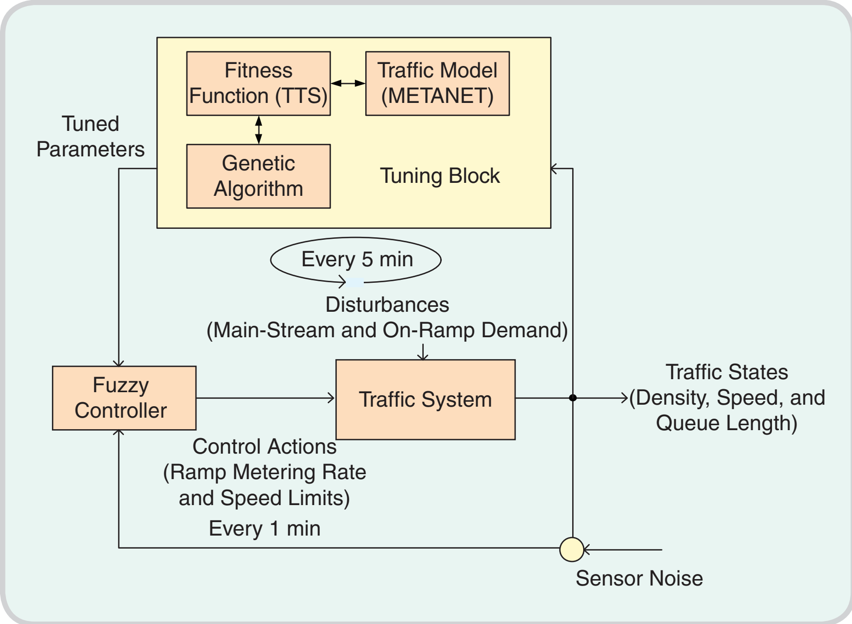

FIG 6 Adaptive genetic-fuzzy control block diagram.

B. Fitness Function

An objective function that is often used in the literature ([6]) is the total time spent (TTS) by all vehicles in the freeway network. It has been proven that the minimization of the TTS results in the maximization of the network output. The precise cost criterion is as follows:

$$J(k) = T\sum_{j=k}^{k+h-1}\left\{\sum_{m,i}\rho_{m,i}(j)l_{m,j}n_m + \sum_{o} w_o(j)\right\} + a_w\sum_{o}\Psi[w_{\text{ramp}}(j)]^2 \tag{13}$$

$$\Psi[w_{\text{ramp}}(j)] = \max\{0, w_{\text{ramp}}(k) - w_{\text{ramp,max}}\}, \tag{14}$$

where the first two terms of (13) correspond to the mainstream travel time and delay associated with origins' queue respectively. The prediction horizon, h is defined heuristically to be seven minutes. The last term which is weighted by a non-negative weighting factor enables the control strategy to limit queue lengths at the on-ramp to be less than the maximum level. Since the fuzzy controller allows smooth transition in the control signal, we eliminate the terms that penalize abrupt changes in the ramp metering and speed limit control signals.

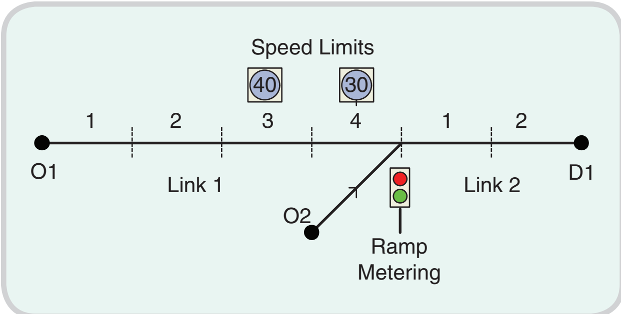

FIG 7 Benchmark network with one on-ramp metering and two speed limits control.

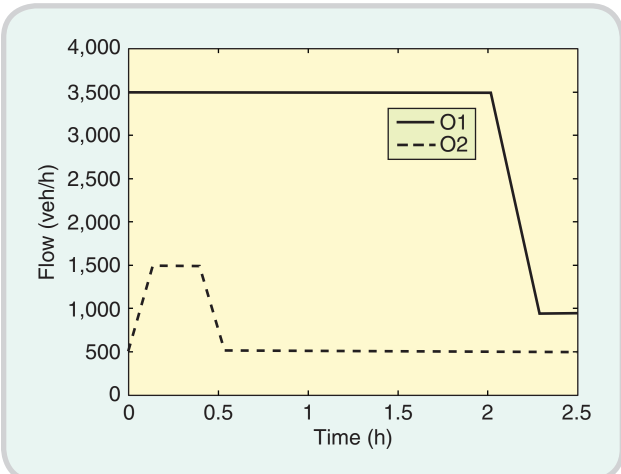

FIG 8 The demand profiles of the simulation.

