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ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM BASED MODELLING OF VEHICLE GUIDANCE

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Abstract

This paper presents modelling of fuzzy logic based driver model for intelligent vehicle guidance-longitudinal movement, using Adaptive Neuro-Fuzzy Inference System (ANFIS). Aim of this research was to build a driver model that could replace the real driver. Fuzzy logic is used to integrate drivers' behaviour and his appropriate driving style into the corresponding fuzzy controller. The fuzzy model that mimics the driver is constructed using ANFIS and data gathered from real driving scenarios that correspond to a particular driver. Autonomous control of the longitudinal motion in terms of reducing fuel consumption is also considered during the design of the controller. Proper dataset for ANFIS training is generated from real driving patterns applied in different environments. Values related to fuel-efficient driving are obtained by applying proper filtering on the dataset. The created fuzzy controller is verified using vehicle simulator that can calculate fuel consumption for a certain type of vehicle with respect to a given diagram of movement.

Keywords: ANFIS, Driver model, Fuel consumption, Fuzzy control, Intelligent vehicle guidance, Modelling.

1. Introduction

Traffic safety attracts more and more attention every day, mostly due to the increased usage of vehicles in urban areas, but also because of the increased flow of people and goods. Increased number of traffic participants and their diversity results in more and more complex models of traffic flow. Vehicle controls are becoming more and more complex. Different researchers are trying to resolve these issues on different levels of abstraction and by using different methods. For example, some recently published papers are related to car-following model – one analyse the influence of driver's memory in the car-following model on the traffic flow [1], the other applies feedback control schema on the car-following model [2], etc. Some others, like [3] are trying to deal with lateral velocity and yaw rate control, and so on. Some researchers are not focused on single vehicles but they model a traffic control system that will optimize vehicle routing [4]. In essence, all of them are trying to improve traffic flow and safety. Many car manufacturers are now developing specific systems to assist the driver while driving. A lot of effort has been invested in recent years to improve the quality and reliability of primary vehicle functions, such as a brake system, or a system for stable cornering behaviour, or a function of protecting the driver when the incident occurs, etc. Application of intelligent methods for driving a vehicle should enable real-time prediction of incidents in order to prevent (avoid) a collision or at least minimize damage in the case of an accident.

It is shown that design of driving intelligent system is more convenient if it is based on the separation of two subsystems [5], i.e., on the car-following model [6], where the first one in the leading vehicle provides a trajectory and the second one in the following vehicle follows the trajectory. The first subsystem should be independent of dynamic characteristics of the vehicle and it should provide a trajectory of the vehicle movement at all times, based on the available information. This trajectory determines the distance between vehicles, speed, and acceleration of the following vehicle. Model designed in this way can be applied to multiple vehicles. The model can also incorporate aspects related to driving style. Data acquisition from real driving scenarios contributes to driving style recognition. Work presented in this paper is mainly focused on the design of the first subsystem, where the advantages of fuzzy logic and ANFIS are exploited. The second subsystem is a controller that needs to be designed in order to follow the desired trajectories, which allows the application of many methods for controllers design and taking into consideration vehicle specificities.

Considering the importance of fuel economy in today's world, where more attention is given to the preservation of the environment and energy saving, design of the fuel economy control system should certainly be put into the focus. Therefore, one part of this paper is devoted to this subject, where the advantages of creating a fuzzy controller using ANFIS were examined.

This paper has six sections including Introduction and Conclusions. In Section 2, classic driver models in the longitudinal direction are presented with a focus on parameters and general driver model that shows poor performance in cases of low traffic density flow rate. Section 3, describes driver models based on the fuzzy logic and its ability to overcome limitations of the above model. ANFIS is described and used as a starting point for further improvement. In Section 4, a driver modelling using ANFIS is described along with training, checking and test results. In Section

5, fuel consumption is taken into consideration by analysing impact of a driving style on fuel consumption and its impact on the design of the controller.

2. Classic Driver Models In Longitudinal Direction

The basic setup of the vehicle tracking system in a longitudinal direction with corresponding parameters is given in Fig. 1, where: v_L is the speed of the leading vehicle, a_L is the acceleration of the leading vehicle, v_F is the speed of the following vehicle, a_F is the acceleration of the following vehicle, d_x is the relative distance, and v_x is the relative speed.

The first driver model began to develop in the 1950s as a general driver model [7]. This model, shown in Fig. 2, is based on the assumption that each driver responds differently to the corresponding excitations. The model describes driver behaviour in longitudinal vehicle tracking and the goal of the model is to generate the desired distance in relation to the reference vehicle. All models used to generate the appropriate vehicle traction trajectories are created assuming that the driver is able to recognize the relative distance and the relative speed of the corresponding vehicles.

