Range Extended for Electric Vehicle Based on Driver Behaviour Recognition

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Keywords: Electric Vehicle, Driver Behaviour, Neural Network and Fuzzy Logic.

Abstract

Driver behaviour has been considered one of the main factors that contribute to increase fuel consumption, CO_2 emissions, traffic accidents and causalities. Thus, the concept of detecting and classifying driver behaviour is vital when tackling these challenges. Recognition of the driver behaviour is a difficult task as in the real-world, the driving behaviour is effected by many factors e.g. traffic, road conditions, duration of the journey etc. Many approaches have considered the use of Computational Intelligence techniques, to develop a driver behaviour detection system. In this paper we concentrate on the impact of driver behaviour on the energy consumption and thereby on the range of electric vehicles. A new architecture is proposed to show how computational intelligence techniques could interact with the contextual information collected from the vehicle, the driver and external environment. A neural network model is used to classify the driver behaviour, and then this classification is used in a fuzzy logic controller to make balanced managements to the range extender operation.

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1 Introduction

Since the early twentieth century, combustion of fossil fuels has been the main source of energy for the industrial world and particularly for automotive sector. Fossil fuels such as petroleum are a finite resource, and it is predicted that the released greenhouse gases (GHG) from burning fossil fuels takes part in global warming [1] and can lead to health complications in afflicted communities

The continuous use of fossil fuels and growing volume of traffic bring many challenging issues, like huge environmental costs, rising cost of fuel, air pollution and global energy regression. Energy and environmental sustainability has become a major concern in the existing automotive industry. One of alternatives is use electricity-powered vehicles. Such vehicles charged from the electricity grid can alleviate the impact of the aforementioned issues.

More than 11% of new vehicles now sold in the UK have CO_2 emissions below 120 g/km. However the vast majority of on-road vehicles are still petrol and diesel powered and the use of electric vehicles (EV) in the UK has to-date played only a small part in this shift.

One of the main obstacle affecting the market take-up of EVs is the short range of use with battery charged, compared to fossil fuel vehicles. The recharging process is relatively slow (taking up to 12 hours), and there is a shortage of charging points away from urban centres, which prevents users from using EVs on long trips; this limits their range of usefulness.

One of the solutions to the range anxiety conundrum is use of the range extenders. Indeed, EVs with built-in range extenders are now available for drivers. Cars like Vauxhall Ampera, Chevrolet Volt or BMW i3 are examples of the recent efforts carried out by the automotive industry to bring the range extender technology to the EVs market. Also, among researchers in academia the range extender concept has been in particular interest in the recent years; e.g. [2, 3, 4, 5].

However, the existing range extension algorithms typically monitor only the battery charge level regardless of the current and imminent load requirements [6, 7, 8]; some also take no account of energy recovery mechanisms such as brake flywheels. These approaches are valid, but inefficient as the vehicle's performance in real-world is affected by many additional factors including environmental conditions (e.g. solar radiation, humidity, wind direction, ambient temperature), journey profile characteristics (e.g. length, incline, road type (highway, suburban, urban)), driving style (calm, normal, aggressive), vehicle states and parameters (power demand, auxiliary and accessory loads, vehicle components' efficiencies).

Among the described factors the driver behaviour has been considered one of the major impacts on the vehicle fuel consumption and emission levels, as abrupt acceleration and deceleration, along with speeding, result in higher fuel consumption [9].

Consequently, the driver behaviour has been an area of interest to academics, resulting in interdisciplinary research from diverse scientific and engineering fields, including system modelling, psychology, automotive and transportation engineering and computer science. Currently, driver behaviour models are mainly applied to the simulation of traffic systems [10], design of intelligent cruise control [11], safety applications [12] and in-vehicle driving assistant systems [13]. Recently, in Intelligent Transport Systems (ITS) developments and applications, more emphasis has been placed on the driver to address uncertainty that might be introduced by individual users of ITS into a particular application. Drivers may adjust their behaviour in a sudden manner, which from an application perspective, may turn out to be both positive and negative. Such mutual interactions between ITS application and ITS users have a significant impact on the application design.

