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### Publication Date

1995

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CALIFORNIA PATH PROGRAM  
INSTITUTE OF TRANSPORTATION STUDIES  
UNIVERSITY OF CALIFORNIA, BERKELEY

# **Fuzzy Traffic Density Homogenizer for Automated Highway Systems**

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**California PATH Research Report**

**UCB-ITS-PRR-9544**

This work was performed as part of the California PATH Program of the University of California, in cooperation with the State of California Business, Transportation, and Housing Agency, Department of Transportation; and the United States Department of Transportation, Federal Highway Administration.

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December 1995

ISSN 10551425

# Fuzzy Traffic Density Homogenizer for Automated Highway Systems

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**July 1995**

# Fuzzy Traffic Density Homogenizer for Automated Highway Systems

by

**C. C. Chien, P. Ioannou and C. K. Chu**

## **Abstract**

A major factor that contributes to congestion on today's freeways is the severe inhomogeneities of the traffic streams. If the traffic density can be controlled, congestion can be eliminated and delays can be reduced. This goal can be achieved by properly controlling the mean speed of traffic on each section of the freeway lane as well as the ramp entering rates. In this paper a fuzzy traffic density homogenizer is proposed to alleviate or avoid congestion by smoothing the traffic density distribution profile over the freeway lanes. The proposed fuzzy traffic density homogenizer consists of two parts: the fuzzy mean speed controller and the fuzzy on-ramp controller. The fuzzy mean speed controller is designed to determine the desired mean speed to be followed by vehicles in each section in order to achieve smooth traffic flow. The fuzzy on-ramp controller is designed to determine the maximum allowable on-ramp traffic volume in each section so that the on-ramp traffic flow does not lead to an amplification of congestion. Simulation results are used to demonstrate that the proposed controllers can eliminate traffic flow instabilities leading to smooth traffic flows.

**Keywords:** Automated Highway Systems, Fuzzy Systems, Macroscopic Traffic Flow Model, Mean Speed Controller, On-ramp Controller, Traffic Congestion, Traffic Density Homogenizer.

## **Executive Summary**

In this paper a fuzzy traffic density homogenizer is proposed to alleviate or avoid congestion by smoothing the traffic density distribution profile over the freeway lanes. The proposed fuzzy traffic density homogenizer consists of two parts: the fuzzy mean speed controller and the fuzzy on-ramp controller. The fuzzy mean speed controller is designed to determine the desired mean speed to be followed by vehicles in each section in order to achieve smooth traffic flow. The fuzzy on-ramp controller is designed to determine the maximum allowable on-ramp traffic volume in each section so that the on-ramp traffic flow does not lead to an amplification of congestion. Simulation results are used to demonstrate that the proposed controllers can eliminate traffic flow instabilities leading to smooth traffic flows.

# Contents

<b>1 Introduction</b>	<b>1</b>
<b>2 Freeway traffic model</b>	<b>2</b>
<b>3 Problem statement</b>	<b>4</b>
<b>4 Fuzzy traffic density homogenizer</b>	<b>5</b>
4.1 Fuzzy mean speed controller . . . . .	6
4.2 Fuzzy on-ramp controller . . . . .	11
<b>5 Simulation results</b>	<b>12</b>
<b>6 Conclusion</b>	<b>14</b>

## List of Figures

1	Density profile of a long segment freeway . . . . .	5
2	Basic configuration of fuzzy logic system. . . . .	7
3	The membership function for $\Delta k_1, \Delta k_2, \Delta k_3$ (normalized) . . . . .	8
4	A single freeway lane with a mean speed controller. . . . .	11
5	A single freeway lane with on-ramp and off-ramp metering systems. . . . .	11
6	The membership function for $k_i$ (normalized) . . . . .	12
7	Density Profile without control . . . . .	17
8	The evolution of density with density control for the case of zero on-ramp, off-ramp traffic: case 2 . . . . .	18
9	The evolution of density with density control but no ramp metering con- trol: case 3 . . . . .	19
10	The evolution of density with density and ramp metering control: case 4	20



# List of Tables

1	Rule Base of Fuzzy Mean speed Control. . . . .	9
2	Rule Base of Fuzzy On-Ramp Control. . . . .	13

# 1 Introduction

The steady increase of traffic demand on freeways during the past decades has led to high rates of congestion in current freeways. To resolve this problem without building new freeways, the idea of Automated Highway Systems (AHS) is proposed. Automated Highway Systems (AHS) is an area that emerged during the last few years with the goal of providing safer, more efficient and environmentally friendly solutions to traffic problems. The basic philosophy of AHS is the optimal utilization of the existing road infrastructure, for improving traffic flow rates, safety, and reducing pollution.

The major factor that contributes to congestion on today's freeways is the severe inhomogeneities of the traffic streams. Examples of these inhomogeneities are speed differences between consecutive vehicles in one lane, speed differences between the lanes, and flow differences between lanes. For example, when the traffic volume approaches the capacity, drivers are forced to drive closer and compete for the available space. Hence, gaps are immediately filled up. Originating in a chain of vehicles closely following each other at high speed and competing for available gaps, shock waves may occur. Under this situation, small disturbances may be generated and amplified. Thus, instability may occur which finally leads to a standstill and congestion. In other words, the inhomogeneities in the traffic stream readily lead to flow disturbances which are responsible for congestion [7].

In an AHS environment two control actions may be used to alleviate congestion and improve the stability of traffic flow. In the first, microscopic control laws [16, 4, 1, 17] can be used to coordinate vehicles in a way that prevents the occurrence of disturbance amplifications; and hence, prevent the occurrence of instability phenomena. In the second, macroscopic control laws can be used to control the density along the lanes and eliminate the traffic density inhomogeneity phenomenon. Hence, the occurrence of disturbances is eliminated and the possibility of congestion is reduced.