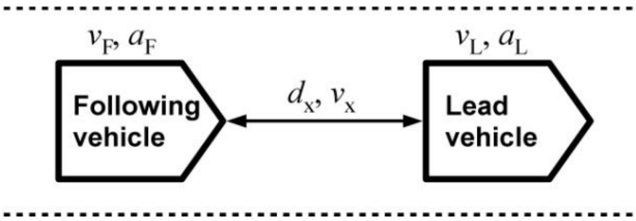


Fig. 1. Parameters in longitudinal motion.

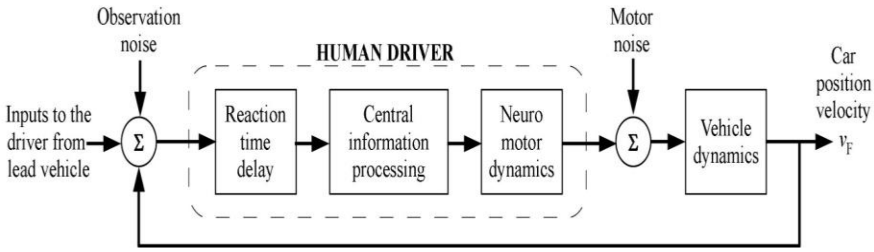


Fig. 2. General driver model [7].

"Real driver model" [8] is based on stimulation in the form of relative speeds of the corresponding vehicles and is generating the acceleration value of the following vehicle. This model is mathematically described by Eq. (1):

$$a_F(t) = \frac{\lambda}{M}\left[\left(v_L(t-\tau_n) - v_F(t-\tau_n)\right)\right] \tag{1}$$

where $a_F(t)$ is the acceleration of the following vehicle, λ is the control mechanism sensitivity factor, M is the vehicle's mass, $v_L(t)$ is the speed of the leading vehicle, $v_F(t)$ is the speed of the following vehicle, τ_n is the reaction time, which includes time of perception and the time necessary to take an appropriate action. In this model, sensitivity λ is constant for all possible situations. Gazis et al. [9] proposed a model in which, this parameter will depend on the relative distance of the observed vehicles. However, the described model has shown poor performance in cases of low traffic density flow rate.

Dorato et al. [10] assumed, contrary to human intuition, that the driver is imitated by the linear optimum regulator. This regulator is based on the minimization of the square function that "penalizes" the sum of the square of the relative distance as well as the sum of the square of the relative velocities of the observed vehicles. It can be noticed that the relative distance is directly proportional to the values of the actual speed of the vehicle.

3. Driver models based on fuzzy logic

Application of fuzzy logic to the driver model [11] design requires mapping of all values of interest in the domain of linguistic variables. The simple fuzzy system that can mimic the driver should include at least two inputs: relative velocity (v_x) – as a difference between the speed of the leading vehicle and the following vehicle, and relative distance (d_x) between vehicles; and single output: the desired acceleration of the following vehicle (a_F). Linguistic values (fuzzy sets) of input and output variables can be defined as: $v_x \in$ {large negative, small negative, zero, small positive, large positive}, $d_x \in$ {very small, small, OK, large, very large}, and $a_L \in$ {large negative, medium negative, small negative, zero, small positive, medium positive, large positive}.

Knowledgebase for the fuzzy system that can mimic the driver can be designed using the above fuzzy sets. Changing of parameters of membership functions can be used for further adjustment of the model in order to obtain the desired performances. Each model can be tested in a simulation environment to measure the desired performances (optimization criteria). Drawbacks of the fuzzy controller designed with two inputs, as described above, is that relative distance does not depend on the speed at which, the vehicle is moving. In real driving conditions, safe distance should be greater as the speed increases. This means that we must introduce additional input to the fuzzy controller for tracking the vehicle speed. It is also convenient to use Sugeno type (or Takagi-Sugeno-Kang-TSK type) of the fuzzy controller where the output gives specific acceleration values for each rule. This also reduces simulation time, since the Mamdani model is much slower [12]. In addition, Sugeno model is suitable for application of ANFIS for his design. Figure 3 outlines the structure of the driver model using fuzzy controller with three inputs and a single output.

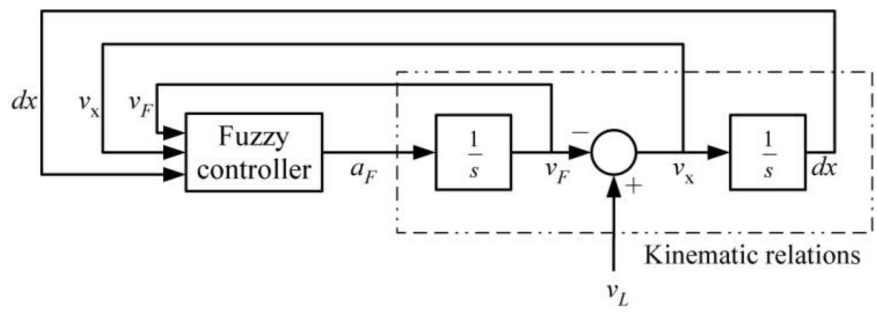


Fig. 3. Block structure of driver model based on fuzzy controller with three inputs.