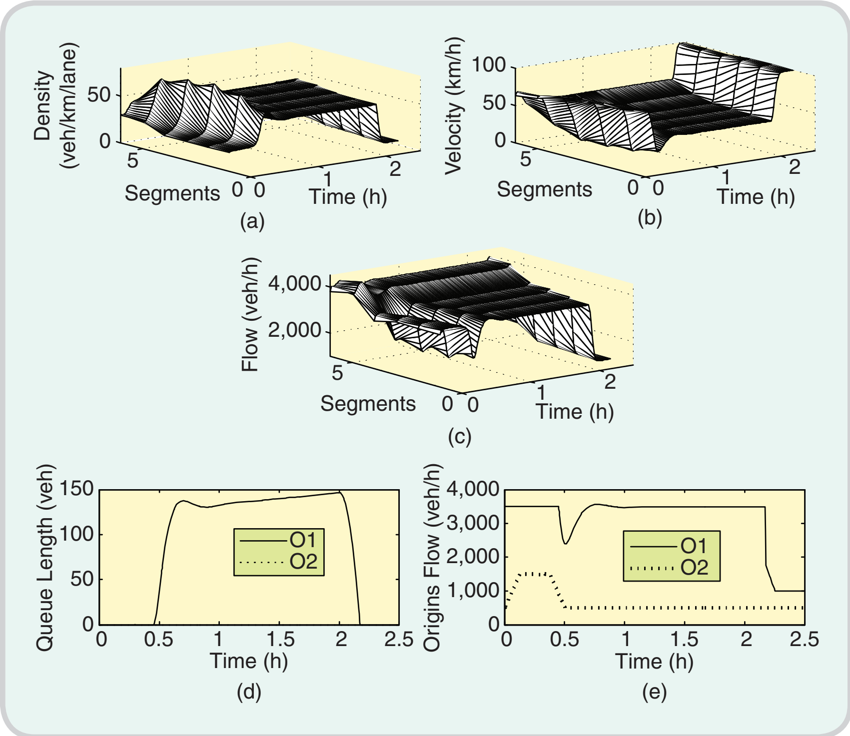

FIG 9 The simulation results for the no-control case: (a) segments traffic density, (b) segments traffic speed, (c) segments traffic flow, (d) origins queue length, (e) origins flow.

VI. Case Study

This section presents the description of a benchmark network and simulation results of different scenarios. The performance of genetic-fuzzy ramp metering and variable speed limits is compared with the no-control case, ALINEA and genetic-fuzzy ramp metering only case. The relevant quantity for comparing is the total time spent (TTS) on the network, i.e., the lower the TTS, the higher the performance of the scenario.

A. Benchmark Network

In order to assess the performance of genetic-fuzzy ramp metering and variable speed limits, a stretch of 6km long consisting of six segments of 1km each, similar to case study proposed in [4] is considered as a case study in this paper (see Fig. 7). The network consists of two origins including a main-stream and an on-ramp. O_1 is the main origin connected to the link L_1. The freeway link L_1 has two lanes with a capacity of 4000 veh/h. The last two segments of link L_1(segments 3 and 4) are equipped with VMS where speed limits are applied. At the end of link L_1 a single-lane metered on-ramp (O_2) with a capacity of 2000 veh/h is attached. The studied freeway follows via the link L_2 with two lanes and two segments to the destination D_1.

In order to prevent the spill-back of queue to the surface street, we limit the maximum queue length at O_2 to the 150 vehicles. The networks parameters as stated in [13] are as follows:

$$T = 10\text{ s},\ \tau = 18\text{ s},\ \kappa = 40\text{ veh/lane/km},\ \vartheta = 60\text{ km}^2\text{/h},$$
$$\rho_{\max} = 180\text{ veh/lane/km},\ a_1 = a_2 = 1.867\ \text{ and}$$
$$\rho_{\text{crit}} = 33.5\text{ veh/lan/km},\ v_{\text{free}} = 102\text{km/h}.$$