In this paper, we design macroscopic control laws to control traffic in different freeway sections in order to prevent the occurrence of congestion. To achieve this goal, a fuzzy traffic density homogenizer is proposed to eliminate the inhomogeneity phenomenon. The proposed fuzzy traffic density homogenizer consists of two parts: the fuzzy mean speed controller and the fuzzy on-ramp controller. The fuzzy mean speed controller is designed to determine the evolution rate of the mean speed in each section to achieve

smooth traffic flow rate. The fuzzy on-ramp controller is designed to determine the maximum allowable on-ramp traffic volume in the sense that the on-ramp traffic flow does not lead to an amplification of congestion on the freeway.

The paper is organized as follows: In Section 2, freeway traffic models are reviewed. In Section 3, a brief problem statement is given. In Section 4, a fuzzy traffic density homogenizer is proposed to eliminate the inhomogeneity phenomenon. Simulation results are presented in Section 5. In Section 6, we present the conclusions and discuss future research directions.

## 2 Freeway traffic model

The design of a macroscopic traffic flow controller is based on a macroscopic traffic flow model. In this Section, we briefly reviewed a freeway traffic flow model developed by Karaaslan, Varaiya and Walrand [5].

Freeway traffic models describe traffic behavior on freeways in terms of appropriate aggregated traffic variables. Due to the analogy between the mathematical description of traffic flow on freeways and fluid dynamics, the first traffic flow model was proposed by Lighthill and Witham [10] based on kinematic wave theory. In this model traffic density is the only state variable which results in poor transient behavior. Payne [14,15], Cremer and May [3] proposed several modified versions to overcome this problem. A much more sophisticated model was proposed by Papageorgiou in [11, 12, 13] which has been tested, validated using real data from the Boulevard Peripherique in Paris [12,13]. However, Papageorgiou's model was found to exhibit several unrealistic phenomena [5]. Due to these concerns, Karaaslan, Varaiya and Walrand [5] proposed a modified model to eliminate these unrealistic phenomena. A detail description of this modified model that describes the flow of traffic in a single lane is given below:

$$q_i(n) = \alpha k_i(n)v_i(n) + (1 - \alpha)k_{i+1}(n)v_{i+1}(n) \quad (1)$$

$$k_i(n+1) = k_i(n) + \frac{T}{L_i}[q_{i-1}(n) - q_i(n)] \quad (2)$$

$$v_i(n+1) = v_i(n) + \frac{T}{\tau}\{V_e[k_i(n)] - v_i(n)\} \\ + \frac{T}{L_i} \frac{k_{i-1}(n)}{k_i(n) + \kappa'} v_i(n) [\sqrt{v_{i-1}(n)v_i(n)} - v_i(n)] - \frac{\mu(n)T}{\tau L_i} w_i(n) \quad (3)$$

where

$$\mu(n) = \begin{cases} \mu_1 \frac{\rho}{k_{jam} - k_{i+1}(n) + \sigma} & \text{if } k_{i+1}(n) > k_i(n) \\ \mu_2 & \text{otherwise;} \end{cases}$$

$i = 1, 2, \dots, N$ ,  $n = 0, 1, 2, \dots$ , and  $a, \rho, \sigma, \kappa', \tau, \mu_1, \mu_2$  are positive constants;  $V_e[k_i(\cdot)]$  represents the steady-state speed-density characteristics;  $w_i(\cdot)$  represents the average influence of vehicles' response on the mean speed evolution at sampling time  $nT$  in section  $i$ ;  $N$  is the number of sections in the freeway lane.

The physical meaning of each term of equation (3) which influences the mean speed of a section can be interpreted as follows [11, 5]:

- The second term  $\frac{T}{\tau}\{V_e[k_i(n)] - v_i(n)\}$  is the relaxation term which includes the speed-density characteristics as a desired value according to the current density  $k_i(n)$ .  $V_e(k_i)$  denotes the steady-state speed-density characteristics. For homogeneous traffic conditions on today's freeway, a fairly general formula for the steady-state speed-density relationship is given by [12, 13]:

$$V_e(k_i) = v_f \left(1 - \left(\frac{k_i}{k_{jam}}\right)^l\right)^m$$

where  $l > 0$  and  $m > 1$  are real-valued parameters;  $v_f$  is the free speed; and  $k_{jam}$  denotes the traffic density at traffic jam. The free speed  $v_f$  depends on human driving characteristics on the particular road under consideration and its value can be estimated by calibrating with real traffic data. For fully automated highway system under homogeneous heavy traffic condition, the steady-state speed-density characteristic depends on the specified safety policy between two consecutive vehicles which is determined based on microscopic considerations. For example, if the specified safety policy is the k-factor (safety-factor) safety policy, i.e.

$$S = c_a v^2 + c_b$$

(where  $S$  is the chosen safety distance to be kept between two consecutive vehicles), then the steady-state speed-density relationship corresponding to this safety policy is

$$V_e(k_i) = \left[\frac{1}{c_a} \left(\frac{1}{k_i} - c_b\right)\right]^{\frac{1}{2}}$$

- The third term  $\frac{T}{L_i}\mu_i(n)[v_{i-1}(n) - v_i(n)]$  is the convection term. It represents the influence of the incoming traffic on the mean speed evolution in segment  $i$ .
- The fourth term  $-\frac{\mu}{\tau}\frac{T}{L_i}w_i(n)$  is the anticipation term. It describes driver response to the down stream \*density. For example, if the density downstream is lower, drivers tend to speed up and vice versa. For today's freeway system,  $w_i(n)$  can be approximately represented by

$$w_i(n) = \frac{k_{i+1}(n) - k_i(n)}{k_i(n) + \kappa};$$

It represents the influence of traffic density downstream on the mean speed evolution. For a fully automated highway system, where the human driver is replaced by an automatic control system, the anticipation term will be greatly affected by the adopted automatic control strategy and automated highway architecture. Hence, a suitable control strategy to determine the anticipation term for achieving high capacity and smooth traffic flow is one of the problems that need to be resolved.

We will use Equations (1)-(3) with

$$w_i(n) = \frac{k_{i+1}(n) - k_i(n)}{k_i(n) + \kappa};$$

to represent the traffic dynamics of current highway systems in our simulations.

The traffic dynamics of an automated highway system however, will be represented by (1)-(3) with a properly designed  $w_i(n)$ . In the next sections, a macroscopic roadway control strategy will be used to determine the proper value of  $w_i(n)$ .