Determining the effects of this behavioural uncertainty can be undertaken in many ways, depending on the stage of the development process and the expected outcomes from the development. In transport research, the driving pattern concept has been widely used to characterise driving behaviour [14]. Speed and acceleration profiles have also been used in evaluations of emissions [15], [16], developing driving cycles [17], [18] and in enhancements of vehicles safety [19]. The driver behaviour is also considered in intelligent energy management of hybrid vehicles [20], [9]. However, identification of driving patterns and detection of actual driver state is difficult task as a large number of uncertainties exist in any driving scenario, due to the long-term and spontaneous abilities of drivers, and their interactions with changing environment.

The aforementioned problem of the driver behaviour recognition and detection could be answered by means of computational intelligence (CI). CI methods implement approaches motivated by human brains, genetic evolutions and natural phenomena. They include many computational algorithms from adaptive system theory and signal processing to numerical analysis.

Transportation problems exhibit a number of characteristics that make them subtend to solution using CI techniques. CI deals with systems whose behaviour is very hard to model with traditional approaches because of the ambiguity and uncertainty resulting from human interactions and system information among the different components.

Among the most important of CI utilisation areas are the prediction of the behaviour of systems where the relationship between input and output is not linear, including predicting traffic situation and predicting the impairment of transportation infrastructure as a function of traffic, construction, and environmental factors.

The reminder of this paper is organised as follows. Section 2 introduces the driver behaviour overview. The proposed driver behaviour recognition architecture based on CI is explained in section 3. Our driver behaviour modelling is shown in section4 and the conclusion is given in section 5.

2 Driver Behaviour Overview

Driving has always been considered a complex task. As well as controlling the vehicle (which is no easy task in itself) the driver has to plan how to reach the desired destination. This includes determination of the correct trajectory to follow while avoiding collisions with vehicles in the proximity. Aside from this, there are often a number of secondary actions being performed while driving (e.g. tuning the radio or using a satellite navigation device). This requires the driver's continuous attention. Increasing traffic makes this challenging task even more difficult; in Great Britain there are currently more vehicles than ever on the road [21].

One of the reasons for studying driving behaviour is to develop a model to capture irregular driving behaviour. Such a model can be used to detect abnormal driving behaviour which can be added to applications available to vehicles fitted with an on-board unit. This would help improve fuel consumption (recharging in the case of electric vehicles) and reduce traffic accidents [22].

The representation of the driver behaviour can be expressed as shown in Equation (1).

$$B = \{D_{t=1}, D_{t=2}, D_{t=3}, \dots \dots \dots \dots, D_{t=n}\} \tag{1}$$

Where (B) represents the behaviour of the driver, (D) is the state of driver behaviour, and (t) is the time slot. The state of the driving is classified into three types, namely calm driving (D_c), normal driving (D_n) and aggressive driving (D_a). driving state is defined through the observable context (C), as represented by Equation (2).

$$(S_{t=i}) = \{C_1, C_2, C_3 \dots \dots \dots \dots, C_k\} \tag{2}$$

According to the previous definition of the driver behaviour [23, 24, 25, 26, 27, 28, 29, 30], we have defined three categories of driving behaviour which are as follows:

1) Calm driving: which involves foresee movement of other road user, traffic lights, speed limits, and gently and relaxed accelerating.
2) Normal driving that reflects moderate acceleration and braking.
3) Aggressive driving that refer to sudden acceleration and heavy braking.

In many situations drivers channel their state of mind directly onto their vehicle through certain driving behaviours and actions; the drivers' abnormal behaviour can be assessed through these actions. Vehicle movements which can be measured include steering wheel movements, lateral position, speed variability, acceleration, deceleration, and response time. For example when the movements of the steering wheel become extreme or start to occur less frequently this indicates abnormality rather than normality in driving behaviour possibly resulting from fatigue which is also indicated by a shift in the lateral position of the driver as he/she becomes drowsy and an increase in the speed variability of the vehicle [31]. Drowsiness also increases the response time to unexpected events. Aggression may be indicated when steering action changes rapidly and speed increases, resulting in increased pressure on the pedals and a decrease in the distance from the vehicle in front [32].

