Optimal fuzzy control system design for car-following behaviour based on the driver–vehicle unit online delays in a real traffic flow

Ali Ghaffari1, Alireza Khodayari2 and Maysam Faraji3

Abstract
Promoting safety and comfort in driving and reducing the traffic, the pollution and the energy consumption are the main purposes of using many control systems in different driving processes. Car following is the dominant and effective behaviour in traffic flow, the automatization of which is crucial to achieving the aforementioned goals. In this paper, a novel optimal fuzzy control system is designed so that the follower vehicle maintains a safe distance from the vehicle in front of it in a traffic queue with a reduction in the energy consumption. This controller is superior in that it considers the online delays in the reaction of the driver–vehicle unit in the design. The instantaneous delay is estimated using the stimulus–reaction idea based on a real car-following data set. Tuning the controller is achieved by using the linear quadratic regulator gains in the fuzzy scaling gains. Considering the reaction delay enables the controller to be used in an advanced driver assistance system to obtain simultaneously a higher degree of safety, greater energy saving and more freedom for the driver. Fewer errors and more optimality in the results demonstrated the better performance of the proposed control system in comparison with those of a real driver and other controllers.

Keywords
Car following, advance driver assistance systems, driver–vehicle unit, reaction delay, linear quadratic regulator, fuzzy logic control system

Introduction
The wide use of vehicles in transportation systems, together with the limited capacity of roads as well as human mistakes, have caused traffic congestion and undesirable impacts. The main problems include an increase in the number of accidents, a longer travelling time, a higher fuel consumption, more pollution and a depreciation in the vehicle. Given the environmental, political and economic limitations, intelligent transportation systems are known as the fastest and the most appropriate way to solve or reduce these problems.1

In a traffic flow, the car-following process is one of the major challenges in driving, which needs these systems. Car following is the movement of each vehicle related to the vehicle in front in a traffic queue. Different approaches are used in car-following research studies for designing control systems in vehicles.2 In some research studies, uncooperative control systems are designed for a vehicle3 while, in others, cooperative control systems are developed by platooning the vehicles4 and enabling communication to occur between neighbouring vehicles, between vehicles and the highway infrastructure, or both.5 Furthermore, intelligent systems are designed on the basis of the extent of the human driver’s participation in driving; this means that an intelligent system is the driver’s adviser,6 is semi-autonomous7 or is autonomous.8 Fully autonomous systems provide great comfort, safety and efficiency but reduce the driver’s freedom in driving. In addition, various limitations in the real world make it necessary to

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design more practical systems based on the available facilities. Therefore, this paper intends to develop a semi-autonomous system such as an advance driver assistance system (ADAS). Regarding the different approaches mentioned above, a variety of control methods and algorithms have been used in designing car-following control systems. The most prominent methods are as follows: classic control,\textsuperscript{9,10} sliding-mode control,\textsuperscript{11,12} linear quadratic regulator (LQR),\textsuperscript{13,14} artificial neural networks,\textsuperscript{15,16} cerebellar model articulation,\textsuperscript{17,18} predictive models\textsuperscript{19,20} and fuzzy logic control.\textsuperscript{21,22} Each method has some limitations and advantages regarding the designing structure. Using the learning characteristics of neural networks and the flexibility of fuzzy logic has been very effective for car navigation with some uncertainties and unknown ranges. Fuzzy control uses decision making similar to that of expert drivers, eliminating the weaknesses of a human.

In this paper, the fuzzy control system is integrated with LQR techniques to attain the advantages of both methods for use in an ADAS considering the online driver–vehicle unit (DVU) delay. This paper is organized as follows: in the next section, designing the proposed car-following control system is reviewed, which involves modelling the car-following behaviour, minimizing the cost functional by LQR and using fuzzy techniques. In the penultimate section, a discussion and the performance results of the proposed controller are given. In the final section, conclusions are drawn.

**Design of the car-following control system**

The objectives in designing the proposed optimal fuzzy logic controller (OFLC) are both to provide a safer distance between vehicles and to reduce the control commands (acceleration and deceleration) as much as possible. First, an optimal control system is designed on the basis of LQR both to provide a starting point for synthesis of the fuzzy controller and to form a baseline for comparing the performance of the OFLC with that of a linear quadratic regulator controller (LQRC).