### 3 Problem statement

A major factor that contributes to congestion on today's freeways is the severe inhomogeneities of the traffic streams. Small disturbances due to inhomogeneities are amplified leading to extended congestion or standstill. If the traffic density can be homogenized, the congestion can be eliminated and the delays can be reduced. This goal can be achieved by smoothing the traffic density distribution profile over the freeway. One efficient way to achieve this goal is to guide vehicles at various sections of the freeway to travel with appropriate speeds. The appropriate speed commands to be received and

followed by vehicles should be generated such that the density distribution along the freeway is uniform leading to higher and smoother traffic flow.

In addition, excessive on-ramp traffic volumes may lead to an amplification of congestion on freeways. Hence, a control algorithm that determines the proper metering rate of on-ramp traffic flow is necessary.

Our objective is to design control algorithms that lead to homogeneous traffic densities by generating the appropriate speed commands to be followed by vehicles at the various sections of the freeway and by controlling the on-ramp entering rates.

## 4 Fuzzy traffic density homogenizer

In this Section, a fuzzy traffic density homogenizer which consists of a fuzzy mean speed controller and a fuzzy on-ramp controller is developed to determine the target mean speed and the metering rate of the on-ramp for each segment of the freeway.

**Why fuzzy control ?** Consider the traffic density profile shown in Figure (1) [5]. Intuitively, to relieve this high congestion situation, the control actions for smoothing

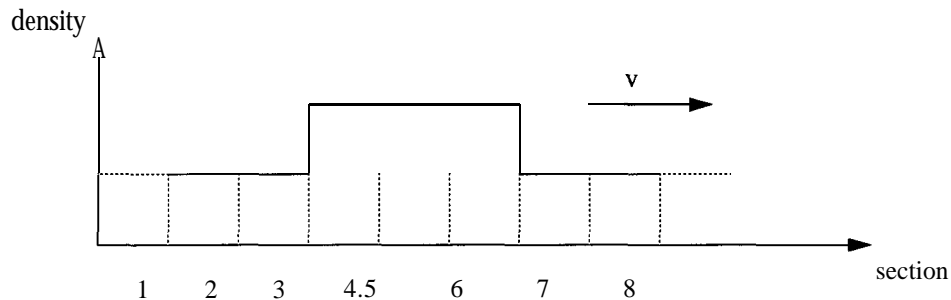


Figure 1: Density profile of a long segment freeway

this profile are [5]:

- 1. Cars in section 6 should speed up.
- 2. Cars in section 7 and 8 should speed up but not as strongly as the cars in section 6.

- 3. Cars in section 5 should speed up but not as strongly as the cars in section 6.
- 4. Cars in section 2 and 3 should slow down.

These intuitive control commands cannot be generated using standard model based control techniques due to the complicated and highly nonlinear nature of the traffic flow model. A proportional type of control strategy for a freeway section with no on-ramp or off-ramps is proposed in [5] and a tedious trial and error effort was used to choose the proportional gains in order to properly imitate the intuitive actions described above. Since a fuzzy logic controller does not rely on the form of the mathematical model but rather on its input output behavior it is more appropriate for the problem under consideration.

The goal of the traffic density homogenizer is to alleviate the congestion situation (hence, smooth the traffic flow) by smoothing the traffic density distribution profile over the freeway. To achieve this goal, a fuzzy traffic density homogenizer is proposed. The fuzzy traffic density homogenizer consists of two parts: the fuzzy mean speed controller and the fuzzy on-ramp controller. The fuzzy mean speed controller is designed to determine the appropriate target speed commands to be received and followed by the vehicles at various sections. The fuzzy on-ramp controller is designed to determine the on-ramp metering rate to limit the maximum on-ramp traffic flow rate in the sense that the on-ramp traffic flow does not lead to an amplification of the congestion. In the following subsections, we discuss the fuzzy mean speed controller and fuzzy on-ramp controller in more detail.

#### 4.1 Fuzzy mean speed controller

Consider the freeway traffic flow model (1)-(3).

$$\begin{aligned}
q_i(n) &= \alpha k_i(n)v_i(n) + (1 - \alpha)k_{i+1}(n)v_{i+1}(n) \\
k_i(n + 1) &= k_i(n) + \frac{T}{L_i}[q_{i-1}(n) - q_i(n)] \\
v_i(n + 1) &= v_i(n) + \frac{T}{\tau}\{V_e[k_i(n)] - v_i(n)\} \\
&\quad + \frac{T}{L_i} \frac{k_{i-1}(n)}{k_i(n) + \kappa'} v_i(n) [\sqrt{v_{i-1}(n)v_i(n)} - v_i(n)] - \frac{\mu(n)T}{\tau L_i} w_i(n)
\end{aligned}$$

Our task is to design  $w_i(n)$  to generate the appropriate target speed commands so that the traffic density distribution over the freeway lane is uniform. This can be achieved by choosing  $w_i(n)$  at section  $i$ , at each sampling time  $n$  to reduce the density difference between neighboring sections. In the following, we propose a fuzzy mean speed controller to determine the proper value of  $w_i(n)$ .

The basic configuration of a fuzzy logic system is shown in Fig. (2) [8,9]. There are four components in a fuzzy logic system (FLS), namely: fuzzification interface, fuzzy rule base, fuzzy inference machine and defuzzification interface. We discuss these components in more detail as follows.

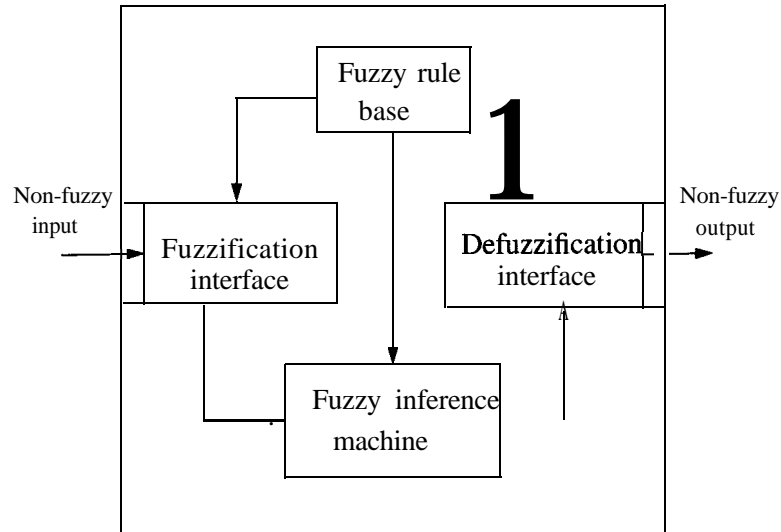


Figure 2: Basic configuration of fuzzy logic system.