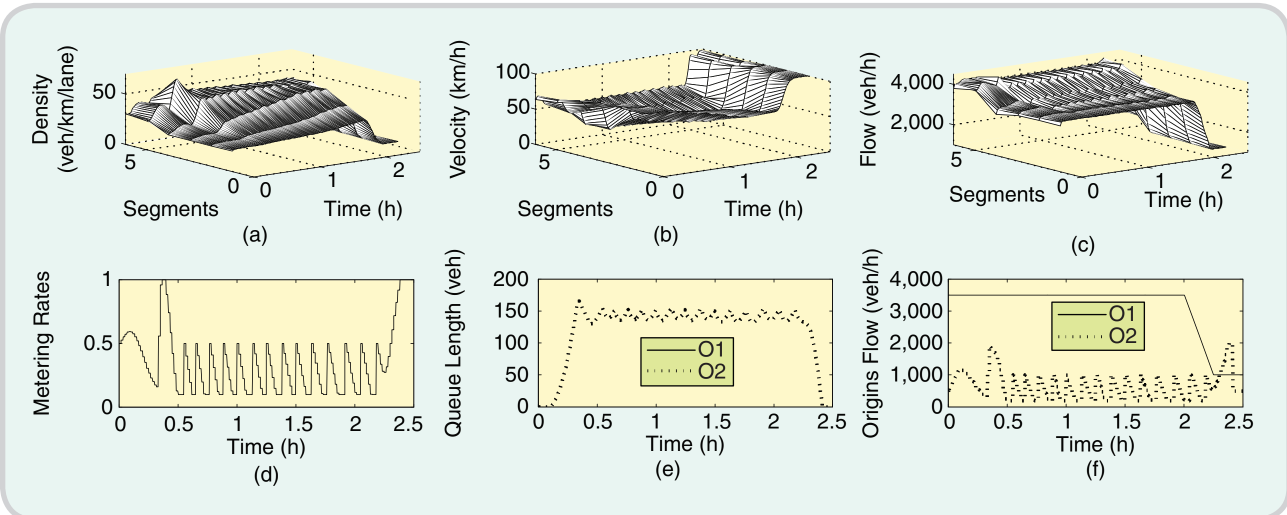

FIG 10 The simulation results for the ALINEA ramp metering case: (a) segments traffic density, (b) segments traffic speed, (c) segments traffic flow, (d) optimal ramp metering rate, (e) origins queue length, (f) origins flow.

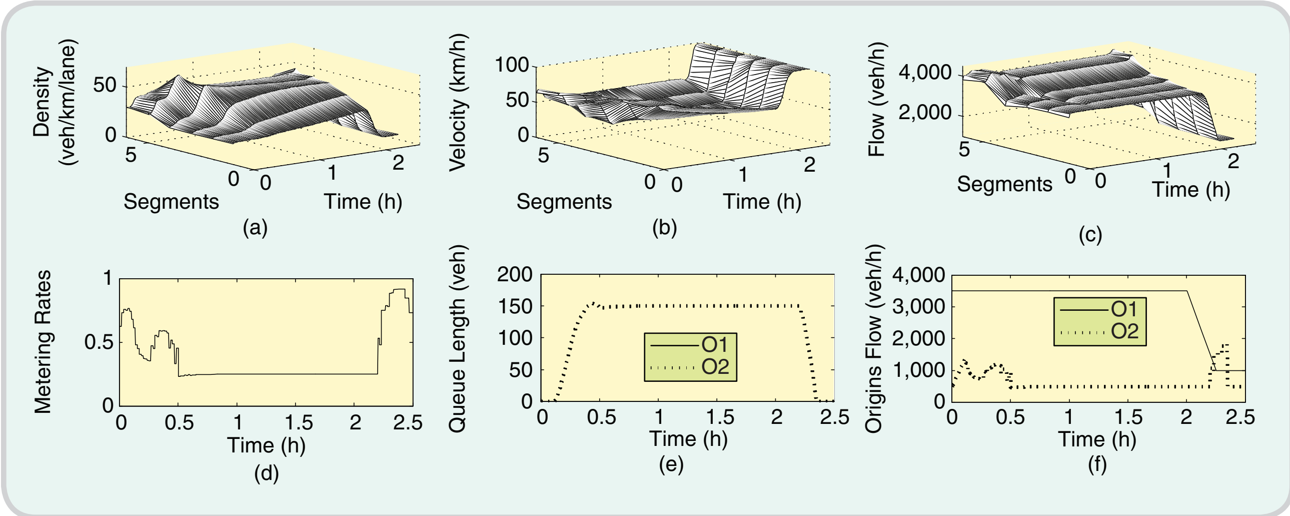

FIG 11 The simulation results for the genetic-fuzzy ramp metering case: (a) segments traffic density, (b) segments traffic speed, (c) segments traffic flow, (d) optimal ramp metering rate, (e) origins queue length, (f) origins flow.

