Electrical Vehicle Modeling: A Fuzzy Logic Model for Regenerative Braking

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Abstract

This paper presents a fuzzy logic model of regenerative braking (FLmRB) for modeling EVs’ regenerative braking systems (RBS). The model has the vehicle’s acceleration and jerk, and the road inclination as input variables, and the output of the FLmRB is the regeneration factor, i.e. the ratio of regenerative braking force to total braking force. The regeneration factor expresses the percentage of energy recovered to the battery from braking. The purpose of the FLmRB development is to create realistic EV models using as least as possible manufacturers intellectual property data, and avoiding the use of EV on-board sensors. To tune the model, real data was gathered from short and long-distance field tests with a Nissan LEAF and compared with two types of simulations, one using the proposed FLmRB, and the other considering that all the braking force/energy is converted to electric current and returned back to charge the battery (100% regeneration). The results show that the FLmRB can successfully infer the regenerative braking factor from the measured EV acceleration and jerk, and road inclination, without any knowledge about the EV brake control strategy.

Keywords: Electric Vehicle, Regenerative Braking System, Fuzzy Inference System.

1. Introduction

Electric vehicles (EV) have become a commercial transportation solution. According to the Electric Vehicles Initiative (http://www.iea.org), the aggregated goal for all countries with known deployment targets is 7.2 million in EV sales for 2020. However, nowadays autonomy is still one of the major obstacles to massive adoption of EVs, resulting in practice on EVs use being restricted to urban areas. In this context, the research and development of EV modeling and simulation tools, particularly aimed for road traffic analysis, plays an important role. For example, the implementation of algorithms for best route following by EVs could lead to energy savings and to the improvement of vehicle autonomy range. A major advantage of EV systems is the possibility of energy regeneration during breaking. However, the amount of regenerated energy depends on how the vehicle implements the distribution of braking energy among the braking sub-systems, i.e. it depends on the amount of energy that is recovered to the battery pack and on the amount of energy released as heat in the mechanical brake system. Energy regeneration requires time to restore movement into energy. Large deceleration rates imply the major use of mechanical brakes [7], decreasing the degree of energy regeneration.

This paper proposes a fuzzy logic approach for modeling the braking force distribution in EV RBS. The EV model used here is an improvement of the model proposed in [12]. There are three main advancements. First, motivated by the fact that there are no equal batteries, the real voltage and current information is used for battery modeling instead of using a general lookup table built for the battery model being used (that typically would be provided by the manufacturer). Second, a better approximation is employed for the computation of the equivalent mass of the vehicle’s rotating parts, giving a more accurate result. Third, a generic fuzzy logic framework is proposed for modeling existing regenerative braking systems, specifically for designing a FLmRB which models the distribution of total braking torque between mechanical non-regenerative torque (e.g. friction-based) and regenerative torque. The results of the proposed FLmRB were compared with real-world data obtained with a Nissan LEAF in road tests. Although the FLmRB has been designed and verified with a Nissan LEAF EV, the FLmRB framework is targeted to design suitable models for any EV by adjusting the fuzzy logic rules using human expert knowledge, or by using an intelligent optimization method, such as the hierarchical genetic algorithm proposed in [13], to learn/improve the structure and parameters of the fuzzy model.

The paper is organized as follows. Section 2 introduces related work. In Section 3, the EV model is given. The FLmRB framework is designed in Section 4. In Section 5, simulations, experiments with a Nissan LEAF EV and corresponding results are presented. Finally, Section 6 gives concluding remarks.
2. Related Work

Several works have proposed approaches for implementation of braking strategies. In [2], an intelligent control strategy to control the pressure of the brake actuator using artificial neural networks is proposed and implemented in an microcontroller. While the aim of the method was to improve the braking process, it cannot be applied to quantify the distribution of the total braking torque between mechanical non-regenerative torque, and regenerative torque in electronic braking systems in EVs. [8] presented five control strategies for energy management systems in fuel cell vehicles. Although fuel cell vehicles are unable to perform energy regeneration, this drawback was reduced by combining the fuel control system with an energy store system, such as a battery, a supercapacitor, or a combination of both. By placing focus on regenerative braking, [4] proposed a GA-based neural network to design an energy recovery system for an electric motorcycle. [21] designed a regenerative braking force controller based on fuzzy logic using desired braking force, vehicle speed, and battery state of the charge (SOC) as the inputs, and the ratio of the regenerative braking force as the output. It also uses battery temperature to produce a compensation coefficient in order to limit the regenerated current.

A control strategy using a couple of fuzzy logic controllers is studied in [6] for adjusting the braking force allocation. As input information, it is used the brake pedal displacement, and the slip ratio of the wheel, not being useful in traffic simulators.

Other similar proposals for new or improved regenerative braking strategies can be found in [20] and [14]. The works cited above in this paper propose either new strategies to perform regenerative braking or some improvement to some already existing RBS. However, there is a lack of an RBS modeling methodology that can be applied in a variety of existing (and specific) EVs for building an RBS model of the distribution of total braking torque between mechanical non-regenerative torque (e.g. friction-based) and regenerative torque. The goal of the work presented in this paper is to develop a methodology for building models of RBS strategies, rather than developing a RBS strategy.

3. Electric Vehicle Modeling

This section briefly presents how the EV was modelled and which characteristics were included in the model. The EV model herein formulated, shown schematically in Figure 1, is based on [11] and [7]. The modeling architecture can be
adapted to be used in traffic simulators, such as the SUMO simulator [10], or simulators which are based on Simulink. The system has three subsystems: Wheel & Gear Subsystem, Power Driver Subsystem, and Energy Storage Subsystem. The subsystems will be presented in the following subsections.