The functions of the fuzzification interface are:

- Measures the values of input variables,
- Performs a scale mapping that transfers the range of values of input variables into corresponding universes of discourse, and
- Performs the function of fuzzification that converts input data into suitable linguistic values.

Define the density differences as follows:

$$\Delta k_1 = k_i - k_{i-1}; \quad \text{one-step backward difference}$$



$$\Delta k_2 = k_{i+1} - k_i; \quad \text{one-step forward difference}$$

$$\Delta k_3 = k_{i+2} - k_i; \quad \text{two-step forward difference}$$

The linguistic labels used to fuzzify the density differences are as follows.

$NL \longleftrightarrow$  Negative Large

$NS \longleftrightarrow$  Negative Small

$Z \longleftrightarrow$  Zero

$PS \longleftrightarrow$  Positive Small

$PL \longleftrightarrow$  Positive Large

The fuzzifiers for  $\Delta k_1, \Delta k_2$  and  $\Delta k_3$  are assumed to be the same. The membership function for  $\Delta k_1, \Delta k_2$  and  $\Delta k_3$  are also assumed to be the same as shown in Figure (3).

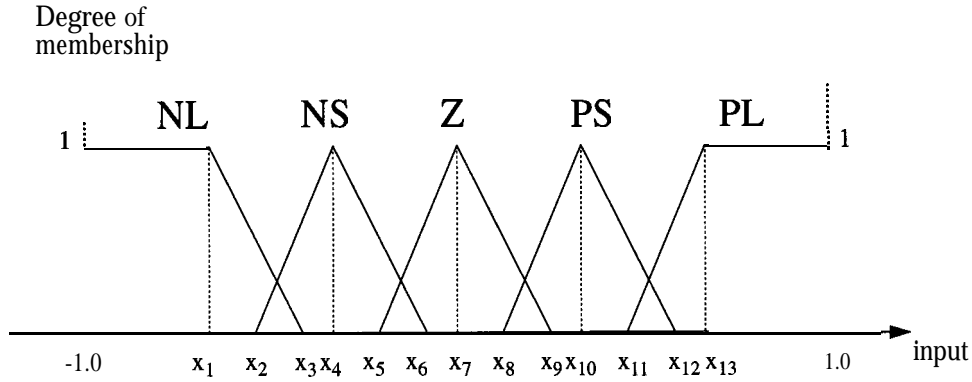


Figure 3: The membership function for  $\Delta k_1, \Delta k_2, \Delta k_3$  (normalized)

The fuzzy rule base comprises the knowledge of the application domain. It is mainly consisted of a “linguistic rule base”. The rule base in the proposed fuzzy logic system has the following form:

IF ( $\Delta k_1$  is  $z_1$ ) AND ( $\Delta k_2$  is  $z_2$ ) AND ( $\Delta k_3$  is  $z_3$ ) THEN ( $w_i(n)$  is  $y$ ).

where  $CONTROL$  represents the value of  $U_i$  of the anticipation term.

Table 1: Rule Base of Fuzzy Mean speed Control.

$\Delta k_2$	$\Delta k_3$	$\Delta k_1$	$w_i(n)$
<i>NL</i>	<i>X</i> <sup>a</sup>	<i>X</i>	<i>PL</i>
<i>NS</i>	<i>NL</i>	<i>X</i>	<i>PL</i>
<i>NS</i>	<i>NS</i>	<i>X</i>	<i>PM</i>
<i>NS</i>	<i>Z</i>	<i>X</i>	<i>PS</i>
<i>NS</i>	<i>PS</i>	<i>X</i>	<i>PS</i>
<i>NS</i>	<i>PL</i>	<i>X</i>	<i>Z</i>
<i>Z</i>	<i>NL</i>	<i>X</i>	<i>PS</i>
<i>Z</i>	<i>NS</i>	<i>NL</i>	<i>PS</i>
<i>Z</i>	<i>NS</i>	<i>NS</i>	<i>Z</i>
<i>Z</i>	<i>NS</i>	<i>Z</i>	<i>Z</i>
<i>Z</i>	<i>NS</i>	<i>PS</i>	<i>Z</i>
<i>Z</i>	<i>NS</i>	<i>PL</i>	<i>Z</i>
<i>Z</i>	<i>Z</i>	<i>NL</i>	<i>PS</i>
<i>Z</i>	<i>Z</i>	<i>NS</i>	<i>Z</i>
<i>Z</i>	<i>Z</i>	<i>Z</i>	<i>Z</i>
<i>Z</i>	<i>Z</i>	<i>PM</i>	<i>Z</i>
<i>Z</i>	<i>Z</i>	<i>PL</i>	<i>NS</i>
<i>Z</i>	<i>PS</i>	<i>NL</i>	<i>Z</i>
<i>Z</i>	<i>PS</i>	<i>NS</i>	<i>Z</i>
<i>Z</i>	<i>PS</i>	<i>Z</i>	<i>Z</i>
<i>Z</i>	<i>PS</i>	<i>PS</i>	<i>Z</i>
<i>Z</i>	<i>PS</i>	<i>PL</i>	<i>NS</i>
<i>Z</i>	<i>PL</i>	<i>X</i>	<i>NS</i>
<i>PS</i>	<i>NL</i>	<i>X</i>	<i>Z</i>
<i>PS</i>	<i>NS</i>	<i>X</i>	<i>NS</i>
<i>PS</i>	<i>Z</i>	<i>X</i>	<i>NS</i>
<i>PS</i>	<i>PS</i>	<i>X</i>	<i>NM</i>
<i>PS</i>	<i>PL</i>	<i>X</i>	<i>NL</i>
<i>PL</i>	<i>X</i>	<i>X</i>	<i>NL</i>

<sup>a</sup>*X* denotes *Don't care*

The fuzzy rule base is shown in Table 1.