Linguistic values (fuzzy set) describing the speed (v_F) of the following vehicle are $v_F \in$ {very small, small, medium, large, very large}, while other linguistic input variables remain the same as in the leading model. Output acceleration values are adjusted according to parameters of input membership functions in order to get satisfactory results in the simulation environment. When designing a fuzzy controller using ANFIS, these settings are adjusted automatically during the process of training, based on real data from the test drives.

There is a way to reduce the number of rules and membership functions of the designed fuzzy controller. Avdagic et al. [13] described that in where it is presented, fuzzy controller whose inputs have relative speed (v_x) and a difference between desired and actual distance (dx_{error}). The difference between desired and actual distance is determined by a formula that includes the exact speed of the following vehicle (v_F), minimum distance (dx_{min}) and a time constant (T_H).

Two membership functions, describing driving style transitions from comfortable to sporty driving, are introduced as an additional input (*Style*), represented with real number value between 0 and 1. Accordingly, fuzzy controller #1 shown in Fig. 4 is designed for generating acceleration (a_F) based on the current traffic situation and preferred driving style.

Fuzzy controller #1 constantly provides the best value of the acceleration to achieve adequate performance. At steady state, the error dx_{error} is zero and the cars have the same speed and constant distance determined with the Eq. (2) where T_H is time headway.

$$dx = dx_{min} + T_H \cdot v_F \tag{2}$$

Choice of the driving style affects the parameter T_H and value of the minimum distance dx_{min}. This influence can be represented by a linear or non-linear function that can be chosen intuitively, as long as it takes into consideration that T_H and dx_{min} increase when switching from sporty to comfortable drive, and decrease when switching in the opposite direction. This function can be realized by applying fuzzy controller #2 as it is shown in Fig. 4. Zero-order Sugeno model is chosen and acceleration values are crisp (singletons) at certain points of acceleration. Following vehicle behaviour for different driving, styles are shown in Fig. 5 by using leading vehicle speed in the form of a restricted ramp.

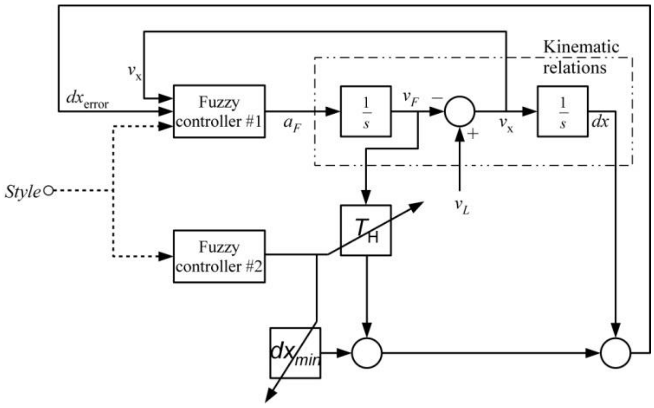


Fig. 4. Structure of system for trajectory generation, based on simplified fuzzy controller.

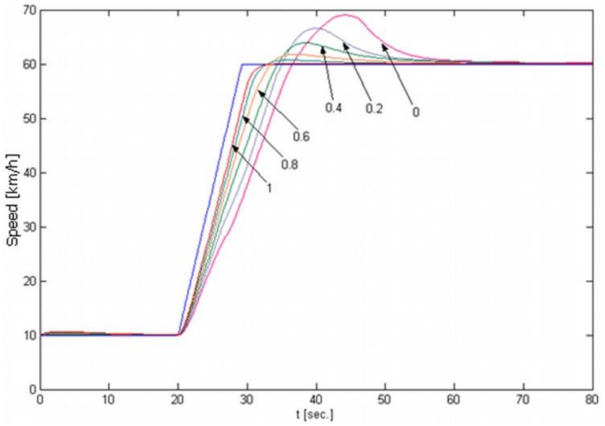


Fig. 5. Output of simplified fuzzy model for different driving styles.

4. Driver Modelling using ANFIS

Now we can consider the design of a driver's model by using ANFIS [14]. It is known that the basic goal of ANFIS is to generate Sugeno fuzzy system from a given input-output dataset. The general structure of ANFIS is depicted in Fig. 6 [15]. Shape and position of the input membership functions are adapted (learned from data) using backpropagation training/learning in combination with least squares method (minimization of learning error). The result of learning is the Sugeno fuzzy system. There are also learning structures for generating Mamdani type of fuzzy system [16], but our practical experience shows that Sugeno type is more suitable for this kind of application as well as for some other applications [17]. Figure 6 also depicts learning complexity that cannot be achieved manually. Empirical fuzzy modelling is often used to build a controller [18, 19]. Usage of ANFIS speeds up this process. Manual fuzzy modelling is hard and inefficient – it is hard to find the optimal model manually. Use of neural networks is efficient but the resulting model is not so understandable to a human. ANFIS provides the efficiency of neural networks and the resulting model is a fuzzy model that human can understand especially the rules part. That is the main reason why ANFIS is chosen.

