# Driving Style Modelling with Adaptive Neuro-fuzzy Inference System and Real Driving Data

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**Abstract.** With different cognitive abilities and driving style preferences, car-following behaviors can vary significantly among human drivers. To facilitate the replications of human driving behaviors on chassis dynamometer using a robot driver, this paper proposes a novel fuzzy logic driver model that attempts to perform humanized driving behaviors in the car-following regimes. An adaptive neuro-fuzzy inference system was developed to tune the fuzzy model using real driving data collected from an instrumented vehicle. Driver's cognition parameters, such as headway distance, vehicle speed and pedal positions, were modelled as system inputs. Meanwhile, driver's action parameters, such as pedal movements and gear selection, were selected as system outputs. Three models that possess different driving styles were calibrated using the system. Afterwards, in order to evaluate its performance of emulating human behaviors, the established fuzzy models were examined in a simulation scenario that is anchored to standard WLTC drive cycle tests.

**Keywords:** Human Factors · Driving Style Simulation · Car-following Model · Fuzzy Logic · Real Driving Data · WLTC

## 1 Introduction

While the concept of driving style was first proposed by Elander et al. in 1993 [1], the variances between each individual's driving habits have been realized for many decades, with the earliest research published in 1949 [2]. As defined by Elander et al., "driving style concerns the way individuals choose to drive, or driving habits that have become established over a period of years. While several different definitions of this concept have been proposed by following researchers [3, 4], it can be inferred that driving style generally refers to the driver's own habitual choice of driving manoeuvre, which consists of the preference of car-following behaviors, driving patterns, and gear shifting strategies, etc [5]. It has been roughly categorized into three groups (aggressive, normal, and defensive) in most studies [6, 7]. Drivers belong to different groups can have very distinct driving preferences, which can cause significant variances in fuel consumption and exhaust emissions. Thus, identifying the difference in

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each individual's driving style can contribute to the development of more personalized advanced driver assistance systems (ADAS), and facilitate the promotion of eco-driving.

While the difference of driving style can be reflected in many scenarios, such as car-following, free flow, driving under instructions, etc., car-following regimes are of particular interest. As a critical research area in microscopic traffic flow studies, car-following behavior mainly refers to the driver's longitudinal control of the vehicle when following a leading vehicle with a headway distance [8]. It can be noted that both the driver's cognition and action characteristics can be reflected in the preferred headway distance and driving patterns. Therefore, car-following regimes can be a prominent driving scenario for driving style investigations.

There have been several different models developed to simulate car-following scenarios. For example, the Gazis-Herman-Rothery model that formulated the acceleration of the following vehicle as a function of its speed, the driver's reaction delay, the relative speed and distance between both vehicles [9]. Meanwhile, Yang and Zu developed a linear model that incorporated the desired following distance as an additional input [10]. Alongside with these equation-based models, several data-driven models were also established. Fuzzy logic [11, 12] and neural network [13, 14] have been adopted to simulate car-following behaviors based on experimental data.

While all these approaches can be used to simulate car-following behaviors, fuzzy logic is more favored because its incorporation of vagueness. This feature increases its similarity to human reasoning, as human drivers' perceptions about the traffic environment is based on inaccurate estimation. However, it should be noted that the determination of membership functions is a major challenge in developing fuzzy logic controllers.

Therefore, as a continuation of previous research [5], this paper proposes to develop an adaptive neuro-fuzzy inference system (ANFIS) to calibrate a fuzzy logic car-following driver model. The performance of this model is evaluated through a simulation scenario that is anchored to standard World-wide harmonized Light duty Test Cycle (WLTC) drive cycle tests. This study is part of a research program aiming to incorporate the variance of driving style into drive cycle research using a robot driver. Therefore, calibrating a driver model with ANFIS and real driving data can increase its similarity to human drivers. This research can improve the understanding of driving style variances, and their correlations with fuel consumption. Moreover, as Real Driving Emissions (RDE) tests will be introduced in future type approval requirements, it should be noted that driving style of the test driver could influence the verification result of the vehicle. Meanwhile, the Portable Emission Measurement Systems (PEMS) in RDE tests may also be less accurate than laboratory equipment. Thus, it would be beneficial to replicate these RDE tests on a chassis dynamometer with driving style variance incorporated. Furthermore, more economical and personalized advanced driver assistance systems (ADAS) and autonomous vehicle control strategies can potentially be developed with this model [15].