In the situation where the density of  $(i + 1)^{th}$  is much lower than that of the  $i^{th}$  section (i.e.  $\Delta k_2$  is *NL*), the control action in the  $i^{th}$  section that should be taken is for vehicles of the section to speed up with a high rate (i.e.  $w_i(n)$  is *PL*). If the density of the  $(i + 1)^{th}$  section is just slightly lower than the density of the  $i^{th}$  section (i.e.  $\Delta k_2$  is *NS*), but the the density of the  $(i + 2)^{th}$  section is much lower than the density of the  $i^{th}$  section (i.e.  $\Delta k_3$  is *NL*), then it can be concluded that the density of the  $(i + 2)^{th}$  section is much lower than the density of the  $(i + 1)^{th}$  section. Thus, the vehicles in the  $(i + 1)^{th}$  section should speed up with a high rate. Hence, the vehicles in the  $i^{th}$  section should also speed up with a high rate (i.e.  $w_i(n)$  is *PL*). The rest of the rules can be derived in a similar way.

The fuzzy inference machine has the capability of simulating human decision-making based on fuzzy concepts. The defuzzification interface performs

- A scale mapping, which converts the range of values of output variables into corresponding universes of discourse, and
- Defuzzification, which produces a nonfuzzy decision output.

For the realization of the logical AND which is implicitly assumed for all rules in the rule base, the min-operator is adopted. We use two more linguistic labels for the control variable  $w_i(n)$ , namely PM (Positive Medium) and NM (Negative Medium). The definition for the rest of the linguistic labels are the same as in the input variables. The centroid defuzzification is used in our FLC to determine the value of  $u_i(n)$ .

After the value of  $w_i(n)$  has been determined, the target speed command to be received and followed by the vehicles at section  $i$  can be determined by the following equation:

$$v_{command} = v_i(n) + \frac{T}{\tau} \{V_e[k_i(n)] - v_i(n)\} + \frac{T}{L_i} \frac{k_{i-1}(n)}{k_i(n) + \kappa'} v_i(n) [\sqrt{v_{i-1}(n)v_i(n)} - Vi(n)] - \frac{\mu(n)T}{\tau L_i} w_i(n)$$

The target speed  $v_{command}$  is transmitted to section  $i$  as shown in Figure (4).

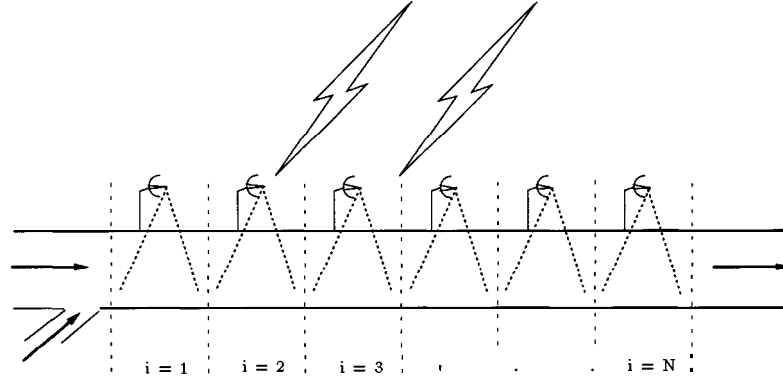


Figure 4: A single freeway lane with a mean speed controller.

## 4.2 Fuzzy on-ramp controller

Consider a single freeway lane with on-ramp and off-ramp metering systems shown in Figure (5). We denote the density difference between the section  $i$  and section  $i + 1$  as

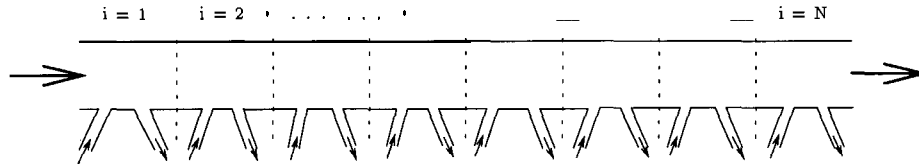


Figure 5: A single freeway lane with on-ramp and off-ramp metering systems.

$$\Delta k = k_{i+1} - k_i.$$

The density difference  $\Delta k$  and the density of the section  $i$  ( $k_i$ ) are the two inputs of the fuzzy on-ramp rule base. The linguistic labels used to fuzzify the density differences are  $NL$ ,  $NS$ ,  $Z$ ,  $PS$  and  $PL$  as defined previously. The linguistic labels used to fuzzify the density of the section  $i$  are  $PS$ ,  $PM$  and  $PL$  which represent *Positive Small*, *Positive medium* and *Positive Large*. The membership function for  $\Delta k$  is assumed to be the same as defined previously in Figure (3). The membership function for  $k_i$  is shown in Figure (6).

The rules in the fuzzy on-ramp rule base have the following form:

$$\text{IF } (\Delta k \text{ is } z_1) \text{ AND } (k_i \text{ is } z_2) \text{ THEN } (r_{i_{max}}(n) \text{ is } y).$$