**Modeling of the car-following behaviour**

In designing the LQRC a mathematical model is used which is based on the car-following dynamics. The car-following behaviour is shown in Figure 1(a). The front car is called the leader vehicle (LV), and the rear car is called the follower vehicle (FV). In this figure, \( x \) shows the position or distance, \( \dot{x} \) is the velocity, \( \ddot{x} \) is the acceleration and \( L \) is the vehicle length. The subscript \( l \) represents the LV, the subscript \( f \) represents the FV, the subscript \( r \) indicates relative, the subscript \( d \) indicates inter-vehicle, the subscript \( s \) means safety and the subscript \( e \) means error.

In car following, the relative position, the relative velocity and the relative acceleration of vehicle pairs are needed in order to adjust the acceleration and velocity.
The control objective is to keep the FV at a safe distance \( x_s \) from the LV, and so the safe-distance error \( x_e \) tends to zero by consuming the least energy. Here the lateral acceleration, the wind power, the slip, the friction, etc., are ignored. The equation giving the distance between two vehicles is

\[
x_d = x_s - L = x_f - x_f - L = x_s + x_e
\]

(1)

The important variable in this equation is the safe distance \( x_s \). To reach a safe inter-vehicle distance, there should be a balance between increasing the safety (collision avoidance by increasing the distance between cars) and reducing the traffic (an increase in the road capacity by reducing the distance between cars).

The general pattern for the safe distance is given by

\[
x_s = \lambda_0 + \lambda_1 x_f + \lambda_2 x_f^2 + \lambda_3 x_f^3
\]

(2)

This formula is based on the acceleration and deceleration of vehicles in collision-avoidance or safe-distance car-following models.\(^{23,24}\) In equation (2), \( \lambda \) is the velocity, \( \lambda_0 \) is the required minimum space between the vehicles when stopping in traffic and it is usually equal to the vehicle length \( L \). \( \lambda_1 \) is the time headway which is defined as the time difference between two consecutive vehicles passing a certain point. The general values for \( \lambda_2 \) and \( \lambda_3 \) are \( \lambda_2 = 0.5a_{\text{max}}^{-1} \) and \( \lambda_3 = -0.5a_{\text{max}} \), so that \( a_{\text{max}} \) is the maximum deceleration of vehicle pairs. In many research studies, the \( \lambda \) values are constants which are based on the type of vehicle, the road and the weather conditions. One of the highly effective factors in the safe distance is the reaction delay of the DVU,\(^{25-27}\) which is usually used instead of \( \lambda_2 \); this is considered in many cases as a constant value and in some others as a variable value.\(^{28,29}\) Any extra terms in equation (2) provide a safer distance by increasing it when the front vehicle stops suddenly. Also, the inter-vehicle distance should be reduced as much as possible in order to increase the traffic capacity and not to let other vehicles locate in this space. Regarding the car-following assumptions, the equation used in this paper as an appropriate approximation for the safe distance is

\[
x_s = L + \tau^* x_f
\]

(3)

This approximation exists in tight vehicle following or in the steady state. In this equation, the safe distance is a function of the DVU delay \( \tau \), the FV velocity and the FV length.

The dynamics of car-following behaviour are modelled in Figure 1(b) in a block diagram based on Figure 1(a) and the model given by Khodayari et al.\(^{20}\) by inserting equation (3) in equation (1). This model is validated using the real car-following data set of two vehicles in an actual traffic flow including the acceleration, the velocity and the position of vehicles. These data are also used in other steps in designing and evaluating. This data set is from the ‘US Highway 101 Dataset’ from the US Federal Highway Administration’s NGSIM data set\(^{31}\).

A data set of vehicles travelling during the morning peak period on a segment of the US Interstate Highway 101 in Emeryville, San Francisco, California, USA, was made using eight cameras on top of 10 Universal City Plaza, which is 154 m tall and is next to the Hollywood Freeway Route 101, in June 2005. As shown in Figure 2, 6101 vehicle trajectories were recorded in three consecutive 15 min intervals, on a road section of 640 m. The data are collected at 0.1 s intervals, and the data set includes detailed vehicle trajectory data on a merge section of the eastbound Interstate Highway 101. Any measured sample in this data set has 18 features of each DVU in any sample time, such as the longitudinal position, the lateral position, the velocity, the acceleration, the time, the number of roads, the vehicle class and the front vehicle.