## 2 Methodology

The collected real driving data and the established adaptive neuro-fuzzy inference system are introduced in this section. Meanwhile, the adopted simulation environment for evaluating the calibration performance is also briefly described.

### 2.1 Real Driving Data Collection

The real driving data used in this study were collected in a previous research [5]. Three participants were requested to drive an instrumented VW Sharan along a selected route, as shown in Figure 1. The vehicle was equipped with an Influx Rebel CT OBD data logger, a Continental 77 GHz long range ARS 308 radar and a Nextbase 512G dashcam. Therefore, both the vehicle state information and headway distance can be recorded with the vehicle. Meanwhile, the sensor fusion approach proposed in previous research [16] was also performed to improve the accuracy of headway distance measurements by fusing data from radar and monocular dashcam. A total of 100 trips were recorded, with an average duration of 63 minutes. Each trip was approximately 45 miles, and consisted of a combination of urban, rural, and highway segments. With the collected real driving data, the car-following events during these recorded trips were isolated, and prominent parameters from drivers' perception, such as headway distance, vehicle speed and pedal position, were extracted and synthesized for model calibration.

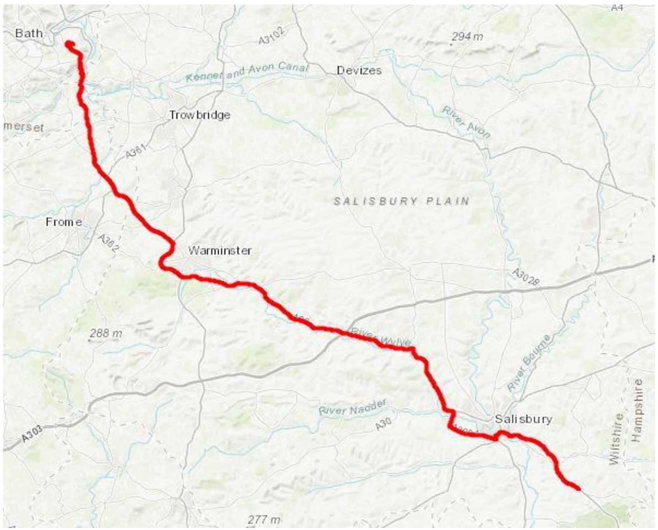



**Fig. 1.** Route for real driving data collection [5]

### 2.2 Adaptive Neuro-fuzzy Inference System

The ANFIS with hybrid learning algorithm proposed by Jang [17] was adopted for this study. This training algorithm is a combination of the least-squares and back-propagation gradient descent methods, which can achieve a faster convergence rate and better performance in avoiding local minima. The architecture of this ANFIS is shown in Figure 2.

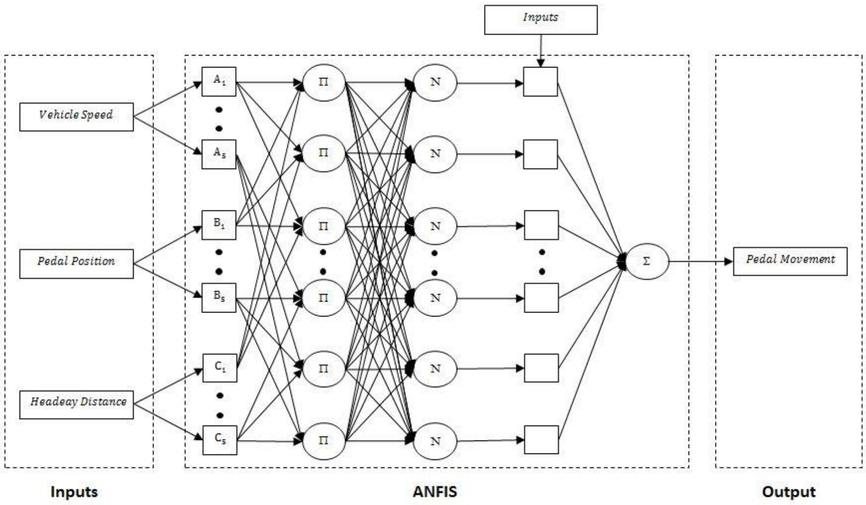



**Fig. 2.** Architecture of established ANFIS

It can be noted from Figure 2 that the established ANFIS has five layers. A brief description of each layer is discussed below:

**Layer 1**: This is the fuzzification layer, with each node representing a specific linguistic variable of input parameters. There are a total of 15 nodes in this layer. 5 nodes (Very Slow, Slow, Medium, Fast, Very Fast) for vehicle speed, 5 nodes (Very Small, Small, Medium, Large, Very Large) for pedal position, and 5 nodes (Very Close, Close, Medium, Far, Very Far) for headway distance. The Gaussian membership function is selected. The output of each neuron is the degree of membership, which can be represented as,

$$O_{1i} = \mu_{A_i}(x) = \exp\left[-\frac{(x - c_i)^2}{2a_i^2}\right] \quad \textbf{(1)}$$

where $\{a_i, c_i\}$ are the premise parameters.

**Layer 2**: This layer contains the fuzzy rules. Each neuron corresponds to a Sugeno type fuzzy rule. The output of each node is the product of all inputs:

$$O_{2i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y)\mu_{C_i}(z) \quad \textbf{(2)}$$

where $w_i$ is the firing strength of each rule.

**Layer 3**: The normalized firing strength is calculated in this normalization layer, which can be denoted as.

$$O_{3i} = \overline{w}_i = \frac{w_i}{\sum_i^n w_i} \quad \textbf{(3)}$$

**Layer 4**: This is the defuzzification layer, where the weighted consequent value of a given rule is determined as,

$$O_{4i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i z + s_i) \quad \textbf{(4)}$$

where $\{p_i, q_i, r_i, s_i\}$ are the consequent parameters.

**Layer 5**: There is a single neuron in this output layer. Its generated value is determined as the summation of all outputs from previous layer, which can be denoted as,

$$O_{5i} = \sum \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \textbf{(5)}$$

In order to evaluate the tuning performance of ANFIS, the collected real driving data were randomly divided into two subsets. 70% of the data were used as training data to calibrate the model, and the remaining 30% were used as testing data for evaluation.

### 2.3 Simulation Environment

To facilitate the evaluation of the established driver model, it was connected to a Simulink dynamic vehicle model developed in previous study [5]. This vehicle model consists of five subsystems, each representing the engine, vehicle body, tires, brake, and gearbox respectively. All these components were parameterized using the specifications of VW Sharan to increase its similarity to the instrumented vehicle. The established vehicle model can receive throttle pedal position, brake pedal position, and gear selection as inputs, and generate corresponding vehicle speed, engine rpm, and fuel consumption as output. The performance of this vehicle model was validated in a previous study through comparisons with the collected experimental data on chassis dynamometer [5]. Meanwhile, a fixed update frequency of 2Hz was adopted for the simulation to imitate the cognitive delay of human drivers [18].