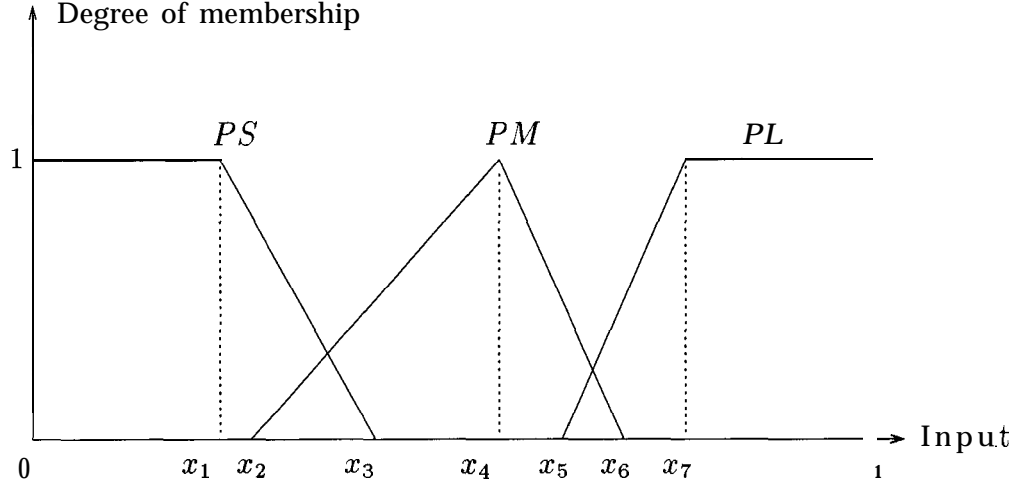


Figure 6: The membership function for  $k_i$  (normalized)

where  $r_{i_{max}}(n)$  represents the maximum allowable on-ramp traffic flow rate or the metering rate of the on-ramp metering system.

The linguistic labels for the control variable  $r_{i_{max}}(n)$  are *Level 7*, *Level 6*, *Level 5*, *Level 4*, *Level 3*, *Level 2*, and *Level 1*. The higher the level, the higher the value of the control variable  $r_{i_{max}}(n)$ .

The rule base is shown in Table 2. For the realization of the logical AND which is implicitly assumed for all rules in the rule base, the algebraic product is adopted. In addition, the centroid defuzzification is used in our FLC to determine the proper value of  $r_{i_{max}}(n)$ .

## 5 Simulation results

Consider a long segment of freeway with only one lane which is divided into 12 sections. Each section is assumed to have only one on-ramp and one off-ramp. The length of each section is 500 meters. The initial traffic volume entering section 1 is assumed to be 1500 No. veh./hour. The initial conditions about the density and mean speed of each section are:

Table 2: Rule Base of Fuzzy On-Ramp Control.

$k_i$	$k_{i+1} - k_i$	$r_{imax}(n)$
<i>PS</i>	<i>NL</i>	7
	<i>NS</i>	7
	<i>Z</i>	6
	<i>PS</i>	5
	<i>PL</i>	5
<i>PM</i>	<i>NL</i>	5
	<i>NS</i>	5
	<i>Z</i>	4
	<i>PS</i>	3
	<i>PL</i>	3
<i>PL</i>	<i>NL</i>	3
	<i>NS</i>	3
	<i>Z</i>	2
	<i>PS</i>	1
	<i>PL</i>	1

Section	1	2	3	4	5	6	7	8	9	10	11	12
Initial density veh/km/lane	18	18	18	18	18	52	52	52	18	18	18	18
Initial velocity km/hour	81	81	81	81	81	29	29	29	81	81	81	81

Four cases are considered. In the first case, we assumed that no control is applied. The on-ramp and off-ramp traffic rate for each section is assumed to be 0 No. veh./hour. Simulation results are shown in Figure (7). Due to the initial high congestion disturbance at sections 6, 7, and 8, congestion is propagated upstream and eventually causes a traffic jam.

In the second case, the fuzzy mean speed controller is applied to control the freeway traffic. The on-ramp and off-ramp traffic rate for each section is also assumed to be 0 No. veh./hour. The simulation results are shown in Figure (8). It is observed that the initial high congestion phenomenon has been damped out and a smooth traffic flow is achieved.

In the third case, we assumed that the on-ramp volume for each section is randomly picked from the number 0 to 400 No. veh./hour; whereas, the off-ramp volume for each section is randomly picked from the number 0 to 300 No. veh./hour. Only the traffic mean speed controller is applied to control the freeway traffic. The simulation results are shown in Figure (9). It is found that the high congestion phenomenon still exists and is amplified due to the high on-ramp and low off-ramp traffic flow rates. In case 4, both the fuzzy mean speed and the fuzzy on-ramp controllers are applied to control the mean speed evolution and to determine the ramp metering rate. The simulation results are shown in Figure (10). It is clear that the high congestion problem has been eliminated.

## 6 Conclusion

A fuzzy traffic density homogenizer is proposed for controlling traffic flow in a single lane of an Automated Highway System. The controller generates the appropriate speed commands for each section of the lane to be followed by the automated vehicles as well as the ramp metering rate in order to achieve a smooth traffic density distribution along the lane. Simulation results are used to demonstrate the effectiveness of the controller.