To validate the model, the curves in Figure 3(a) to (e) present the velocities and the positions of the two vehicles and the inter-vehicle distance of the real and modelling data. To show quantitatively the acceptable errors of these variables, three criteria of errors in modelling are calculated and listed in Table 1.

In Table 1 the errors listed are the mean absolute percentage error (MAPE), the r.m.s. error (RMSE) and the standard deviation of error (SDE). According to the equation

\[
\text{MAPE} = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{x_i - \hat{x}_i}{x_i} \right|
\]

(4)

the MAPE can be considered as a criterion for model risk for using it in real-world conditions. According to the equation

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \hat{x}_i)^2}
\]

(5)

the RMSE is a criterion for comparing the error dimensions in various models. According to the equation

\[
\text{SDE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \frac{|x_i - \hat{x}_i|}{x_i} - \frac{\text{MAPE}}{100} \right)^2}
\]

(6)

the SDE indicates the persistent error even after calibration of the model.\(^{32}\) In these equations, \( x_i \) is the real value of the variable being modelled (observed data), \( \hat{x}_i \) is the real value of the variable given by the model and \( N \) is the number of test observations. According to Table 1, all the errors are acceptable and show the suitability of the proposed model.

The delay is time varying and converts equation (3) into a non-linear equation. However, the instantaneous DVU delay would be required for the moment when the control laws of the OFLC are applied to the FV by a supervisory controller in an ADAS. Consequently in
this paper, equation (3) is a distinct linear equation for all the possible values of delay by considering these values constant but different in each equation. The method for considering and estimating the DVU reaction delay is discussed in the next section.

Therefore the resulting state-space equations are

\[
\dot{x}(t) = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0 & -\tau \\ 1 & -1 \end{bmatrix} u(t)
\]

\[
y(t) = \begin{bmatrix} 1 & 0 \end{bmatrix} x(t)
\]

This state space is based on optimality objectives and the necessity that all state variables are controllable and observable. These variables are the safe-distance error and the relative velocity respectively: \((x = [x_v, \dot{x}_v]')\).

The safe-distance error is also considered as the system output. The inputs are the LV acceleration \(u_l\) as the disturbance input and the FV acceleration \(u_f\) as the control input: \((u = [u_l, u_f]')\).

\textbf{The delay in the reaction of the driver–vehicle unit}

The delay in the DVU reaction is the sum of the delays caused by the driver’s reaction in commanding and the vehicle systems in executing. The reaction delay of human drivers can vary rapidly because of changes in the factors such as task demands, motivation, workload and fatigue. The driver’s reaction time was defined as the summation of the perception time and the foot movement time by earlier car-following research. In psychological studies, the driver’s reaction process is further represented in four states: perception, recognition, decision and physical response. It has been recognized that the reaction delay of each driver is an indispensable factor for identification of car-following models.\(^3\,3^3\) Many studies have estimated the reaction time based on indoor experiments and driving simulators. To estimate the reaction delay of the DVU from real data, several approaches have been proposed. In this paper the estimation is based on one of the newest successful ideas called the stimulus–reaction idea.\(^3^4\,3^5\,3^6\)

In this idea, the reaction times of acceleration and deceleration are analysed using the observed data of many LV–FV pairs in an actual traffic flow. This idea is based on the fact that the delay time is the time between the variation in the relative velocity and the acceleration of the FV, which is the concept of the stimulus and the reaction. Variations in the relative velocity and the FV acceleration are the maxima or the minima of the velocity trajectory or the FV acceleration.
The instantaneous reaction of the DVU is the time difference between two subsequent variations: the relative velocity as the stimulus and the FV acceleration as the reaction.

Figure 4 indicates the DVU delay for the real data set used in the section on the car-following behaviour modelling, which is calculated employing the above-mentioned idea.

In this article, delays are considered in the range from 0 s to 3 s at 0.1 s intervals (31 different values). As a result, there are 31 different time-invariant equations for equation (7) for each 31 values of delay.