3 Driver Behaviour Architecture Based on CI

In this section all the aforementioned findings are gathered to formulate a driver behaviour architecture based on CI. The proposed architecture, illustrated in Figure 2 is primarily based on the three sub-models of driver behaviour. The task of the CI unit is to determine actual driver behaviour. For this purpose, the CI unit will interact with the driver, vehicle and environment units:

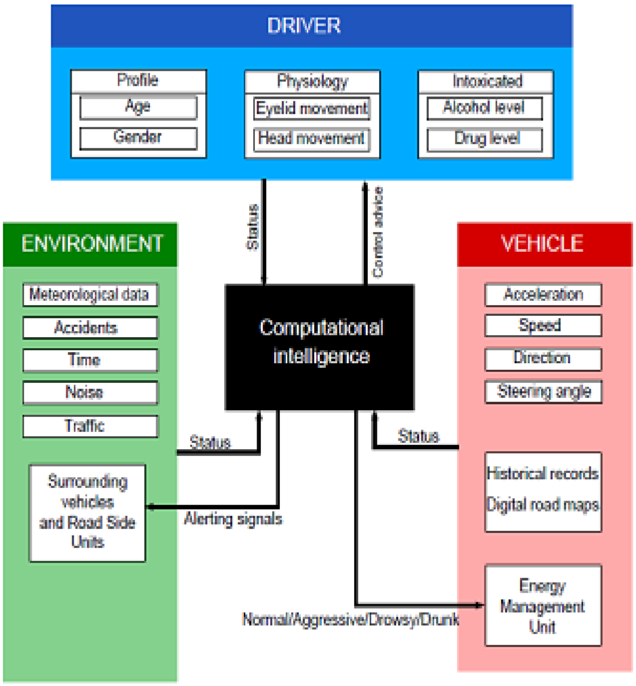

Figure 2: Driver behaviour Detection Architecture based on CI.

- Drivers unit. This unit comprises three main classes of information, namely driver profile, physiology and intoxicant, which are defined below:
  - Driver profile: This provides the system with the required information about the driver, such as age, which is critical for measuring the recklessness of the driver given that, for instance, young drivers have a tendency to drive too fast, while older drivers may drive in a more reasonable manner. Gender is also a good indication of driving behaviour, with males being considered to have a tendency to be more impulsive than females.
  - Physiology: This type of evidence provides the system with information regarding the driver's physical movements, i.e. if the driver's head remains in an unusual position (not straight) for a period of time, indicating that the driver is tired (abnormal). Further evidence is provided by eye movement, i.e. detecting that the driver's eyes have been closed for a period of time, indicating that the driver is tired or drowsy.
  - Intoxicant: This refers to the driver's alcohol blood concentration (ABC) and drug level during the driving process. Increasing ABC or drug levels has a significant impact on driving performance.

- Vehicle Unit: This is responsible for providing the CI unit with the required evidence relating to vehicle information. As shown in Figure 2 it comprises three main blocks:
  - Engine unit and related equipments: This provides the CI system with the required data relating to vehicle information, such as speed control, acceleration, the vehicle's position in the lane, and its direction with regard to its destination.
  - Historical record: This is considered to be crucial for managing the detection of driver behaviour in each time slice to be recorded for use later as one of the inputs for the CI unit.
  - Digital road map: This provides the vehicle with an up to date digital road map to compare the destination and direction of the vehicle.
  - Battery/Engine management unit: This comprises an optimisation algorithm that will take into account the driver's behaviour and manage the available sources of energy thereby reducing fuel consumption, maintaining battery charging levels or extending the journey.
- Environment unit: This unit reveals the way in which the CI unit interacts with environmental variables, such as temperature, meteorological data, time zones, road geometry, noise, traffic situations and the surrounding vehicles and road side units (RSUs). The CI will also generate a warning signal to alert surrounding vehicles and roadside units placed along the road.

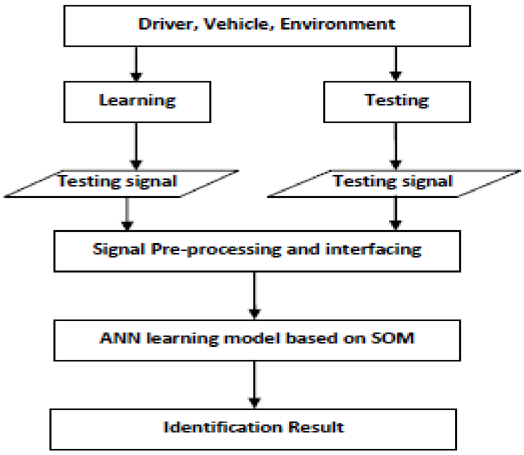

Figure 3: Proposed Method for Modelling Driver behaviour

4 Driver Behaviour Modelling

The suggested method for modelling driver behaviour recognition can be summarised into three actions: (1) extracting features from collected data and different drivers; (2) constructing an artificial neural network (ANN) model for extracted data to classify driver behaviour styles; and (3) extending the range of the energy management system (REEMS) to run on the basis of a fuzzy logic model. Fuzzy logic transforms expert-based knowledge in the form of rules into a decision making system. The main advantage of fuzzy logic is that it can be tuned and adapted as necessary, thus enhancing the degree of freedom of control. Also it is a non-linear structure that is especially useful in a complex system. The flowchart of the process is shown in Figure 3.