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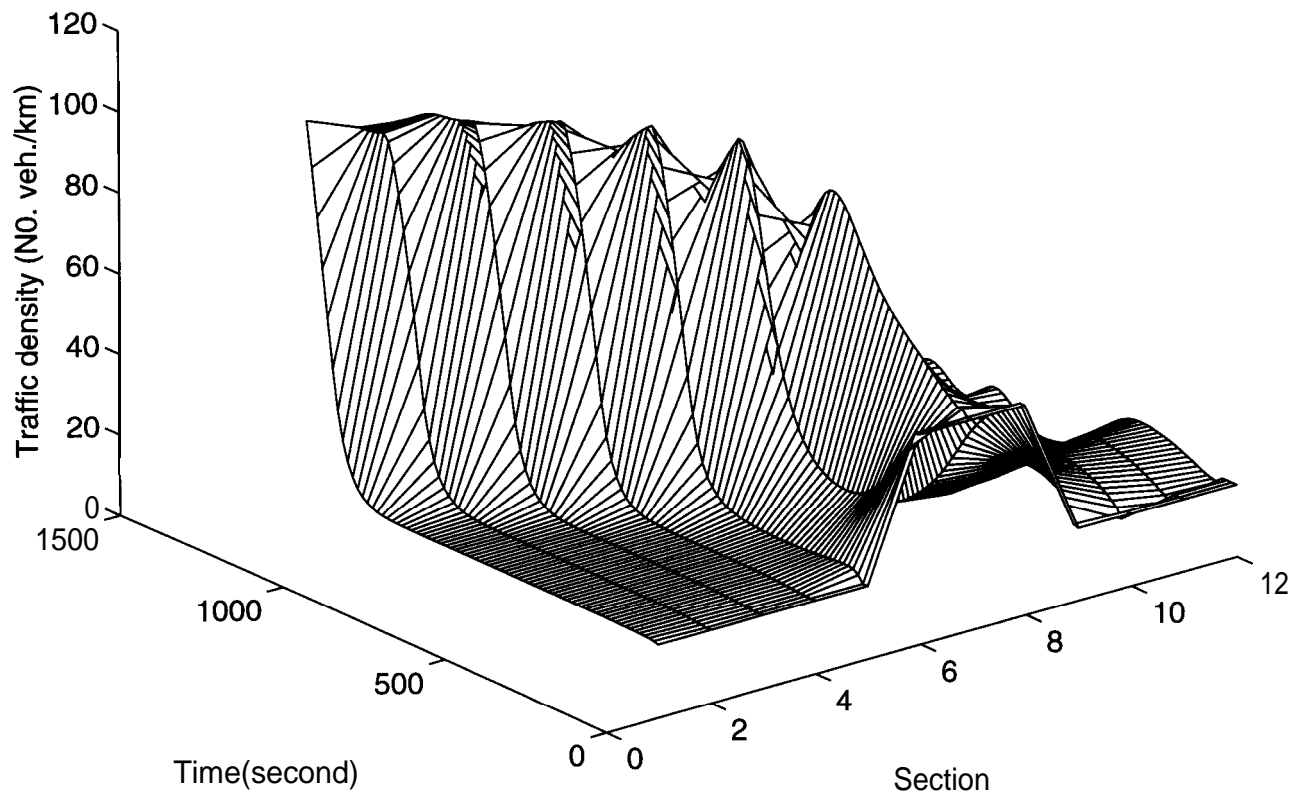
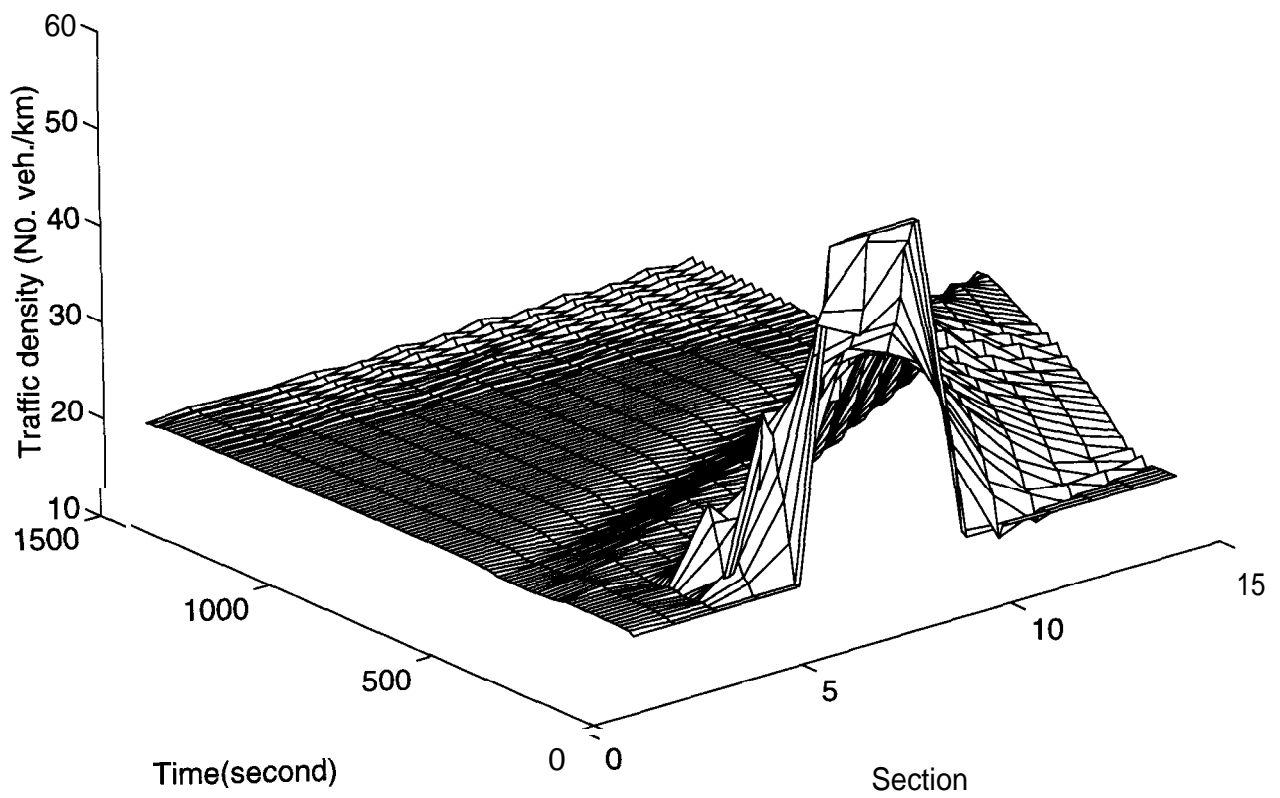


Figure 7: Density Profile without control



*Figure 8:* The evolution of density with density control for the case of zero on-ramp, off-ramp traffic: case 2