Also we assume that the drivers fully obey the control speed displayed by speed limiters ($\alpha = 0$).

The main-stream demand has a constant value of 3500 veh/h for 2 hours and finally drops to 1000 veh/h for 15 minutes. The demand on the on-ramp increases from 500 to 1500 veh/h at the beginning and remains for 15 minutes then drops to the 500 veh/h again (Fig. 8).

B. Results

In no-control case, when demand increases on the on-ramp the congestion occurs and propagates through link 1. Consequently the density on the main-stream increases and the queue of approximately 150 vehicles is formed at the origin 1 (Fig. 9). In this case the measured value of TTS is 1443.7 veh-h.

In Fig. 10 the results of ALINEA ramp metering controller is presented. Since during ramp metering the queue cannot be allowed to grow larger than the available capacity of the vehicles at the on-ramp, the metering rate has to be increased as long as the queue length is above the threshold. As a result the oscillation of metering rate influences the traffic states and reduces the performance of the control. The TTS in the ALINEA controller case is 1374.5 veh.h with an improvement of 4.8% in TTS.

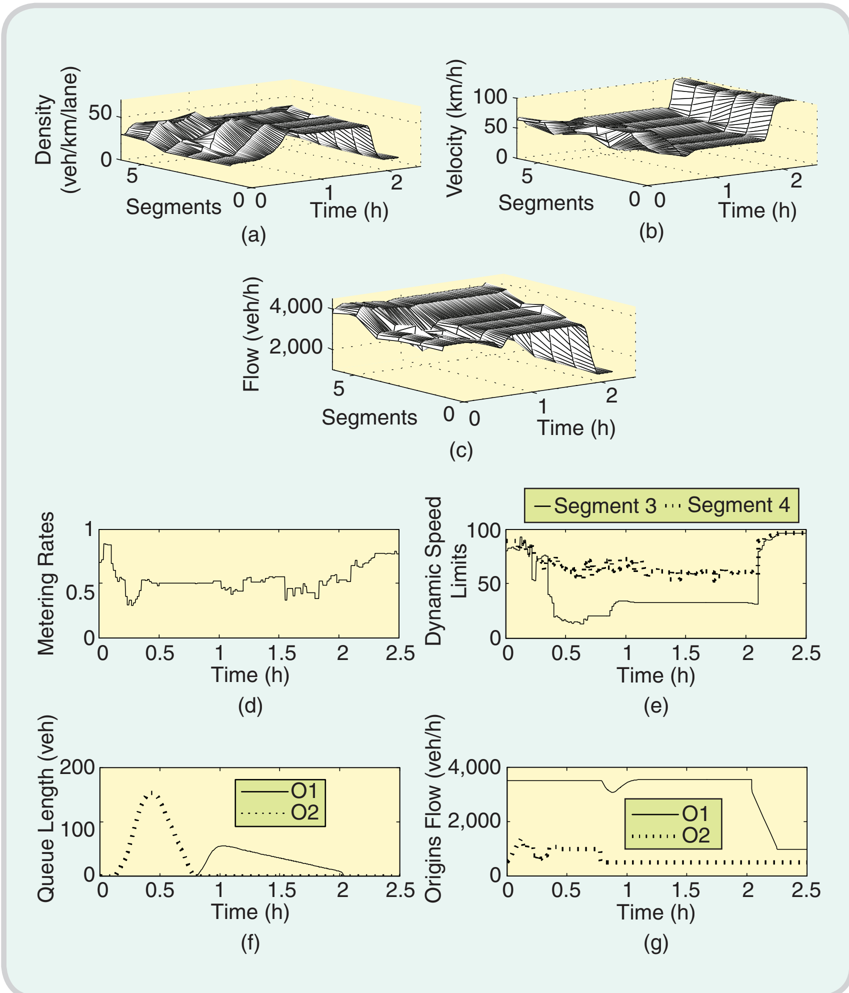

FIG 12 The simulation results for the genetic-fuzzy ramp metering and speed limits control case: (a) segments traffic density, (b) segments traffic speed, (c) segments traffic flow, (d) optimal ramp metering rate, (e) optimal speed limits values, (f) origins queue length, (g) origins flow.