4.1 Data Acquisition and equipped vehicle

An electric car (Nissan-Leaf) was used in this project to collect real data within an actual driving environment. Driving signals obtained from the CAN-Bus unit were connected to the vehicle. These signals are sampled at 500 Hz. CAN-Bus information is used to analyse and classify driver behaviour. Data reduction is a crucial step in any analytic and modelling process as original data generally contains irrelevant information that takes up memory and affects the performance of the model. In this experiment different drivers were used to generate the necessary driving data. Figures 4 to 6 present the data generated by driver1 featuring speed and throttle performance, the trip profile and the State of Charge (SOC) and the battery's temperature while Figures 7 to 9 present the data generated by driver2.

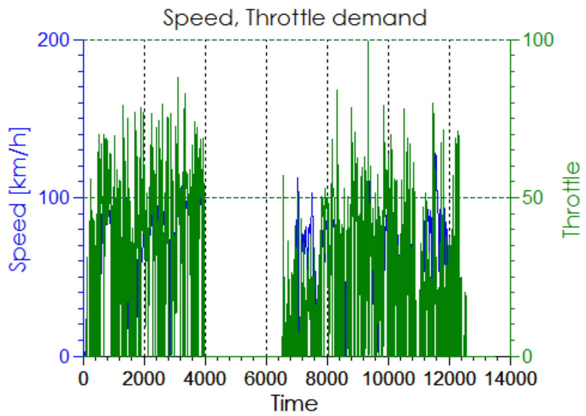

Figure4: Vehicle speed and throttle for driver1 obtained via CAN-Bus

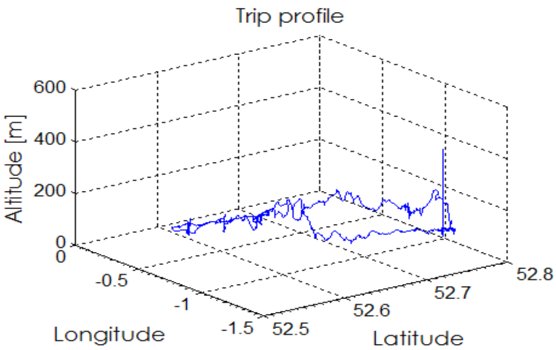

Figure 5: Trip profile for driver1 obtained via CAN-Bus

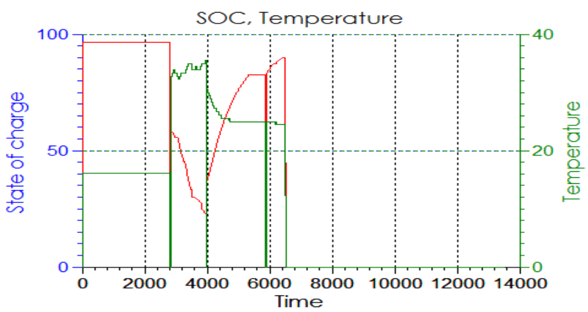

Figure6: SOC and Battery temperature obtained via CAN-Bus

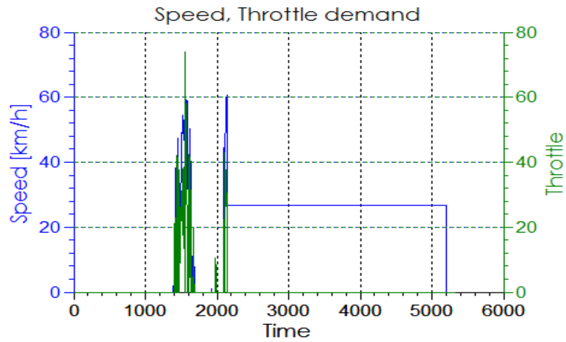

Figure7: Vehicle speed and throttle for driver2 obtained via CAN-Bus

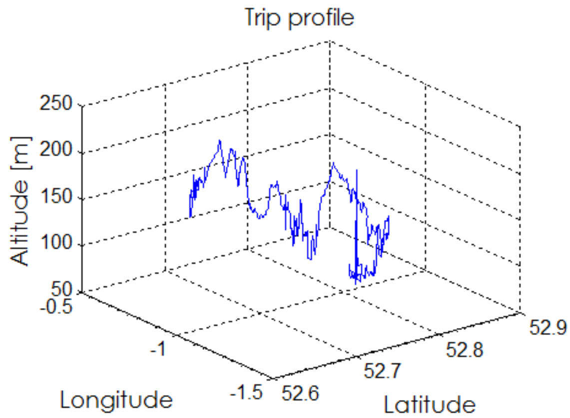

Figure8: Trip profile for driver2 obtained via CAN-Bus

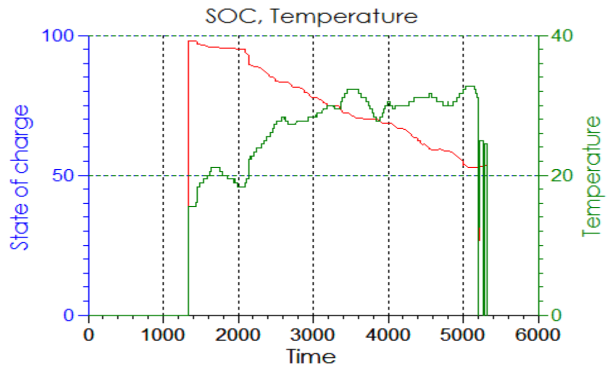

Figure 9: SOC and Battery temperature obtained via CAN-Bus

4.2 Driving state classification based on Neural Network

The collected raw data was processed by the neural network model. As set of experiments involving a number of units of data was used. Each data unit represented a vector (vehicle's speed (s), acceleration (a) and acceleration change frequency (Δa)). The sampling frequency was 500Hz. An unsupervised neural network learning model (Self Organisation Map) was used to cluster the inserted data by similarity. The network formed its own classification of data without external help. The network was able to identify common features across the range of input patterns. The output neurons compete among themselves to be activated, with the result that only one is activated at any one time. The self organisation map (SOM) architecture is shown in Figure 10. The self-organisation process involves four major components [33]:

- Initialization: All the connection weights are initialised with small random values. The weight of the competition layer is then adjusted through self organisation; the distribution of the data pattern in the output layer is reflected by a large amount of training samples.

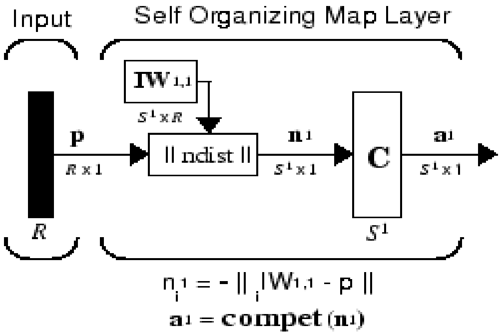

Figure 10: The ANN architecture

- Competition: the respective values for each input pattern of a discriminate function are computed by the neurons which provide the basis for competition. The particular neuron with the smallest value of the discriminate function is declared the winner. The input pattern as x = {x_i: i = 1, …, D} and the connection weights between the input units i and the neurons j in the computation layer can be written as shown in Equation (3).

$$w_i = \{w_{ji} : j = 1, \ldots, N; i = 1, \ldots, D\} \qquad (3)$$

  Where N is the total number of neurons.

  The squared Euclidean distance between the input vector x and the weight vector w_i for each neuron j is defined as our discriminate function in Equation (4).

$$d_{j(x)} = \sum_{i=1}^{D} (x_i - w_{ji})^2 \qquad (4)$$

- Cooperation: The winning neuron determines the spatial location of a topological neighbourhood of excited neurons, thereby providing the basis for cooperation among neighbouring neurons. The cooperative process is shown in Equation 5.

$$T_{j,I(x)} = e^{-S_{j,I(x)}^2/2\delta^2} \qquad (5)$$

  Where *I(x)* is the index of the winning neuron

- Adaptation: The excited neurons decrease their individual values of the discriminate function in relation to the input pattern through suitable adjustment of the associated connection weights, such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced. The appropriate weight update equation is given in Equation (6).

$$\Delta w_{ji} = \eta(t).T_{j,I(x)}(t).(x_i - w_{ji}) \qquad (6)$$

  Where *η(t)* is the learning rate at time (epoch) *t*

4.3 Fuzzy logic control strategy for Electric Vehicle Range Extender

Extending the range of EVs is the main target of the REEMS project and this work is the first step towards achieving that target. REEMS will use vehicle instantaneous demand, along with SOC, as input into the CI system that will optimise the power flow while considering the predicted journey-related power requirements, adjusted to the current driver behaviour, against available stored energy.