The resulting Sugeno fuzzy system can be validated (checked) by data not used in training. When learning from data, it is important to control overfitting through use of datasets for training, validation (checking), and testing.

In order to demonstrate the functionality of ANFIS in this section, data from the simulation environment with a fuzzy model of the driver is used to see how well ANFIS learns to identify a particular driver. Due to a lack of real driver behaviour information, collected from sensors that measure absolute and relative speed and acceleration, we assume that the driver behaves according to the model based on fuzzy controller described in Section 2. Data for training, validation and test were generated from the simulation environment. Following vehicle speed, relative speed, relative distance and generated acceleration were exported from the workspace and used as a dataset for ANFIS.

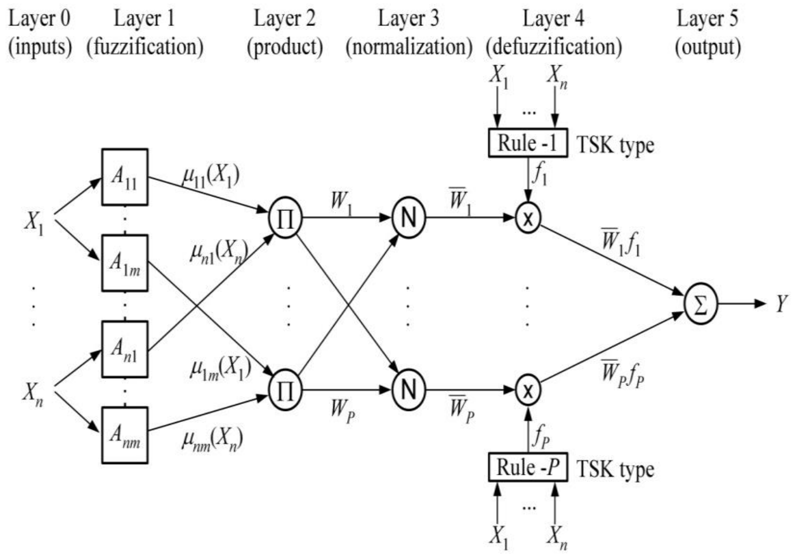


Fig. 6. General ANFIS structure [15].

Andre et al. [20] discussed that certain driving cycles can be used as a leading vehicle speed diagrams. Based on the chart, speed of the leading vehicle, the fuzzy model generates a trajectory of movement of the following vehicle and a range of scenarios can be simulated to choose those that are suitable for ANFIS training, checking, and testing. The initial design of fuzzy controller using ANFIS is based on the default choice regarding the number of membership functions and shapes of membership functions of the initial FIS structure. Parameters of membership functions automatically change during the training process. After several attempts, satisfactory results were achieved using five triangular membership functions for each input. Training error in 60th epoch was 0.083057. The parameters of the model were chosen according to the minimum error using checking data (see Fig. 7). The measure of output data fitting can be expressed as average error:

- For training data: 0.083,
- For checking data: 0.118, and
- For test data: 0.116.

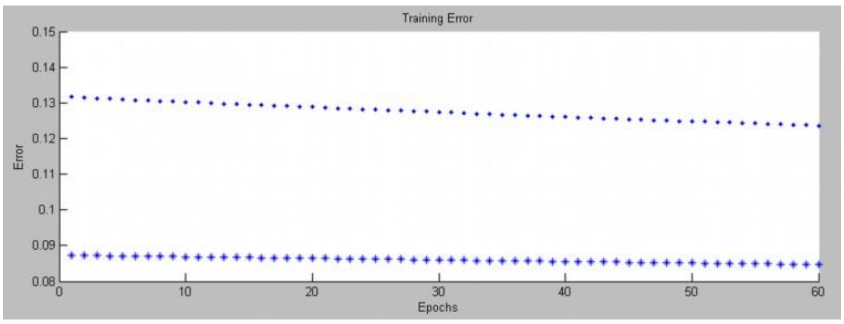


Fig. 7. Training error and checking error during epochs.

Diagrams of matching output for all three datasets are shown in Fig. 8. The resulting model has the following parameters:

- Node numbers: 286,
- Overall parameter number: 170,
- Training data pairs: 1701,
- Checking data pairs: 1701, and
- Number of fuzzy rules: 125.