3.1. Wheel & Gear Subsystem

The Wheel & Gear Subsystem takes from the vehicle drive data, the time-referenced speed \( v \) and (road) inclination angle \( \alpha \) as input variables and produces five outputs: torque required by gearbox \( \tau_g \), motor angular speeds \( \omega_{rpm} \) and \( \omega_{rad} \), acceleration, \( a \), and derivative of the acceleration, the Jerk, \( \dot{a} \). To obtain \( \tau_g \), the mechanical force \( F_{te} \) needed to produce the desired speed at inclination \( \alpha \) has to be calculated. This mechanical effort \( F_{te} \), i.e. the force transmitted by the motor to the gearbox/transmission and from this to the vehicle driving wheels, can be expressed as:

\[
F_{te} = \mu_r m_c g \cos(\alpha) + \frac{1}{2} \rho A C_d v^2 + m_a g \sin(\alpha) + (m_v + m_I) a, \tag{1}
\]

where \( F_{rr} \) is the rolling resistance force, \( F_{ad} \) is the aerodynamic drag force, \( F_{hc} \) is the hill climbing force, \( F_v \) is the linear acceleration force, and \( g \) and \( \rho \) are physical constants representing the acceleration due to the gravity, and the air density, respectively. \( \mu_r \) is the tire rolling resistance coefficient, \( A \) is the frontal area of the vehicle, \( C_d \) is the vehicle’s drag coefficient, \( \alpha \) is the road inclination angle, \( v \) is the vehicle speed, and \( a \) is the vehicle acceleration. The vehicle mass, \( m_v \), takes into consideration the vehicle mass itself with battery pack (curb weight, \( m_c \)), as well as the load and occupants masses.

In order to obtain a more accurate model of \( F_{te} \), the rotational acceleration should be considered, in order to model the force needed to accelerate the rotating parts. EVs’ electrical motors can achieve high angular speeds (e.g. the Nissan LEAF maximum motor speed is 10390 [rpm]). The increase of vehicle equivalent mass due to the angular moments of the rotating components, \( m_I \), is approximated by the following model adopted from [7]:

\[
m_I = m_c (0.04 + 0.0025 G^2), \tag{2}
\]

where \( G \) is the gear ratio.

It should be noted that \( F_{te} \) and \( \tau_g \) will be positive if the battery pack is supplying current to the motor, or negative if the current is in opposite flow, charging the battery pack. The first two terms in (1), \( (F_{rr} + F_{ad}) \) are frictional forces, thus they are non-negative. Therefore, only the last two terms of (1) \( (F_{hc} + F_v) \), together, are able to make \( F_{te} \) negative. This can happen when the EV is going downhill \( (\alpha < 0) \) or is decelerating \( (\alpha < 0) \). \( F_{te} \) is provided by the traction motor, which develops enough motor torque \( \tau_m \), to supply \( F_{te} \) via gearbox and transmission. Considering the losses on the gearbox and transmission, \( \tau_e \) can be approximated by:

\[
\tau_g = \begin{cases} 
\frac{F_{te} r}{G} \frac{1}{\eta_t}, & \text{if } F_{te} \geq 0, \\
\frac{F_{te} r}{G} \frac{1}{\eta_t}, & \text{if } F_{te} < 0,
\end{cases}
\tag{3}
\]

where \( \eta_t \) is the transmission and gears efficiency, and \( r \) is the wheel radius. \( \tau_g \) will be considered a traction torque if \( \tau_g \geq 0 \) \( (F_{te} \geq 0) \) or a braking torque \( \tau_g = \tau_b \) otherwise \( \tau_g < 0, F_{te} < 0 \). Traction torque is provided by the electric motor which drains current from battery and delivers mechanical power to the wheels. Braking torque is provided by the brake system, composed partially by the mechanical brake and partially by the electric motor acting as generator, which applies its electrical torque to the wheels (usually the front wheels).

3.2. Power Driver Subsystem

The Power Driver Subsystem, shown in Figure 2, models the electric motor/controller. This subsystem takes the torque required by the gearbox \( \tau_g \), which is the torque the Power Driver Subsystem has to supply, and calculates: (i) the torque \( \tau_{req} \) required from the motor, taking into account the motor torque limits \( (\tau_{max} \text{ and } \tau_{min}) \), i.e. the maximum traction and braking torques achieved by the motor, (ii) the amount of mechanical torque \( \tau_{mech} \) applied by the mechanical brake system during braking phases, (iii) the motor efficiency \( \eta_m \), and (iv) \( P_{req} \), the required power that the battery pack shall supply.

The evaluation about whether \( \tau_g \) exceeds the tractive or regenerative capacity of the motor (torque limits) during traction and braking, respectively, is done in the \( Tq \text{ Limit}^+ \) and \( Tq \text{ Limit}^- \) subsystems, respectively. If \( \tau_g > \tau_{max} \), this means that the motor cannot give such traction torque, which implies the motor...
to become limited to \( \tau_g = \tau_{\max} \). As a consequence, from (3), \( F_e \) also becomes limited, which implies a reduction of the vehicle speed that results from (1). Otherwise, if \( \tau_g < \tau_{\min} \), this means that the motor cannot give such braking torque, and part of the braking torque must be supplied by the mechanical braking system, giving a mechanical torque \( \tau_{\text{mech}} = \tau_g - \tau_{\min} \). Thus, the required torque \( \tau_{\text{req}} \), i.e. the torque required from the motor after discounting from \( \tau_g \) the part that is beyond the motor limits, is:

\[
\tau_{\text{req}} = \begin{cases} 
\tau_{\max}, & \text{if } \tau_g > \tau_{\max}, \\
\tau_g, & \text{if } \tau_{\min} \leq \tau_g \leq \tau_{\max}, \\
\tau_{\min}, & \text{if } \tau_g < \tau_{\min}.
\end{cases}
\] (4)