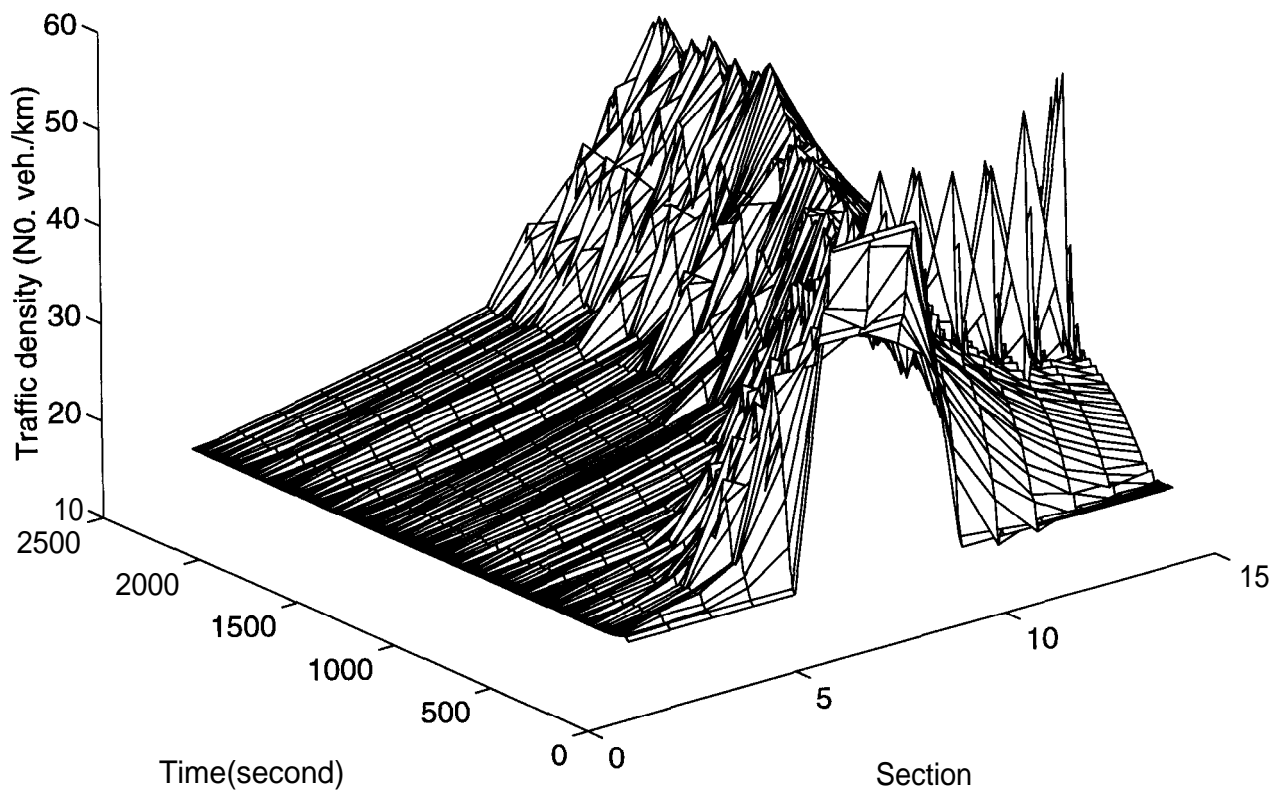


Figure 9: The evolution of density with density control but no ramp metering control: case 3

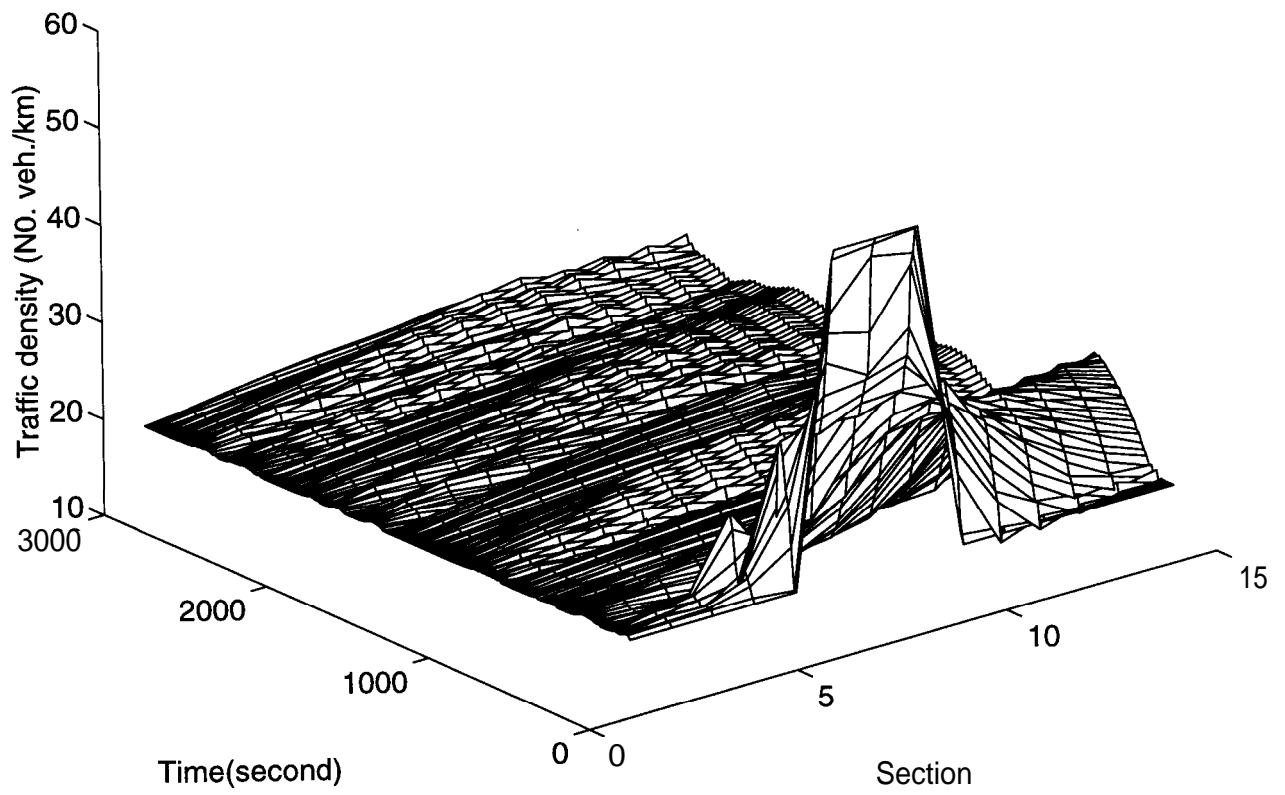


Figure 10: The evolution of density with density and ramp metering control: case 4