**Design of the LQR control laws**

Basically, the optimal control problems are calculating the control laws by minimizing the cost functional (the performance index). The cost functional of this problem including quadratic terms related to the state variables and the inputs is given by the equation

<table>
<thead>
<tr>
<th>Table 1. Modelling errors.</th>
<th>Value of the following errors</th>
<th>MAPE</th>
<th>RMSE</th>
<th>SDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FV position</td>
<td>2.256</td>
<td>8.982</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>FV velocity</td>
<td>2.599</td>
<td>0.424</td>
<td>0.013</td>
<td></td>
</tr>
<tr>
<td>LV position</td>
<td>0.640</td>
<td>2.703</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>LV velocity</td>
<td>1.987</td>
<td>0.422</td>
<td>0.017</td>
<td></td>
</tr>
<tr>
<td>Inter-vehicle distance</td>
<td>2.585</td>
<td>0.462</td>
<td>0.022</td>
<td></td>
</tr>
</tbody>
</table>

MAPE: mean absolute percentage error; RMSE: r.m.s. error; SDE: standard deviation of error; FV: follower vehicle; LV: leader vehicle. respectively. The instantaneous reaction of the DVU is the time difference between two subsequent variations: the relative velocity as the stimulus and the FV acceleration as the reaction.
\[ J = \int_{0}^{\infty} \left[ x^T(t) Q x(t) + u^T(t) R u(t) \right] dt \]  

(8)

where \( Q \) is the regulator matrix which is the weight for state variables and \( R \) is the regulator matrix which is the weight for plant inputs.

To minimize this index, the minimum Pontryagin principle and the Hamiltonian function are used. Thus, the optimal control input would be equal to

\[ u(t) = u_L(t) + u_F(t) = Kx(t) \]

(9)

The optimal gain \( K \) is given by

\[ K = [1 -1] R^{-1} B^T P \]  

(10)

Since the maximum acceleration and deceleration of vehicles are limited, the FV’s optimal control input is constrained as given by

\[ u_c(t) = \begin{cases} K x_c(t), & |K x_c(t)| \leq a_{\text{max}} \\ a_{\text{max}}, & K x_c(t) > a_{\text{max}} \\ -a_{\text{max}}, & K x_c(t) < -a_{\text{max}} \end{cases} \]  

(11)

According to equation (10), the calculation of \( K = [k_1 \ k_2] \) requires the DVU delay as well as the matrices \( R, Q \) and \( P \) is the solution of the Riccati equations. For each of the 31 different values of delay, 31 different Riccati algebraic equations

\[ P(\tau) \dot{A} + A^T P(\tau) - P(\tau) B(\tau) R^{-1} (\tau) B^T(\tau) P(\tau) + Q(\tau) = 0 \]  

(12)

are solved and then the optimal gains are computed.

The non-linear change in the gains calculated versus the DVU delay is presented in Figure 5. In the discussion and results section, the results obtained by applying the gains of the LQRC are compared with those obtained with the OFLC.

**Optimal fuzzy control system design**

Figure 6 shows the proposed fuzzy controller structure. The four inputs of the controller are as follows: the safe-distance error, the safe-distance derivative error, the relative speed and the derivative of the relative speed. The output is the FV acceleration. In this figure, the four main components of the fuzzy control system and the \( g \) scaling gains for the inputs and the output are illustrated.

The fuzzy controller utilizes five membership functions on the inputs and output of the controller, which are uniformly distributed across their universes of discourse. The defined membership functions consist of
the following: PL, positive large; PS, positive small; ZE, zero; NS, negative small; NL, negative large. In the rule base, 410 independent if–then rules are used. The fuzzy inference system is a Mamdani type, and other specifications are listed in Table 2.

Appropriate tuning of the controller is achieved by the scaling gains which scale the normal membership functions. This scaling is carried out on the basis of using the LQR gains because of its success in operations with fuzzy control. According to the approach used by Kwong et al. and Widjaja and Yurkovich, the \( k \)-optimal LQR gains are transferred to the \( g \) scaling gains using

\[
g_i g_o = k_i \quad (13)
\]

In this equation, the subscript \( i \) is \{1, 2, 3, 4\}, and the subscript \( o \) represents the output. Therefore, fuzzy scaling gains are obtained and used to implement scaling according to the following scheme.