The \( Tq \ Limit+ \) subsystem works with positive values of \( \tau_g \) (traction) and adjusts target speed as appropriate, and the \( Tq \ Limit- \) subsystem works with negative values of \( \tau_g = \tau_t \) (braking) and distributes braking torque between the brake plates and motor as appropriate. In equation (4) it is assumed that braking is performed with as much as possible electrical braking torque, only subject to electrical motor braking torque limits. However, an EV can use some different braking strategy that should be modeled. Thus, (4) is reformulated as follows:

\[
\tau_{\text{req}} = \begin{cases} 
\tau_{\text{req}}^+ = \tau_{\max}, & \text{if } \tau_g > \tau_{\max} \text{ (traction)}, \\
\tau_{\text{req}}^+ = \tau_g, & \text{if } 0 \leq \tau_g \leq \tau_{\max} \text{ (traction)}, \\
\beta \tau_g, & \text{if } \tau_g < 0 \text{ (braking)},
\end{cases}
\] (5)

where \( \tau_{\text{req}}^+ \) is the torque required from the motor on traction events, \( \tau_{\text{req}}^- \) is the torque required from the motor on braking events, i.e. the regenerative braking torque, and the regenerative braking factor \( \beta \) is a function of some collection of variables that represent the instantaneous driving situation (e.g. acceleration, jerk, road inclination), \( \tau_{\text{req}}^- = 0 \) on a braking event and \( \tau_{\text{req}}^- = 0 \) on a traction event.

An important goal of this paper is to propose the FLmRB framework for determining a model of \( \beta \) in order to characterize the braking strategy of an EV. Regardless of the braking strategy (e.g. (4), or (5)), the total braking torque \( \tau_b \) is defined for \( \tau_g < 0 \) and is given by:

\[
\tau_b = \tau_g = \tau_{\text{mech}} + \tau_{\text{reg}},
\] (6)

where \( \tau_{\text{mech}} \) is the mechanical braking portion of the total braking torque and \( \tau_{\text{reg}} \) is the regenerative braking portion. The \( Tq \ Limit+ \) subsystem in Figure 2 is implemented by (6), and by the proposed FLmRB described in Section 4.2.

Finally, taking into account the motor efficiency \( \eta_m \), and the power required by the accessories energy consumption, \( P_{\text{acc}} \), the power requirement of the vehicle, \( P_{\text{req}} \) is calculated by:

\[
P_{\text{req}} = \begin{cases} 
\frac{\tau_{\text{req}}^+ \omega_{\text{rad}}}{\eta_m} + P_{\text{acc}}, & \text{if } \tau_{\text{req}}^+ \geq 0, \\
\tau_{\text{req}}^- \omega_{\text{rad}} \eta_m + P_{\text{acc}}, & \text{if } \tau_{\text{req}}^- < 0.
\end{cases}
\] (7)

### 3.3. Energy Storage Subsystem

The Energy Storage Subsystem (Figure 1) input is \( P_{\text{req}} \), which either represents the power required from the vehicle battery system both to develop the tractive effort and for accessories energy consumption, \( P_{\text{acc}} \), or represents the power supplied back
to the battery during regenerative braking. From \( P_{eq} \), (7), at each time interval, the following variables are calculated as described in this subsection: the required battery current \( I_{bat} \), the new battery terminal voltage \( V_t \), and the new battery state of charge \( SOC \).

EV drive range depends on several variables external to the vehicle, such as road pavement quality and status, and weather conditions like rain, air temperature, and wind speed. Temperature of the vehicle, such as road pavement quality and status, and weather variables like inertial measurement units, GPS, and hall effect current probes. In the conducted experiments to model the regenerative braking behavior, the temperature effect has not been considered in the SOC estimation algorithm, due to the lack of cell temperature related data. The experimental tests for model building were conducted with air temperature close to 25°C and no energy consumption from the EV climate control systems.

In this work, the goal is to develop a method to model the EV energy and range, specially taking into consideration regenerative braking, with minimal dependence on information obtained from EV monitoring and control systems, but using preferably variables that can be measured from independent instruments like inertial measurement units, GPS, and hall effect current probes. The use of the Nissan LEAF has motivated the users to create discussion forums, such as the online forum for the Nissan LEAF car owners, such as the online forum for the Nissan LEAF car owners, such as the online forum for the Nissan LEAF car owners, such as the online forum for the Nissan LEAF car owners.

For modeling the EV battery pack, two approaches were considered. The first approach is based on the voltage/discharge capacity plots of the cells inside the 24 kWh battery installed in the LEAF which are available at the Automotive Energy Supply Corporation web page [1] (plots 90A, 60A, 1C, and 1/3C). The approach is based on two lookup tables built from these plots, and representing the open circuit battery voltage, \( E_{oc} \), versus SOC and \( R^+_{in} \). The second approach, which performed better, is based on the work of Plett [16] to model \( E_{oc} \) and follows the current integration method also known as coulomb counting. It consists of using real voltage and current data obtained from experimental trials to create the battery model. The battery model used herein is represented in Figure 3. It consists of an internal voltage source \( E_{oc} \), two ideal diodes, and two inner resistances \( R^+_{in} \) and \( R^-_{in} \) which represent the battery internal discharging and charging resistances. The voltage at the terminals of the battery is given by:

\[
V_t = E_{oc} - R^-_{in} I_{bat}, \quad \text{if discharging, (8)}
\]

where \( R = R^-_{in} \) in a discharging situation and \( R = R^+_{in} \) in a charging situation. \( R^+_{in} \) and \( R^-_{in} \) are piecewise constants estimated in 10% SOC intervals and stored in a lookup table. Assuming that \( E_{oc} \) follows the Combined Model as described in [16], and using (8), yields:

\[
V_t = K_0 - R^-_{in} I_{bat} = \frac{K_1}{SOC} - K_2 \ln(SOC) + K_3 \ln(1 - SOC).
\]  

(9)