The CI unit is based on the fuzzy logic concept whereas the prediction of journey power requirements and driving style recognition were developed with use of ANNs. This paper focuses only on the development of the ANN model for driver behavior recognition.

In this research, the main control strategy is to extend the range of EVs based on maintaining a balanced SOC by considering driver behaviour, while at the same time keeping the corresponding fuel consumption and emissions as low as possible.

A Fuzzy controller design consists of four conceptual blocks: a fuzzification interface, a rule base, fuzzy inference mechanism, and defuzzification interface, as shown in Figure 11.

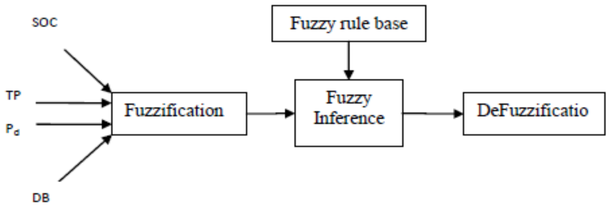

Figure 11: Fuzzy Logic controller scheme

In this study, the fuzzy logic controller scheme consists of four inputs (the Battery State of Charge (SOC) and Trip Profile (TP), the Power demand (P_d) and Driver Behavior (DB)) and one output (the Range Extender mode ON/OFF).

- Fuzzification: the input variable SOC, TP and P_d consist of three membership functions: L, M, H. DB also consists of three membership functions C, N, and A. The output variable Range Extender (RE) consists of two membership functions: OFF, ON. The membership functions are illustrated in Figures 12 to 16.

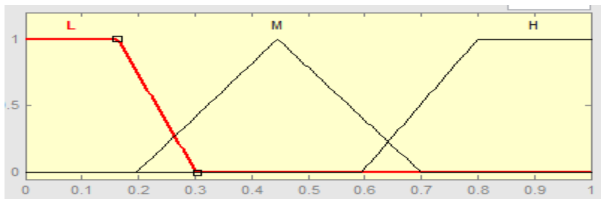

Figure 12: Membership function for input variable SOC

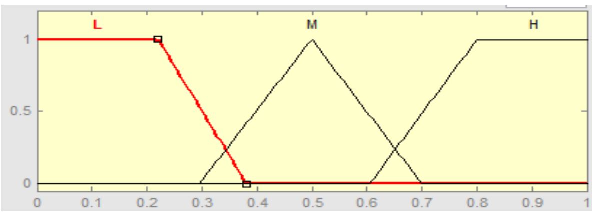

Figure 13: Membership function for input variable TP

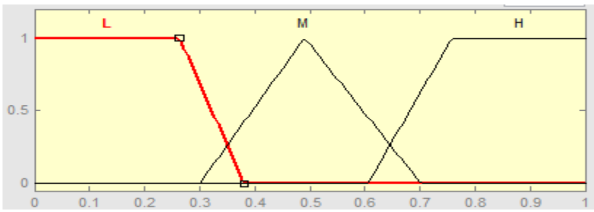

Figure 14: Membership function for input variable P_d

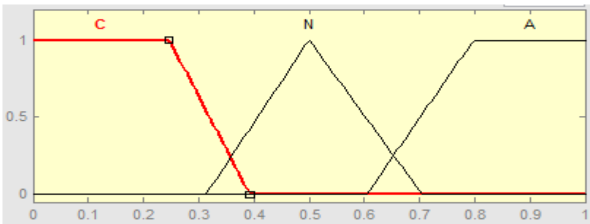

Figure 15: Membership function for input variable DB

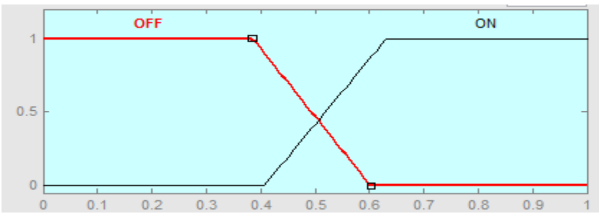

Figure 16: Membership function for output variable RE

- Fuzzy control rule: given the aim which is to extend the range of EVs the fuzzy control rules can be expressed in if-then form. A sample of the control rules is given in Figure 17.