1. **LQR gains** are available for the safe-distance error (the gain \( g_1 \)) and the relative velocity (the gain \( g_2 \)). Regarding the importance of these variables, first, the gain \( g_2 \) is selected in this step and the gain \( g_1 \) is calculated by equation (13) in the third step. The gain \( g_2 \) is selected by widely analysing the range of relative velocities for the above-mentioned real traffic data set. The gains \( g_2 \) are presented in Figure 7(a) versus the DVU delay.

2. The output scaling gain is calculated by the use of \( g_2 \) with the formula \( g_o = k_2/g_2 \). Figure 7(b) shows the curve of the calculated output scaling gain versus the DVU delay.

3. The gain \( g_1 \) is computed from the gain \( g_o \) and the equation \( g_1 = k_1/g_o \). The changes in the calculated gain \( g_1 \) versus the DVU delay are shown in Figure 7(c).

4. The LQR gains for the safe-distance derivative error (the gain \( g_3 \)) and the relative-velocity derivative (the gain \( g_4 \)) are not available. Therefore, these two scaling gains are selected as \( g_3 = 0.05 \) and \( g_4 = 0.14 \) on the basis of analyses of system dynamics and a real data set.

5. The inputs and output membership functions are scaled using the scaling gains. This is performed by reverse multiplying the input scaling gains, and direct multiplying the output scaling gains in the ranges of the related membership functions. Finally, other changes are made in the forms of the membership functions to achieve the desired objectives. Figures 8(a) to (e) show the membership functions.

**Discussion and results**

Using the available real data set, verification of the designed controller is investigated. To evaluate the controller, its output is applied to the FV at 0.6 s, 8 s, 14 s, 21 s and 29 s, in an ADAS. In these times, the online DVU delays from Figure 5 are equal to 0.3 s, 1.4 s, 0.6 s, 0.5 s and 1.1 s respectively. The LQR gains and fuzzy scaling gains related to these initial conditions are shown in Table 3.

Figures 9 and 10 show the performance results of the OFLC compared with those of the LQRC and the thick real driver for five initial conditions. In these figures, the thick red solid curves are related to the OFLC, the thin black solid curves to the real driver and the blue dashed curves to the LQRC.

### Table 2. OFLC specifications.

<table>
<thead>
<tr>
<th>Case</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>And</td>
<td>Product</td>
</tr>
<tr>
<td>Or</td>
<td>Probabilistic or (algebraic sum)</td>
</tr>
<tr>
<td>Implication</td>
<td>Product</td>
</tr>
<tr>
<td>Aggregation</td>
<td>Sum</td>
</tr>
<tr>
<td>Defuzzification</td>
<td>Centroid of area</td>
</tr>
</tbody>
</table>

![Figure 6. Proposed optimal fuzzy controller.](image)
A safe-distance error comparison is shown in Figure 9. Unlike the performance of the real driver, the safe-distance error tends to zero on activation of the controllers, which shows their better performance in maintaining a safe inter-vehicle distance. In addition, the most satisfactory results of the OFLC are obvious and show a faster response and less error. The safe-distance error is based on equation (1) and so other quantitative error criteria are shown in Table 4 in order to prove the predominance of the OFLC. In this table the MAPE and RMSE are computed according to equations (4) and (5) by inserting \( \xi_1 \) instead of \( \hat{\xi}_1 \) and \( \xi_d \) instead of \( \xi_d \).

The larger errors of the human driver arise because of the human weakness in realizing and controlling the safe distance accurately. The lower values of these two errors for the OFLC in the comparison with those for the LQRC and the real driver are obvious in Table 4. The other optimality objective, which is to reduce the control commands, is shown in Figure 10(a) to (e). In this figure, the control commands (acceleration or deceleration) of the FV, which are given by the real driver, the LQRC and the OFLC, are shown for the five initial conditions. As seen in this figure, there is a smaller domain and fewer fluctuations in the acceleration or deceleration in comparison with those for the real driver. Based on the work by Kamal et al.41 and Berry,42 reducing the acceleration and braking rate has a direct relation to the energy saving. When the control commands of the OFLC and the LQRC are compared, the fact that they function similarly is obvious. Their difference can be seen at the start of their activation. This is because the fuzzy controller is tuned so that the safe-distance error tends to zero more quickly because of the greater degree of flexibility in its adjustment. Thus, safety is considered a higher priority than energy saving is. In Figure 10 the difference in the amounts of optimality is also seen for each delay. This is due to the different safety policies for different delays in designing the optimal control laws. However, the supervisory controller in an ADAS can be designed so that, after reaching a safe situation, the optimality of the commands will be more efficient.