Parameters \( K_0, \ldots, K_4 \) are constant, \( K_0, \ldots, K_4 \) and \( R^+_{in} \) and \( R^-_{in} \) are obtained using a least squares approximation based on current, voltage, and SOC readings obtained from the EV CAN bus. The data collected from trials at a specific sampling rate with the EV dashboard fuel bars going from full to empty was registered in a time ordered data set containing three variables \((V_t, I_{bat}, SOC)\), \( k = 1, \ldots, N \), where \( k \) is the number of the sample, and \( N \) is the trial length (i.e. the total number of samples). In order to obtain the parameters in (9), a column vector \( Y = [V_1, V_2, \ldots, V_N]^T \)

is built with the battery voltage measurements, and a matrix \( H = [h_1, h_2, \ldots, h_N]^T \)

is constructed with the rows formed by data vectors

\[
h_j^T = [1, -I_{bat}, -I_{bat}, -\frac{1}{SOC}, -\ln(SOC), \ln(1 - SOC)]
\]

where the index corresponds to the time instant \( j \). \( Y \) and \( H \) are assembled for the formulation of the \( Y = H\theta \) least squares problem that is then used to jointly estimate the parameters of equation (9). If \( I_{bat} > 0 \), a discharge current occurs and \( I_{bat} = I_{bat}, I_{bat} = 0 \); else if \( I_{bat} < 0 \), then \( I_{bat} = 0 \), and \( I_{bat} = I_{bat} \). When \( I_{bat} = 0 \) both \( I_{bat} = 0 \), and \( I_{bat} = 0 \). Therefore:

\[
I_{bat} = (I_{bat} + |I_{bat}|)/2, \quad I_{bat} = (I_{bat} - |I_{bat}|)/2.
\]

Under these conditions, assuming that \( H \) has full rank, and that the number of data patterns is greater than or equal to the number of parameters in vector \( \theta \) (i.e. \( N \geq 7 \)),

\[
\theta = [K_0, R^+_{in}, R^-_{in}, K_1, \ldots, K_4]^T.
\]

then a solution for the vector of parameters can be computed using the pseudo-inverse least squares method, as follows [3]:

\[
\theta = (H^T H)^{-1} H^T Y.
\]

Then, \( E_{oc} \) can be calculated from (8), and (9) (see also Figure 3) by:

\[
E_{oc} = K_0 - \frac{K_1}{SOC} - K_2 SOC + K_3 \ln(SOC) + K_4 \ln(1 - SOC).
\]  

(10)

\[1\text{http://www.mynissanleaf.com/}, accessed on August, 08, 2014.]
After this procedure, a closer fit for $R_m^+$ and $R_m^−$ is calculated using least squares estimation again to obtain $R_m^+$ and $R_m^−$ from (9) and (10) using the collected $V_i$, $I_{bat}$, $SOC_t$, values. This is achieved using (10) to build $E_{oc}$ with the collected $SOC_t$ values, i.e. $E_{oc_k} = E_{oc} \text{ for } SOC = SOC_t (k = 1, \ldots, N)$. Then, a matrix $\tilde{H} = [h_1, h_2, \ldots, h_N]^T$ is defined to have rows $\tilde{h}_j = [I_{bat}^j, I_{bat}^{−j}], \tilde{Y} = [E_{oc_k} - V_1, E_{oc_k} - V_2, \ldots, E_{oc_k} - V_N]^T$, and $\tilde{Y} = \tilde{\Theta} \tilde{h}$, where $\tilde{\Theta} = [R_{m^+}^j, R_{m^−}^j]^T$. The solution for $\tilde{\Theta}$ using $\tilde{Y}$ and $\tilde{H}$ is: $$\tilde{\Theta} = (\tilde{H}^T \tilde{H})^{-1} \tilde{H}^T \tilde{Y}.$$

The total power provided by the battery, $E_{oc}I_{bat}$, is modeled as the sum of $P_{req}$ and the power dissipated in the battery internal resistance: $E_{oc}I_{bat} = R_m^+P_{req}$, where $R_m^+ = R_m^−$ (if charging) or $R_m^− = R_m^+$ (if discharging). Depending on the current flow, the outputs of the Energy Storage Subsystem (Figure 1), $I_{bat}$, and $SOC$, are finally calculated as follows:

$$I_{bat} = \begin{cases} \frac{E_{oc} - \sqrt{E_{oc}^2 - 4R_m^+P_{req}}}{2R_m^+}, & \text{if discharging}, \\ \frac{E_{oc} - \sqrt{E_{oc}^2 - 4R_m^−P_{req}}}{2R_m^−}, & \text{if charging}, \end{cases}$$

$$SOC = \begin{cases} SOC_0 - \frac{1}{C} \int I_{bat}(t) \, dt, & \text{if discharging}, \\ SOC_0 - \frac{\eta_b}{C} \int I_{bat}(t) \, dt, & \text{if charging}, \end{cases}$$

where $\eta_b$ is the recharging efficiency of the battery, and the output $V_i$ is obtained from (8).

### 4. Regenerative Braking Framework

This section introduces basic principles of RBS and details the proposed FLmRB.

#### 4.1. Regenerative Braking

Braking systems of EVs are designed to recover back to battery as much energy as possible from the amount of energy that would be normally dissipated by a mechanical brake system, converting kinetic and potential energies into electric current, that is used to recharge the EVs’ battery pack. The recharging efficiency $\eta_b$ is less than 1 due to battery internal resistance, and cable and contact resistance. With a suitable control strategy, it is possible to make the electric traction motor operate as a generator, producing negative torque on the wheels and recovering electric energy. This possibility achieves greater importance if the vehicle is driving in a stop-and-go pattern in urban areas. Regenerative braking may act strongly in urban scenarios, enabling the increase in the vehicle operating range. If the electric motor can produce sufficient torque to supply the total required braking torque on wheels, $\tau_b$, all the corresponding energy, excluding losses, is converted into electric current by the power controller and fed back into the battery pack. Otherwise, i.e. if the electrical brake is not sufficient to attain the required total braking torque, then the controller calculates how the total braking torque will be split between wheels brake plates (mechanical brake) and the electric motor (electrical brake, commanded by the controller). This distribution of braking torque must achieve the requirement of quickly reducing the vehicle speed by using the total braking torque, and maintaining the vehicle direction controllable by the steering wheel. The global goal is to ensure both the EV’s braking performance and its ability to recover as much braking energy as possible [7]. The mechanical braking torque, $\tau_{mech}$, is distributed between front and rear wheels, while the electrical one, $\tau_{req}$, is applied only to the driven axle (the front axle for passenger cars, normally). Therefore, equation (6) can be expressed by:

$$\tau_b = \tau_{mech}^F + \tau_{mech}^R + \tau_{req},$$

where $\tau_{mech}^F$ is the mechanical braking torque on the front wheel, and $\tau_{mech}^R$ is the mechanical braking torque on rear wheels. In terms of front and rear axles, $\tau_{mech}^F + \tau_{req}$ is often produced over the front axle and $\tau_{mech}^R$ over the rear one. This distribution is based on the traditional theory of braking force distribution and the Economic Commission for Europe (ECE) regulation [5]. The brake control strategy defines the braking force strength to properly reduce the vehicle speed, and the distribution of braking effort between front and rear wheels to guarantee vehicle stability, and defines the strategy to recover as much braking energy as possible. Basically, there are three different brake control strategies defined by [7]: (1) series braking with optimal braking feel, (2) series braking with optimal energy recovery, and (3) parallel braking.

Commonly, traffic simulators are applicable in traffic management tasks, such as traffic lights evaluation, route choice, re-routing, evaluation of traffic surveillance methods, vehicular communications, traffic forecasting [10]. In these contexts, it is not important for traffic simulators to take into consideration yaw stability. Thus, in this work the slip of the tire and the braking force distribution between the front and the rear wheels was not taken into consideration. Instead, $\tau_{mech}$ was considered as a whole. In this work, the goal is to model $\beta$, the portion of $\tau_b$ which is regenerated, i.e.:

$$\beta = \frac{\tau_{req}}{\tau_b}. \quad (14)$$

#### 4.2. Fuzzy Logic Model for Regenerative Braking

Fuzzy inference systems (FISs) are widely used to implement new brake control strategies used in RBSs as discussed in Section 2. In this work, to model existing RBSs control strategies, a Mamdani FIS is proposed in order to map between a selected set of input variables and the regenerative ratio $\beta$. Brake pedal displacement information is usually used in regenerative braking controllers, but the way this information is processed and mapped to real vehicle braking is dependant on EV maker’s braking mapping strategy. One of the goals for the FLmRB is to be integrated in microsimulation software, which is usually used to analyze traffic flow, vehicle consumption and emission, traffic jam, car following models, and so on. In this context, the
important issue is the target vehicle speed, not its individual internal variables which determine the observed vehicle braking performance. A RBS model which has the pedal displacement information as one of its inputs is not generic. Thus, it was decided not to include this information in the FLrmb model. The proposed FLrmb objective is to use only data obtained externally to vehicle’s control and communication architecture.

In order to identify among the measurable variables, those that most influence the regenerative braking, and are the most well suited to be used as inputs to the FLrmb, short-distance urban tests were made with a Nissan LEAF EV, and the results of the tests were compared with simulations, considering 100% regeneration in the simulations. The test site and pathways followed by the EV are shown in Figure 4. In Figure 5, it is shown a set of results of tests which are relevant for the discussion, and where the simulated values of $I_{bat}$ were obtained considering a regeneration factor $\beta = 1$. In the encircled area in Figure 5a, it can be observed, by the small value of the measured current when compared to the simulated current, that just a small amount of braking energy was regenerated. The difference is actually wasted by the mechanical brake. Large deceleration rates require more braking force than the motor can supply or the battery can receive safely. In Figure 5b, with high jerk, most of the energy was also consumed by the mechanical brake. The explanation is that in a heavy braking event the vehicle must slow down quickly and the motor is unable to produce the required braking torque [7]. Figure 5c shows the joint influence of acceleration, jerk, and inclination over the regeneration factor. The vehicle acceleration and road inclination of a moving vehicle are variables which are clearly correlated to the mechanical energy of the vehicle. Consequently, it is plausible that these variables are also correlated to the value of energy recovered by regenerative breaking. Motivated by the above observations, three input variables were chosen for the FLrmb: (1) vehicle acceleration, $a$, (2) vehicle jerk, $\varphi$, and (3) road inclination, $\alpha$.

The output of the FLrmb is the regenerative braking factor, $\beta$, which is used in the $T_q$ Limit- subsystem, described in Section 3.2, to calculate the amount of regenerative braking torque. The FLrmb is designed as a FIS composed by the following operators: singleton fuzzifier, minimum t-norm, Mamdani minimum implication, maximum aggregation, and centroid defuzzifier. For more details about FIS design and operators reference [19] is suggested. The overall structure of the FLrmb is shown in Figure 6.

4.2.1. FLrmb Input Variables

The selected input variables are:

- **Acceleration** ($a$): when the vehicle is decelerating ($a < 0$), the regeneration factor grows with the increase of deceleration. The acceleration of an automobile during an abrupt braking is about $0.7 [g]$ [15]. The set of linguistic terms defined for the acceleration linguistic variable, $a$, is $T_a = \{A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}\}$ with universe of discourse of $[-0.7, 0.05] [g]$. The fuzzy membership functions associated to $A_1, \ldots, A_{10}$ are shown in Figure 7a, and are defined by triangular and trapezoidal shapes;

- **Jerk** ($\varphi$): the regeneration factor is decreased when the jerk increases. The set of linguistic terms defined for the jerk linguistic variable, $\varphi$, is $T_\varphi = \{J_1, J_2, J_3, J_4, J_5, J_6, J_7, J_8, J_9, J_{10}, J_{11}\}$ with universe of discourse of $[-3.5, 3.5] [m/s^3]$. The membership functions associated to $J_1, \ldots, J_{11}$, are shown in Figure 7b, and are defined by triangular and trapezoidal shapes;

- **Inclination** ($\alpha$): in order to provide flexibility and generality for most of the occurring road inclinations, it was assumed a $[-20\%, +20\%]$ grade operating range. The set of linguistic terms defined for the inclination linguistic variable, $\alpha$, is $T_\alpha = \{I_1, I_2, I_3, I_4, I_5\}$ with universe of discourse of $[-20, 20]\%$. The membership functions associated to $I_1, \ldots, I_5$ are shown in Figure 7c, and are defined by triangular and trapezoidal shapes.