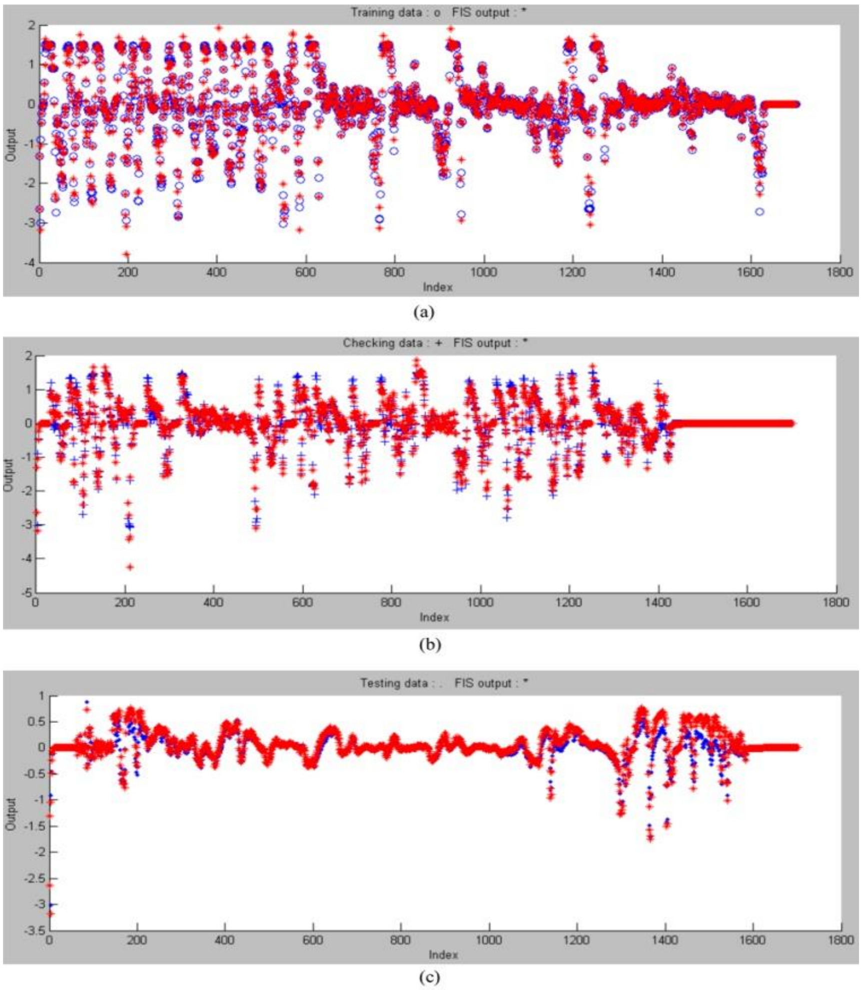


Fig. 8. Diagrams of matching output value for:
(a) Training data, (b) Checking data and (c) Test data.

5. Fuel Consumption Considerations

In recent years, more and more attention is given to the problems of preserving the environment. Car technology that takes into account the problem of environmental pollution is becoming more important than before. Internal combustion engines are a major source of pollution that leads to global warming. Dependence on oil, as the main source of energy for cars, may soon contribute to the global crisis due to the reduction of oil reserves in the world. Therefore, the problem of transport from one place to another that favours fuel efficiency becomes a very important strategy for both conventional as well as for hybrid vehicles [21]. The greatest potential for improving the fuel economy probably lies in the improvement of technology in vehicles production. However, this approach can have a relatively long implementation. An effective way to reduce fuel consumption in a shorter period of time is an attempt to change the behaviour of the driver while driving. In autonomous driving, this means that an appropriate controller or driver model should be designed. Another advantage of this approach is that it remains valid even after the improvement of technology in vehicles production, and will also contribute to further reduction of consumption and reduced pollution.

5.1. Impact of a driving style on fuel consumption

Impact of driver behaviour on fuel consumption is discussed in several papers. According to Voort and Maarseveen [21], appropriate model to describe an optimal driver behaviour with respect to fuel consumption is developed and described. This includes certain available measured values (speed, acceleration, engine speed, gear position, braking force, etc.) and the characteristics of the vehicle (mass, engine power, aerodynamic characteristics, etc.). The idea of this model is to design a system that will provide appropriate advice to the driver to reduce fuel consumption. This approach does not consider autonomous driving vehicles and driver’s relief from vehicle control. Berry [22] analysed the impact of a driving style on fuel consumption data and the general picture of the driver behaviour while driving in various environments with the aim of finding a potential change in driving style to minimize fuel consumption. Some observations made by Berry [22] are presented below in order to identify variables that are essential for the design of fuzzy controller using ANFIS for autonomous control of vehicles in terms of fuel economy.