The superiority of the proposed controller in enhancing the driving safety arises because the OFLC is designed on the basis of a non-linear fuzzy system using LQR optimal gains. In fact, the OFLC has inherited the optimality advantage of LQR. Moreover, the flexible characteristics of the fuzzy system allow manipulation of the non-linear fuzzy surface of the OFLC. This means that the operational areas of the fuzzy controller can be developed beyond the designed linear areas from the linearization. Furthermore, there is an ability to develop it, irrespective of fundamental changes or the use of complex mathematical modelling. From the use of human knowledge in the rule base, the OFLC could have a performance similar to that of a flawless skilled human driver.

Figure 7. (a) Relative-velocity scaling gain; (b) acceleration or deceleration scaling gain; (c) safe-distance error scaling gain.
DVU: driver–vehicle unit.
Conclusions

In this study, a more efficient control system in the car-following process, which is able to work in an ADAS, is designed to increase car-following safety. To achieve this, the instantaneous delay of a DVU is considered in designing and is estimated using the stimulus–reaction idea with a real car-following data set. The proposed controller is designed on the basis of the idea of synthesizing the fuzzy logic and LQR techniques. Since optimal control is used, it was intended to reduce the control commands (the acceleration or deceleration rate) to obtain an energy saving as long as the safety is not compromised. The OFLC provides appropriate optimal control laws to the supervisory controller to be
Figure 10. FV acceleration or deceleration of the real FV driver, the LQRC and the OFLC with the five initial conditions: (a) $t_0 = 0.6$ s; (b) $t_0 = 8$ s; (c) $t_0 = 14$ s; (d) $t_0 = 21$ s; (e) $t_0 = 29$ s.

Table 4. Values of the MAPE and the RMSE for maintaining a safe distance.

<table>
<thead>
<tr>
<th>Value for the following initial conditions</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAPE Real driver</td>
<td>40.93</td>
<td>32.44</td>
<td>34.13</td>
<td>30.19</td>
<td>22.89</td>
</tr>
<tr>
<td>MAPE LQRC</td>
<td>0.90</td>
<td>2.48</td>
<td>1.50</td>
<td>3.38</td>
<td>6.18</td>
</tr>
<tr>
<td>MAPE OFLC</td>
<td>0.50</td>
<td>2.04</td>
<td>1.13</td>
<td>2.82</td>
<td>5.17</td>
</tr>
<tr>
<td>RMSE Real driver</td>
<td>5.50</td>
<td>5.08</td>
<td>5.18</td>
<td>4.47</td>
<td>4.44</td>
</tr>
<tr>
<td>RMSE LQRC</td>
<td>0.30</td>
<td>1.59</td>
<td>0.59</td>
<td>1.02</td>
<td>2.15</td>
</tr>
<tr>
<td>RMSE OFLC</td>
<td>0.25</td>
<td>1.50</td>
<td>0.54</td>
<td>0.97</td>
<td>2.05</td>
</tr>
</tbody>
</table>

MAPE: mean absolute percentage error; RMSE: r.m.s. error; LQRC: linear quadratic regulator controller; OFLC: optimal fuzzy logic controller.
applied to the FV in an ADAS to increase the pleasure of driving.

The results (validated by a real traffic data set) show the more desirable performance of the OFLC in comparison with that of a real driver. Also, in comparison with the LQR controller, a better operation is shown so that this controller has all the optimality of the LQR controller together with the flexibility of a fuzzy nonlinear surface to obtain more desirable results.

Some further research studies are suggested in this area in several ways such as designing a control system for non-straight, curved and more complex roads and also for different climate conditions, or designing a supervisory controller that complements the OFLC for an ADAS.

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