4.2.2. FLrmb Output Variable

The output of the proposed FLrmb is the regeneration factor, $\beta$, the ratio between the regenerative braking torque applied by the traction motor and the total braking torque. The set of linguistic terms defined for the regeneration factor linguistic variable is $T_\beta = \{R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8\}$ with universe of discourse of $[0, 1]$, where 0 means only mechanical braking and 1 means only regenerative braking. The membership functions associated to $R_i, \ldots, R_{10}$, are shown in Figure 7d, and are defined by triangular and trapezoidal shapes.

4.2.3. FLrmb Rules

Using the input and output linguistic variables defined in the previous subsections, a FIS is designed to infer the regeneration factor. The designed FIS contains a set of multiple-inputs single output (MISO) IF-THEN rules with three inputs and one output, of the following form:

IF premise1 AND premise2 AND premise3 THEN conclusion.

The set of fuzzy rules $F_{rules}$ is composed by one fuzzy rule for each combination of linguistic terms of the antecedent linguistic variables (defined in $T_a$, $T_\varphi$, $T_\alpha$). Thus the number of rules is $|F_{rules}| = |T_a| \times |T_\varphi| \times |T_\alpha| = 10 \times 11 \times 7 = 770$. All the FLrmb design and tuning, including for example the choice of the t-norm, implication and aggregation operators, the defuzzification methods, and the design of the number of membership functions, and the consequent linguistic terms of the rules, are obtained from human knowledge, in pilot studies, and by trial and error. The tuning of the consequent terms is guided by the goal of matching as well as possible the simulated and real values of the battery current. The FLrmb design was started with a few number of linguistic terms and increasing the number of terms during the analysis to make them more flexible. Since the model was obtained through human know-how and from short distance tests, the options taken for FLrmb modeling where
Table 1: Fuzzy Rules of the FLmRB. Antecedent variables: acceleration (a), jerk (ϕ), and road inclination (α). Consequent variable: regenerative braking factor (β).

<table>
<thead>
<tr>
<th>Rule</th>
<th>Antecedent Conditions</th>
<th>Consequent Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule 1</td>
<td>If a is $A_1$ and ϕ is $J_1$ and α is $I_1$</td>
<td>Then β is $R_3$</td>
</tr>
<tr>
<td>Rule 2</td>
<td>If a is $A_1$ and ϕ is $J_1$ and α is $I_2$</td>
<td>Then β is $R_1$</td>
</tr>
<tr>
<td>Rule 386</td>
<td>If a is $A_6$ and ϕ is $J_1$ and α is $I_1$</td>
<td>Then β is $R_4$</td>
</tr>
<tr>
<td>Rule 539</td>
<td>If a is $A_7$ and ϕ is $J_1$ and α is $I_2$</td>
<td>Then β is $R_{10}$</td>
</tr>
<tr>
<td>Rule 540</td>
<td>If a is $A_8$ and ϕ is $J_1$ and α is $I_1$</td>
<td>Then β is $R_1$</td>
</tr>
<tr>
<td>Rule 541</td>
<td>If a is $A_8$ and ϕ is $J_1$ and α is $I_2$</td>
<td>Then β is $R_5$</td>
</tr>
<tr>
<td>Rule 770</td>
<td>If a is $A_{10}$ and ϕ is $J_1$ and α is $I_1$</td>
<td>Then β is $R_{10}$</td>
</tr>
</tbody>
</table>

chosen in order to enable to have a proper human insight of the rules. The rules have the following structure:

IF a is $A_i$ and ϕ is $J_j$ and α is $I_k$ THEN β is $R_x$.

where $A_i \in T_a$ for $i = 1, \ldots, 10$, $J_j \in T_ϕ$ for $j = 1, \ldots, 11$, $I_k \in T_α$ for $k = 1, \ldots, 7$, and $R_x \in T_β$ for $x = 1, \ldots, 10$. Part of the set of fuzzy rules is shown in Table 1\(^2\).

5. Experiments and Results

This section presents the Nissan Leaf model parameters, the data acquisition system, and the simulation results of the proposed FLmRB.

5.1. Vehicle Specifications

The model presented in Section 3 is suitable to be applied/instantiated to any EV. A Nissan LEAF, 2011 version, was used in the experiments presented in this paper. The vehicle parameters used in this work are shown in Table 2a. Table 2b shows the lookup tables for the values of $R_{in}$ and $R_{in}^*$, which have been calculated by the method presented in Section 3.3. The motor efficiency $\eta_m$ (see Figure 2) was obtained from [17]. It also takes into consideration the efficiencies of the inverter and AC cables. $\eta_m$ is modeled as a function that takes values in the range [85%, 95%], as the motor torque $τ_{req}$ varies in the range [0, 280] [Nm], and the motor speed $ω_{rpm}$ varies in the range [0, 10390] [rpm].

5.2. Data Acquisition System

The data acquisition system used in the experimental tests included an Xsens MTi-G, 6-DOF Attitude and Heading Reference System\(^3\) (AHRS), which was used for the measurement of the instantaneous position, inclination, and speed. The current and voltage of the battery pack were acquired via the EV CAN bus to an onboard computer and stored at a frequency of 10 [Hz]. To validate the EV readings, a current probe was also used to measure the inverter current. A diagram of the data acquisition system is shown in Figure 8. The data sets resulting from the tests and used in the experiments are available at http://home.isr.uc.pt/~rui/publications/.