As is presented by Berry [22], the driver's behaviour in terms of fuel consumption is conveniently considered in three-speed ranges as follows:

- Low speed (driving through local streets in residential areas) – average speed below 32 km/h. The amount of acceleration has the greatest impact on fuel consumption.
- Moderate speeds (city driving) – average speed between 32 and 72 km/h. Acceleration values also affect fuel consumption, but not as in the previous range.

High speed (driving expressways and highways) – average speed over 72 km/h. Amounts of high speed most affect fuel consumption and can allow a greater amount of acceleration.

5.2. Design of fuzzy controller using ANFIS

Generating training data that will consider the amount of acceleration in all three bands specified above is crucial when designing a fuzzy controller using ANFIS in terms of fuel efficiency. The basic idea for generating data for training involves the processing driving cycle of the leading vehicle in order to make a reduction in the acceleration of the following vehicle. This reduction can be achieved by using already developed driver model based on fuzzy logic [13] in a way that the value of the parameter that determines the driving style is different depending on the speed band. It is shown that the value of this parameter (noted as K), which is in the range from 0 to 1, in fact, determines the output acceleration (singleton values of a fuzzy controller). In order to generate appropriate training data, it is convenient to add a special fuzzy controller that gives a value of the parameter K based on the input speed and its membership functions defined for each band. Extremely comfortable driving (K = 0) provides good conditions for fuel efficiency with respect to the amount of acceleration, however, following the leading vehicle is questionable and this driving style would probably not be practical. While choosing parameter K throughout the simulation process, the relative distance should be monitored and car properties should be as close as possible to the most common driving cycles of the leading car. This is actually achieved by adjusting the parameters of the membership functions of the introduced special fuzzy controller. Model for generating training data is presented as a block diagram on Fig. 9.

Membership functions of the input variable v_F of the special fuzzy controller are depicted in Fig. 10. Singleton values of parameter K are Small (0), Medium (0.5), and Big (1). Fuzzy rules are defined as:

IF v_F is Small THEN K is Small
IF v_F is Medium THEN K is Medium
IF v_F is Big THEN K is Big

This provides continuous updating of K values that will vary according to the input values v_F and its member functions. Andre et al. [20] mentioned that the speed of the leading vehicle is based on three drive cycles chosen from cycles listed. This provides appropriate data sets (training, checking and test) for a design of fuzzy controller using ANFIS. Inputs to ANFIS are the speed of the following vehicle, the relative speed of vehicles, and the distance. The output from the controller is the desired acceleration. After 60 epochs of training a 0.06 error are achieved. The parameters of the model are chosen according to the minimum checking error data (upper line on Fig. 11).

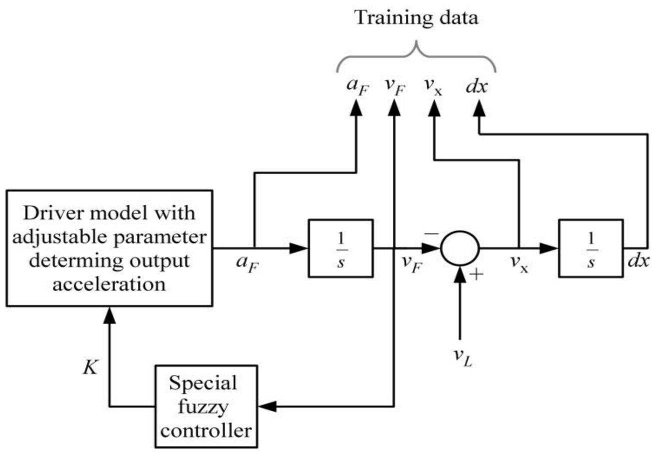


Fig. 9. Block diagram of model for generating training data.

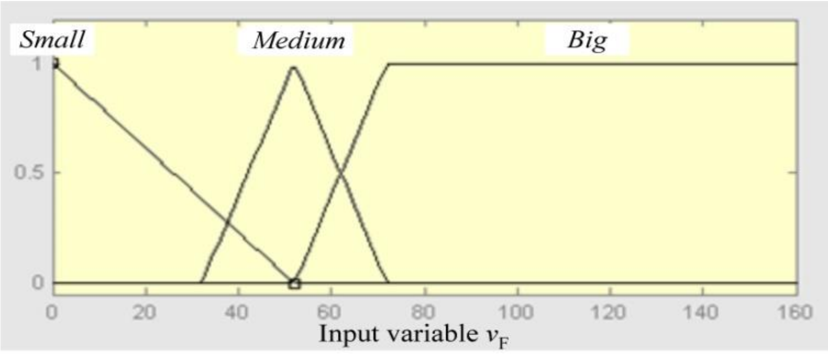


Fig. 10. Membership functions of the input variable *Vf* of special fuzzy controller.