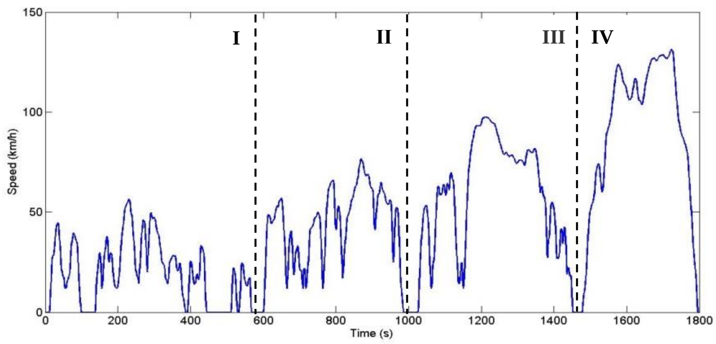



**Fig. 3.** Speed profile of WLTC drive cycle

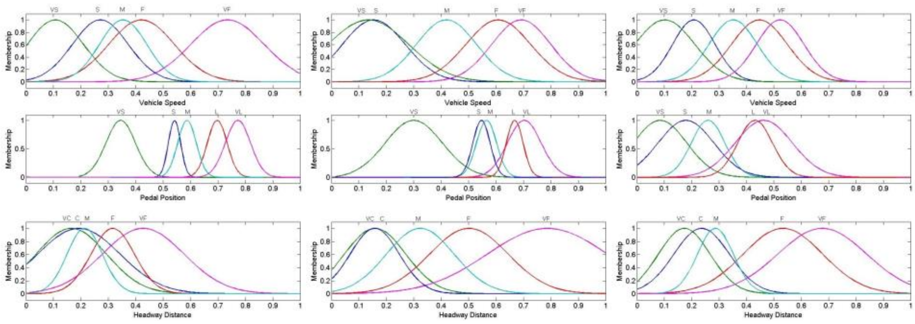
Alongside with the vehicle model, a car-following simulation scenario was also created. In order to incorporate driving style variances into drive cycle research, the speed profile of WLTC was assigned to an imaginary leading vehicle. As shown in Figure 3, the speed profile of Class 3 WLTC was selected according to the power-weight ratio of the instrumented vehicle. Therefore, instead of directly providing the speed profile to the host driver, the drive cycle information was converted to the variations of headway distance. This setting can better reveal the difference of drivers' cognition and action characteristics. Meanwhile, different driving styles recorded in real world car-following scenarios can also be reflected in this simulation scenario. It should be noted that although the difference between the desired and actual speed profile will increase, the influence of driving style can be better revealed in procedures that are anchored to the standard drive cycle tests. Owing to the lack of real driving data over 110 km/h, only the first three segments of the drive cycle were selected as the driver models were specifically tuned for this speed range.

## 3 Results

The results are presented in three sections, discussing the tuning results of the ANFIS, the driving style variances, and the correlation with fuel consumption.

### 3.1 Tuning Results of ANFIS

Three driver models representing each human participant were calibrated using the established ANFIS. The tuned membership functions were illustrated in Figure 4.




(a) Driver 1 (b) Driver 2 (c) Driver 3

**Fig. 4.** Membership functions of three driver models

As shown in Figure 4, the tuned membership functions vary significantly among the three driver models, indicating their different driving styles. It can be noted that the first model's membership functions of vehicle speed and pedal position are more located to the right, while headway distance more to the left. This phenomenon indicates that the first driver model tends to be more aggressive as it has a higher cognition level of fast speed and large pedal position, and a lower level of large headway gap. Similarly, the third model tends to be more defensive with the opposite trends of membership functions. Meanwhile, the second model can be regarded as a normal driver comparing with the other two models. This finding is in coincidence with a previous driving style classification study based on the same dataset [15], which improves the validity of the tuning results.

To evaluate the tuning performance of the established models, the Root Mean Square Error (RMSE) was adopted to compute the difference between data and ANFIS output. The final RMSE were 0.1011, 0.0794, and 0.0856 respectively. Thus, it can be noted that the tuned driver models possess the driving styles of human participants.

### 3.2 Driving Style Variances

As the established three driver models possess relatively different driving styles, they were examined in the proposed car-following simulation scenario to evaluate their difference. The headway distance and throttle pedal position were selected as the prominent factors to reveal the variances.