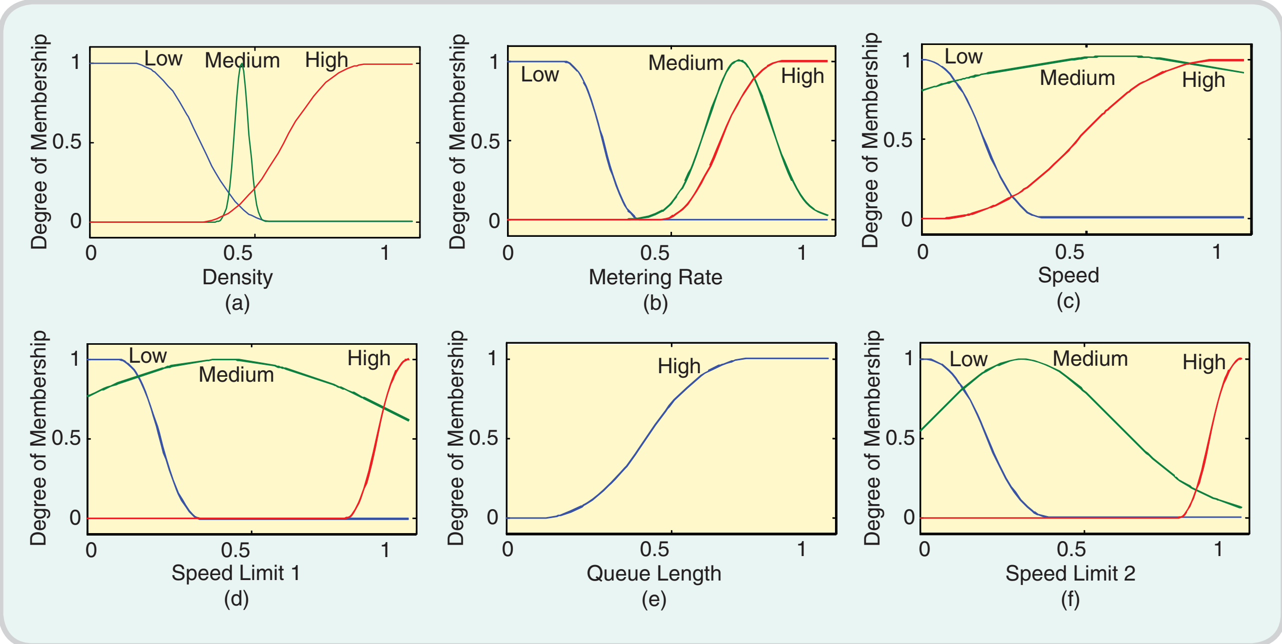

FIG 13 Normalized membership functions for inputs and outputs variables after tuning.

The third scenario is fuzzy-genetic ramp metering only case. The controller scheme is similar to what we have done for the ramp metering and the speed limit control case except we eliminated the two speed controllers from the consequent part of the rules in the inference block of fuzzy controller. It is illustrated in Fig. 11 that the metering rate and evolution of traffic states are much smoother than the ALINEA case. In this case the controller is able to keep the queue length to the maximum level (150 vehicles). The TTS is 1370.9 veh.h, shows an improvement of 5.0%.

Finally, the last scenario is the genetic fuzzy ramp metering and variable speed limits control. The speed limits reduce the inflow of the critical segment and cause a lower density, which enable a higher outflow. The TTS in the speed limits and ramp metering case is 1222.5 veh.h, which is an improvement of 15.3% (see Fig. 12).

Fig. 13 shows the tuned membership function from sample iteration during the simulation.

VII. Conclusion

In this paper, the genetic-fuzzy ramp metering and variable speed limits control were applied to congestion control of the freeway network. The proposed method showed a superior performance in comparison with the traditional ALINEA controller and the genetic-fuzzy ramp metering only case.

To keep the queue length less than the maximum permissible value, the ALINEA controller overrode the algorithm which results in oscillated control signal and consequently oscillation in traffic states. However, in fuzzy control it could get us to the maximum queue length with much smoother control signal.

As we expected the combination of the ramp metering and the speed limit control improved the performance of the control significantly and our approach could implement it efficiently.

The adaptive tuning of the fuzzy controller parameters with the genetic algorithm could make the control system flexible to the changes in demand profile and the traffic system.

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