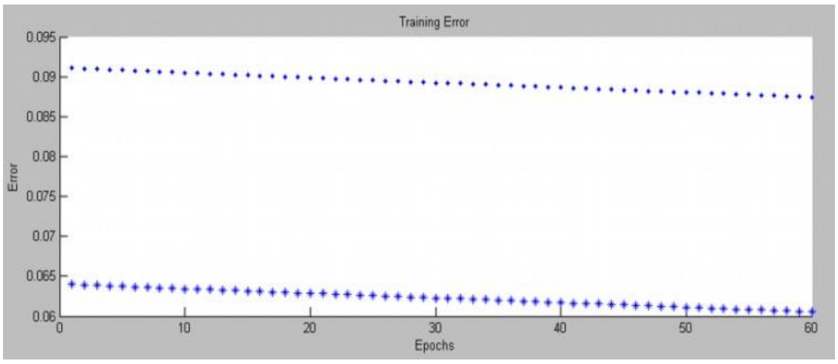


Fig. 11. Training error and checking error during epochs.

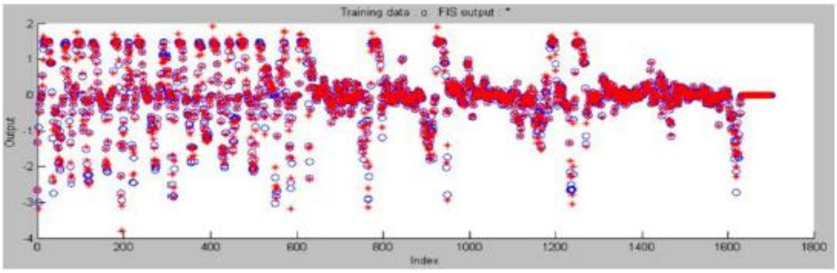
Highlighted results in Table 1 were achieved after choosing various shapes of membership functions and a various number of membership functions. The measure of output data fitting is expressed as an average error given in Table 1. The further increase in the number of membership functions does not make any significant improvements. The appropriate model was chosen according to following error values: for training data 0.06047, for checking data 0.0873, and for test data 0.0599. The resulting model has the following parameters:

- Node numbers: 286
- Overall parameter number: 170
- Training data pairs: 1701
- Checking data pairs: 1701
- Number of fuzzy rules: 125

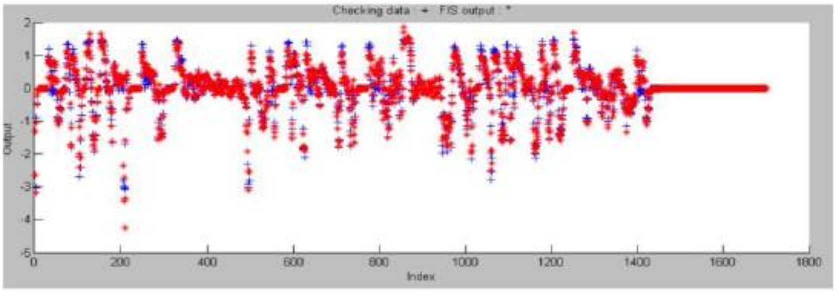
Diagrams of matching output for all three data sets are shown in Fig. 12. The time necessary to train ANFIS depends on the number of inputs and size of the dataset. In this case, there were three inputs and the number of samples for training was 1800. The time required for training was a few seconds, which can be considered as small computation time.

Table 1. Results for different FIS parameter combinations.

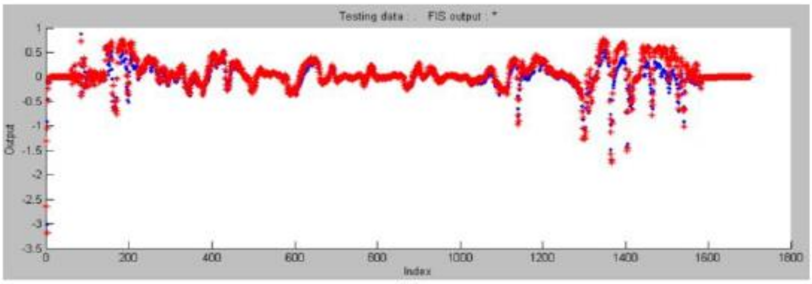
Root mean square error		Shape of input membership functions					
		Triangular			Bell		
		Number of functions			Number of functions		
		[3 3 3]	[4 4 4]	[5 5 5]	[3 3 3]	[4 4 4]	[5 5 5]
Dataset	**Training**	0.1279	0.0989	**0.0605**	0.187	0.1419	0.0778
	Checking	0.1342	0.1531	**0.0873**	0.2723	0.2614	0.1774
	Test	0.0666	0.0634	**0.0599**	0.0886	0.0957	0.0675



(a) Training data.



(b) Checking data.



(c) Test data

Fig. 12. Diagrams of matching output value.