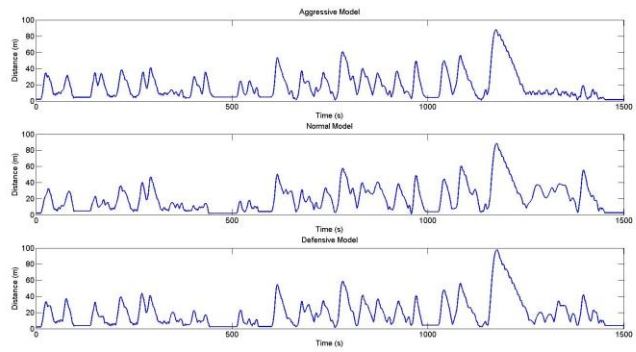



**Fig. 5.** Headway distance profiles of three driving styles

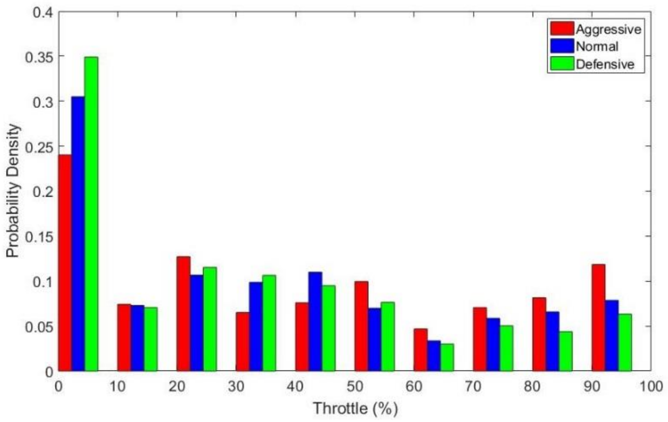



**Fig. 6.** Throttle pedal distributions of three driving styles

From Figure 5, it can be noted that the established driver models have different headway distance profiles. While their basic shapes were similar, the average headway gaps were computed as 17.7m, 18.7m and 20.4m respectively. This finding correlates with the common definitions of these driving styles, as aggressive drivers are more likely to tailgate, and defensive drivers prefer a larger safe distance. Meanwhile, as shown in Figure 6, the aggressive model shows a greater proportion of large throttle movements (15.3% more than defensive when throttle > 50%), while the defensive model is more distributed in small throttle scale (73.6% when throttle < 50%). This phenomenon indicates that the aggressive model has a higher tendency of harsh acceleration, and the defensive model is milder on vehicle manoeuvre. Therefore, it can be noted from both findings that the tuning performance of ANFIS was satisfying.

### 3.3 Correlation with Fuel Consumption

Alongside with headway distance and throttle pedal position, the correlations between simulated driving styles and fuel consumption were also investigated. The probability density distribution of fuel consumption was computed to demonstrate its variations between different driving styles. As illustrated in Figure 7, it can be noted that the aggressive driver shows a larger possibility of high fuel consumption manoeuvres than the other models, especially for driving events that consumed more than 6 liters/h (6.3%). Meanwhile, the defensive driver occupies the largest proportion (63.4%) in low fuel consumption range ($0 - 3$ liters/h). While the differences between fuel consumption were not significant, it can still be noted that the aggressive model tends to have more high fuel consumption manoeuvres, while the defensive model has fewer.

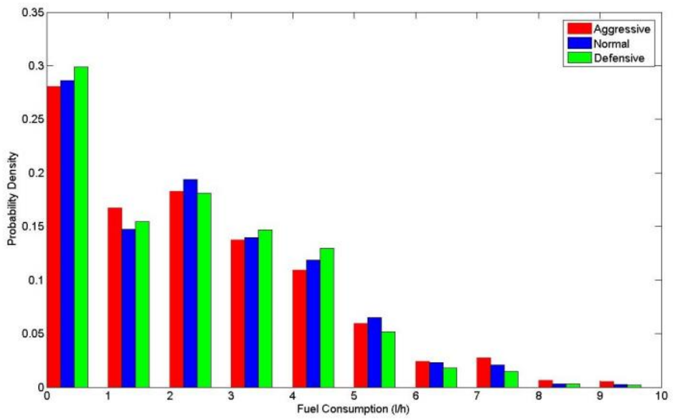



**Fig. 7.** Fuel consumption distributions of three driving styles

## 4 Conclusions

The primary aim of using an adaptive neuro-fuzzy inference system to calibrate a fuzzy logic car-following driver model from real world driving data was achieved. With the collected real driving data of three human participants, corresponding driver models were developed using the proposed approach. Afterwards, these models were connected to a Simulink vehicle model to examine their performance in imitating human driving styles. Meanwhile, the correlations between these simulated driving styles and fuel consumption were also investigated.

It was found that the tuning performance of the established ANFIS was satisfying. The models' output had a high correlation with the collected real driving data. Meanwhile, the driving style variations revealed from headway distance, throttle pedal position, and fuel consumption also validated the tuning performance.

The major contribution of this paper is to develop fuzzy logic driver models that can perform humanized car-following behaviors recorded in real world driving scenarios. Moreover, the proposed simulation scenario can incorporate driving style variances into procedures that are anchored to the standard drive cycle tests, and hence add more variations to the existing drive cycle tests.

As future work, these established driver models will be used to control a robot driver, and hence operate real vehicles on a chassis dynamometer. Therefore, the performance of these models can be experimentally evaluated.

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