7. If (SOC is L) and (TP is M) and (Pd is L) and (DB is N) then (RE is ON) (1)
8. If (SOC is L) and (TP is M) and (Pd is L) and (DB is A) then (RE is ON) (1)
9. If (SOC is M) and (TP is L) and (Pd is M) and (DB is N) then (RE is OFF) (1)
10. If (SOC is M) and (TP is M) and (Pd is M) and (DB is N) then (RE is OFF) (1)
11. If (SOC is M) and (Pd is L) and (DB is N) then (RE is OFF) (1)
12. If (SOC is M) and (Pd is L) and (DB is A) then (RE is OFF) (1)
13. If (SOC is M) and (TP is L) and (Pd is not H) and (DB is C) then (RE is OFF) (1)
14. If (SOC is M) and (Pd is not L) and (DB is A) then (RE is ON) (1)
15. If (SOC is M) and (TP is M) and (Pd is L) and (DB is A) then (RE is ON) (1)
16. If (SOC is M) and (TP is H) and (Pd is L) and (DB is A) then (RE is ON) (1)

Figure 17: fuzzy control rules

The control surface is shown in Figure 18. By observing the control surface one could conclude that the more aggressive the driver and the lower the SOC, the more often the range extender switches to ON. In contrast, the more calm the driver and the higher the SOC, the more often the range extender switches to OFF.

Figure 19 illustrates the effect of driver behaviour on the mode of operation of the range extender. According to fuzzy logic rules, an aggressive driving style will switch the range extender on, which makes it a critical factor which must be taken into consideration. A calm and normal driving style will reduce the probability of switching the range extender on which has an impact on other factors such as TP, P_d and SOC.

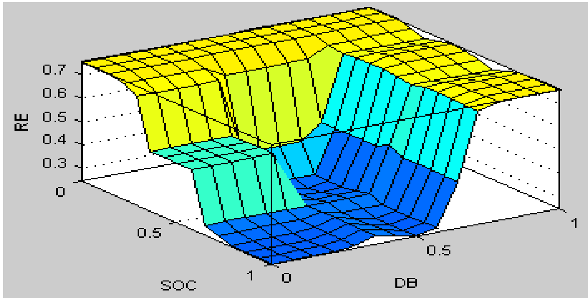

Figure 18: Fuzzy logic control surface

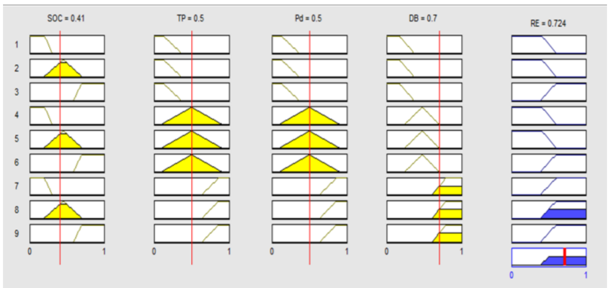

Figure 19: Impact of aggressive style (DB) on the range extender operation.

5 Conclusions

Driver behaviour can enhance vehicle performance by, for instance, limiting its fuel consumption. A calm driving style can help reduce the occurrence of car accidents. CI has introduced an effective way of detecting uncertainty in driving behaviour, by taking many variables into account to determine and classify the driver's state. This paper presented the main elements of driver behaviour and related information.

A new proposed architecture has been introduced to show how the CI can interact with the contextual information collected from the vehicle, the driver and external environmental conditions. The proposed REEMS system is based on fuzzy logic and ANN approaches enhanced with data collected from real world EV trials and high-fidelity performance models derived experimentally in the De Montfort University Engine Research Laboratory using live data obtained from the vehicle CAN network and external sensors. A further test will be carried out taking into consideration all other variables mentioned in the architecture detailed above.

Acknowledgements

This work is funded by the East Midlands ERDF via the Transport iNET.

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