\(^2\) The complete set will be available

\(^3\) http://www.xsens.com/products/mti-g/, accessed August, 08, 2014
5.3. Methodology Applied in FLmRB Modeling

In the first step, short-distance tests were made in a urban area and data were collected to establish the relationship between input and output variables, aiming at adjusting membership functions and fuzzy rules of the FIS. The membership functions parameters were adjusted by trial and error through the know-how obtained in analyzing these short-distance tests data. The Matlab Fuzzy Logic Toolbox and its Fuzzy Logic controller block were used, allowing the tuning of the membership functions parameters and design the fuzzy rules. Selected tests used in this step are illustrated in Figure 5. During the tests, a variety of situations, such as harsh braking, harsh acceleration, and freewheel, among other strategies were explored. Tests were executed in flat streets, and in streets with positive and negative slopes.

The focus was to determine the influence of the vehicle acceleration and jerk, and street inclination over the regeneration factor. After having adjusted the FLmRB, a number of long-distance tests were made in the city of Coimbra, in urban and sub-urban areas, for verification purposes and fine-tuning.

5.4. Simulation Results

The proposed FLmRB was evaluated by comparing simulated (FLmRB) and real-world data in two long-distance tests in urban and suburban areas, named as Test#1 and Test#2, with 103 [km], and 112 [km] in length, respectively. Figure 9 shows the speed profiles for Tests #1 and #2, which have average speeds of 72.2 [km-h⁻¹], and 45.1 [km-h⁻¹], respectively. Test#1 was made in a suburban area, and Test#2 was made mainly on urban areas. Figure 10 presents, as an illustrative example, the time evolution results of the FLmRB output, the \( \beta \) parameter, in a segment of Test#2. However, although \( \beta \) is the output of the model, a figure showing this parameter may not be the most informative because \( \beta \) is not accessible to be measured and compared in an EV. Thus, the effectiveness of the FLmRB is better verified through the charge balance of the EV’s battery in comparison with the simulation, via the battery state of the charge (SOC), battery current, and battery voltage variables. Table 3 summarizes the results of simulations, both using FLmRB and not using FLmRB (100% regeneration). The second column of the table shows the mean squared error (MSE) between the battery current estimated with the FLmRB, and the measured battery current. The third column shows the MSE between the battery current estimated without the FLmRB, and the measured current. There are two computations of MSE for each test, first, considering all values of battery current (“all”), and second, considering only the negative values of battery current (“neg”). The “(neg)” values take into consideration only the regenerated current. A lower error is observed when using FLmRB and not using FLmRB (100% regeneration).
the measured $SOC$ of Test#1 was 19.3 [%] and the $SOC$ simulated with the FLmRB was 19.25 [%], while, without FLmRB, the estimated $SOC$ was 21.35 [%]. At the end of Test#2, the measured $SOC$ was 13.6 [%], and the $SOC$ simulated with the FLmRB was 14.22 [%], while, without FLmRB, the estimated $SOC$ was 19.29 [%]. In Table 4, the MSE of the battery $SOC$ is presented. Better results are achieved in the case of the FLmRB tests.

Figures 13 and 14 show the amount of electrical and mechanical braking torques applied, obtained in the test runs with the

<table>
<thead>
<tr>
<th>Table 4: Battery SOC MSE.</th>
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<tr>
<td>with FLmRB</td>
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<tr>
<td>------------</td>
</tr>
<tr>
<td>Test#1</td>
</tr>
<tr>
<td>Test#2</td>
</tr>
</tbody>
</table>
Figure 8: Data Acquisition System.

Figure 9: Speed profiles of (a) Test#1, performed in suburban areas, and (b) Test#2, performed mainly in urban areas.

Figure 10: Example of the time evolution of the FLmRB output, the $\beta$ parameter, obtained in a part of Test#2.

Figure 11: Battery current of (a): Test#1; (b): Test#2.

Figure 12: SOC of the Battery pack. (a): Test#1; (b): Test#2.

obtained from:

$$E_{\text{traction}} = \frac{G}{r} \cdot \eta \cdot \int_0^T v \cdot \tau_{\text{req}} \, dt,$$

(15)

$$E_{\text{mechanical brake}} = \frac{G}{r} \cdot \frac{1}{\delta} \int_0^T v \cdot |\tau_{\text{mech}}| \, dt,$$

(16)


\[
E_{\text{Regenerative}} = \frac{G}{r} \cdot \frac{1}{\eta_T} \int_0^T v \cdot |\tau_{\text{req}}| \, dt, \quad (17)
\]

using numerical integration by the rectangle method with a sampling interval of \( \Delta t = 0.1 \text{[seg]} \), where \( T \) is the duration of the run. Table 5 shows their total cumulative amounts at the end of the runs, as well as their amounts per km. In Test#1 approximately 3.18 [kWh] were recovered with regenerative braking, and in Test#2 approximately 5.05 [kWh] were recovered. These values are in accordance with the literature [7]. Figure 15b (Test#2) depicts the higher benefit/applicability obtained from regenerative braking in inner urban areas where brakes are actuated more often (compare with Test#1, Figure 15a) leading to a greater amount of energy that is regenerated. Figure 9b (Test#2) shows the higher occurrence of speed variations when compared to Figure 9a (Test#1), thus confirming the existence of more opportunities for energy regeneration. Specifically, from Figures 15a and 15b, it is seen that, for/after the same distance travelled, in Test#2 the energy recovered is higher than in Test#1. On the other hand, the energy supplied from, and recovered to, the battery pack, calculated by

\[
E_{\text{Supplied}} = \int_0^T V_t \cdot \max(0, I_{\text{bat}}) \, dt, \quad (18)
\]
Figure 16: Battery energies obtained by the integration of voltage and current: supplied energy, $E_{ supplied}$ (18), recovered/regenerated energy, $E_{ regenerative}$ (19), and total energy, $E_{ Battery}$ (20).