5.3. Model validation

To see the effectiveness of the trained fuzzy controller in terms of reducing fuel consumption and emissions of harmful exhaust gases, the ADVISOR model is used. The ADVISOR software package, depicted in Markel et al. [23] and

ADVISOR [24], gives a possibility to develop a dynamic model of the vehicle and is able to calculate the amount of fuel consumption and pollution emission based on presented driving cycles. ADVISOR relays on MATLAB/Simulink and enables simulation of different driving styles. In this work, it used a predefined dynamic structure of a typical commercial vehicle.

First is necessary to configure vehicle components and their behaviour-parameters like vehicle type, engine type, wheels diameter, etc. After that is necessary to define the speed diagram by using trajectories (predefined or user-defined). It is also necessary to set events to simulate. Some of those events can be simulated for one driving cycle, multiple cycles, or by using special procedure. After simulation parameters are set, simulation is run. Data about the speed of the leading vehicle and the data about the speed of the following vehicle are presented to ADVISOR and fuel consumption as well as CO emission is calculated (estimated) by the ADVISOR.

ADVISOR is used to enable comparison of fuel consumption and emissions of pollution on the leading vehicle with standard trajectory and following vehicle with ANFIS generated trajectory. Following vehicle also has different speed diagram. Figure 13 gives an overview (summary) of fuel consumption and emissions of pollution for a driving cycle through the city of Nuremberg (a driving cycle is taken from Siemens Transportation Systems - Germany, and is available in ADVISOR environment), for both vehicles – leading and following. Results show that trained fuzzy controller saves about 10% fuel for the same distance.

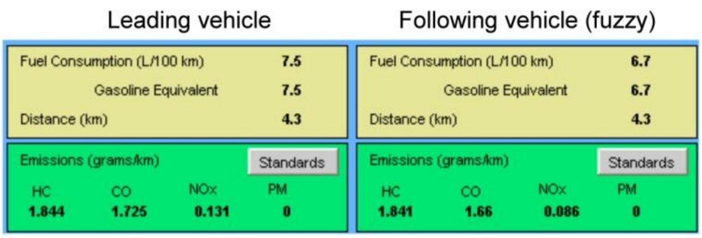


Fig. 13. Values of fuel consumption and exhaust emission.

6. Conclusions

Building a specific driver model with the purpose of taking control of longitudinal vehicle movement involves modelling various driver properties related to real driving. Restricting to models that only perform the task of keeping distance by particular formula does not guarantee wide applicability. In our previous work, we successfully used manually modelled fuzzy systems, but manually adjusting fuzzy system is quite a difficult job while in ANFIS structure parameters of the fuzzy system are adjusted automatically throughout the process of training.

Results of simulation on ADVISOR showed that this kind of controller can perform better than a human driver. That is not easy to achieve by manual modelling of the fuzzy system. This research shows how well fuzzy controlled system created using ANFIS can mimic the actions of a specific driver based on acquired data from the real or simulated driving.

Preservation of the environment and control of harmful exhaust gases emissions is very important. Efficiency validation of the designed fuzzy controller is achieved by using advanced vehicle simulators that are available today. These simulators, such as the aforementioned ADVISOR, can give an estimate of the fuel consumption of a particular type of vehicle by giving a set of dynamic characteristics of the vehicle and presented speed in time.

Attention must also be given to driving cycles through various environments, which are in many cases collected from real traffic. The fuzzy system, which takes into account this information, is a significant improvement since it can create a good environment for generating training data that will lead to the design of desired system useful in engineering applications of autonomous vehicle control.

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Nomenclatures

a_L	Acceleration of the leading vehicle $a_L \in$ {large negative, medium negative, small negative, zero, small positive, medium positive, large positive}
a_F, $a_F(t)$	Acceleration of the following vehicle
d_x, dx	Relative distance-$d_x \in$ {very small, small, OK, large, very large}
dx_{error}	Difference between desired and actual distance
dx_{min}	Minimum distance
K	Driving style, $K \in [0,1]$
M	Vehicle’s mass
T_H	Time constant
v_L, $v_L(t)$	Speed of the leading vehicle
v_x	Relative speed / velocity – $v_x \in$ {large negative, small negative, zero, small positive, large positive}
$W_1 ... W_p$	Weights between layer 2 and 3 in neural network/ANFIS
$\bar{\bar{W}}_1 \ldots \bar{\bar{W}}_p$	Weights between layer 3 and 4 in neural network/ANFIS
$X_1 ... X_n$	Neural-network inputs (ANFIS inputs)

Greek Symbols

λ	Control mechanism sensitivity factor
$\mu_{i,j}$	Weights between layer 1 and 2 in neural network/ANFIS
τ_n	Reaction time (time of perception + time to take action)

Abbreviations

ANFIS	Adaptive Neuro Fuzzy Inference System
TSK	Takagi-Sugeno-Kang (or Sugeno) type of fuzzy system

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