Figure 17: Battery energies obtained by the integration of voltage and current: supplied energy, $E_{ supplied}$ (18), recovered/regenerated energy, $E_{ regenerative}$ (19), and total energy, $E_{ Battery}$ (20).

\[
E_{ Regenerative} = \int_0^T V_i \cdot \min(0, I_{ bat}) \, dt, \quad (19)
\]

\[
E_{ Battery} = \int_0^T V_i \cdot I_{ bat} \, dt, \quad (20)
\]

are shown in Figures 16 and 17, and their total cumulative amounts at the end of the runs are shown in Table 6. By comparing Tables 5 and 6, it is observed that the differences between the supplied energy and the traction energy are 1.73 [kWh] and 2.46 [kWh] in Test#1 and Test#2, respectively. Actually, these differences correspond to the mechanical and electrical losses in the set comprised by the motor, the inverter, and the AC cables connecting them.

The attained overall efficiency of the set comprised by the motor, the inverter, and the AC cables connecting them, in traction, $\eta_{ overall}^t$, was 92.08% in Test#1 and 90.99% in Test#2. The overall efficiency in braking, $\eta_{ overall}^b$, was 90.62% in Test#1 and 90.19% in Test#2. These values were calculated by

\[
\eta_{ overall}^* = \frac{\int_0^T \tau_{ req} \cdot v \, dt}{\int_0^T \tau_{ req} \cdot \frac{1}{\eta_m} \, dt}, \quad \eta_{ overall} = \frac{\int_0^T \tau_{ req} \cdot v \cdot \eta_m \, dt}{\int_0^T \tau_{ req} \cdot v \, dt},
\]

and they are in accordance with the information provided in [17]. $\eta_{ overall}^*$ is the ratio between the total energy that the motor delivers to the gearbox and the total energy delivered to the motor. $\eta_{ overall}$ is the ratio between the total energy delivered to the motor and the total energy that the motor delivers to the gearbox. The motor operating points of the two tests are shown in Figure 18. Each operating point is a (torque, speed) pair of the run. It can be observed that during the runs, the entire range of motor speed (with the vehicle speed within the legal limits of the roads), and the entire range of motor torque were explored. The speed distributions of the operating points shown in Figure 18 are in accordance with the higher or lower average speeds of both tests. Figure 18, makes visible the motor operation zones for two distinct types of routes: Test#1, is made at higher speeds around 90 [km/h], and Test#2, has a bigger concentration of lower sampled speeds around 50 [km/h]. Although the EV motor/controller achieves high energy efficiencies of as high as 95%, it is clear that the operation points are located more frequently in the range of [85, 92] [%]. Regrettably, this is not the zone of best efficiency. These efficiency values do not take into account the transmission and tire losses that are also higher at low motor torques.

6. Conclusion

From the results of the learned FLmRB, it can be concluded that a RBS model of a particular EV can be successfully learned by using the proposed fuzzy expert system methodology. Namely, using the vehicle’s acceleration and jerk, and road inclination, and using a suitable fuzzy reasoning model, it has been shown that it is possible to infer the regeneration factor ($\beta$), the ratio of regenerative braking force to total braking force, during braking, while disregarding the brake pedal information. To validate and demonstrate the performance and effectiveness of the proposed framework, tests were made with real data ob-
tained from a Nissan LEAF EV in long-distance road runs. The results of the tests were used to compare the real-world data with the results of two types of simulations (also using real-world input data), one using FLmRB and the other considering 100% regeneration. Results show that β can be calculated by FLmRB, and that by using FLmRB, the estimated battery current is closer to the real values when compared to the case of simulation with 100% regeneration. It was also shown that the proposed FLmRB also enables adequate estimation of the SOC. To infer β for other real EVs, it should be performed the tuning of the learned fuzzy logic system/model (FLmRB), including in particular the consequent membership functions parameters, so as to infer an adequate and representative mapping between appropriate gathered EV data in one hand, and the EV energy flow in terms of regenerative braking on the other hand. In addition, the proposed approach provides the basis to achieve higher accuracy in EV simulations, making possible more rigorous EV energy scientific studies in the future. For example, using this expert system in a traffic simulator like SUMO, it is possible to simulate several vehicles differently tuned.

In the current stage, the EV’s RBS model is tuned by manual adjustment of the FLmRB parameters, after pilot studies analysis and also by trial and error. Also, a current limitation of the FLmRB is its complexity, i.e. it is used one FIS rule for each possible combination of the input variables (e.g. 770 rules for the presented model).

As a future work, the authors would like to propose the application of methods to reduce the learned model complexity by applying one of the existing methods in the literature for fuzzy system simplification [e.g., 9]. Moreover, it is also proposed as a future work the development of an automatic learning method for tuning the FLmRB rules to any other EV using real-world data, and test the methods with other EVs.

### 7. Acknowledgments

This work has been supported by QREN-MAIS Centro under project CENTRO-07-ST24-FEDER-002028. Ricardo Maia and Marco Silva have been supported by the Portuguese Foundation for Science and Technology (FCT), under grants SFRH/BD/44644/2008, and SFRH/BD/38998/2007, respectively. The authors acknowledge the help of Ricardo Faria in the tests for gathering the data sets with Nissan LEAF vehicle.

### Table 6: Energy supplied by, and energy recovered to, the battery.

<table>
<thead>
<tr>
<th>Test#1</th>
<th>Test#2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy Supplied (E_{Supplied})</strong></td>
<td><strong>MSE (kWh)²</strong></td>
</tr>
<tr>
<td>• measured</td>
<td>18.81</td>
</tr>
<tr>
<td>• simulated</td>
<td>0.019</td>
</tr>
</tbody>
</table>

### References


