Regenerative Fuzzy Brake Blending Strategy on Benchmark Electric Vehicle: the FIAT 500e

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***Abstract*—Enhanced regenerative brake performances and increased battery reliability in modern Electric Vehicles could be allowed by a proper reduction of electric braking applications at severe operative conditions. In this paper, authors intend to develop an algorithm for the optimized coordination between Regenerative Brake System and Hydraulic Brake Plant, also known as Brake Blending strategy. Proposed solution aim at maximizing the recovered energy during braking manoeuvres while ensuring an increased battery durability, by avoiding accelerated ageing phenomena occurring at high temperatures and limit State Of Charge values of the energy storage system. The controller, based on fuzzy logic, is validated through simulation activities on a benchmark electric vehicle showing improved reliability performances and extended lifespan of the storage system.**

***Index Terms*—electric vehicle, brake blending, electric braking, fuzzy logic, battery reliability**

I. Introduction

The synergetic coordination between electric and hydraulic brakes in modern Electric Vehicle (EV), aimed at ensuring a maximum energy recovery, is a very challenging task due to the complexity of the involved phenomena, which concerns several and heterogeneous physical domains [1], [2]. Also, reliability constrains, which inevitably affects electric powertrain systems, should be accounted in the design of the *Brake Blending (BB) Controller*, making it capable to automatically select the most cautionary conditions [3]. Using a fuzzy logic approach could be a feasible solution for the design of this algorithm, being able to account both modelled and poorly conditioned limitations [4], [5].

The availability of a Regenerative Braking System (RBS) in EVs offers to designers the possibility to implement newly and innovative brake strategies [6], [7] that can enhance the vehicle driving range by increasing the regenerated energy. Optimize this feature, thus, could be a crucial point and an highly desired solution to reduce overall energy consumption [8], [9]. These aspects constitute a constrained optimization allocation problem [10], [11].

Extensive work has been done in literature in order to properly model electric powertrain torques availability and to apply related constrains in the adopted control policies [12]. However, since a deterministic approach can be detrimental and, in some cases, lead to an underestimation of the involved limitations, a probabilistic based approach is proposed. To determine how the brake demand should be split between hydraulic and regenerative braking plant, the so-called *Brake Blending* strategy, we decide to follow a fuzzy logic methodology, which could be a useful tool in the optics of integrating the above mentioned aspects [13], [14].

Despite common fuzzy applications [15], in which the involved aspects are abstracted to define a probabilistic strategy, in this paper authors successfully build and implement a fuzzy controller which can completely take account of power and energy limitations of battery and Electric Motor (EM), based on its own models and their ideal power characteristics. Another non secondary advantages arising by the utilization of *mamdami* inference method concern the reduced perception of the driver during variations of the efforts exerted by the involved systems. This allows smoother transitions in torques allocation between available braking actuators, ensuring better reliability of the electric driveline and improved dynamics behaviour of the vehicle, avoiding abrupt acceleration variations. This know-how is used to build an effective and efficient Fuzzy Brake Blending (FBB) controller, which can take account also of bad conditioned and hardly modelled constrain terms, such as the battery temperature and ageing [16].

In this work, authors intend to evaluate the improvement permitted by the FBB controller in terms of regenerated energy and battery ageing. The proposed solution is validated through simulation activities based on a benchmark vehicle: the ***FIAT 500e***. Nevertheless, a wide range of different EVs architectures are investigated in the current State-of-Arts, so the controller is designed to ensure scalability and portability properties, in order to be implementable for several e-powertrain configurations and multiple vehicles Use Case (UC)s. This activity has been conducted in collaboration with Centro Ricerche FIAT (CRF), who shared important experimental data for the model validation and the controllers calibration.

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II. Simulation Framework

In this section we firstly describe the benchmark vehicle UC and related powertrain architectures. Then the proposed brake blending fuzzy logic algorithm is exposed.

A. Benchmark Vehicle: FIAT 500e

The investigated vehicle is the *FIAT 500e* (Fig.1), a fully Front Wheel Drive (FWD) EV, in which a single EM is used to actuate the front wheels through a differential mechanism.

The evaluation of the results is done supposing, for the reference UC, two different powertrain architectures showed in Fig.2: a) the conventional FWD configuration and b) a Four Wheel Drive (4WD) layout, actuated by independents In-Wheel Motor (IWM)s. The parameters remain the same for both the investigated configurations: in the case b) the total electric power of the four IWMs is equal to the power of the EM of the case a).

The 7 Degree Of Freedom (DOF) EV model consist of several mechanical, electrical and electronic sub-systems, useful for an accurate simulation of the vehicle behaviour during real driving scenarios, i.e.:

- **Driver model**: produces acceleration and braking commands, in-between [0,1] value range, based on the specified reference manoeuvres.
- **Torque regulation controller**: constituted by a simple Electronic Braking Distributor (EBD) controller (which apply different distribution ratio between front and rear axles torques in function of the longitudinal load transfer), and the proposed FBB controller.
- **Electric motor model**: includes the Motor Control Unit (MCU) and the electric actuators models, which deliver traction or braking torques to the wheels, working respectively in the 1° and the 4° quadrants, tracing the ideal traction/braking Torque vs Speed characteristic [12].
- **Energy storage model**: which comprise the High Voltage (HV) battery and the corresponding Battery Management System (BMS). The latter is used for the battery parameters estimation, while the HV battery powers the EM in the traction phases and stores the regenerated energy during electric braking phases. To consider the Power Inverter Module (PIM) (inverter + DC-DC converter) we impose a proper Voltage-Current profile for the charging and discharging of the battery [17].
- **Hydraulic brake model**: a functional decomposition model able to reproduce the behaviour of a real dissipative automotive disc brake [7].
- **Chassis model**: a 3 DOF model (longitudinal, lateral and yaw motions) which account aerodynamic and Centre Of Gravity (COG) position effects on the vehicle dynamics/kinematics.
- **Wheel model**: a further 1 DOF is added by the rotation around z-axis of each wheel. Tire-road contacts is modelled according to the Pacejka "Magic Formula Pure Longitudinal slip" model [18].

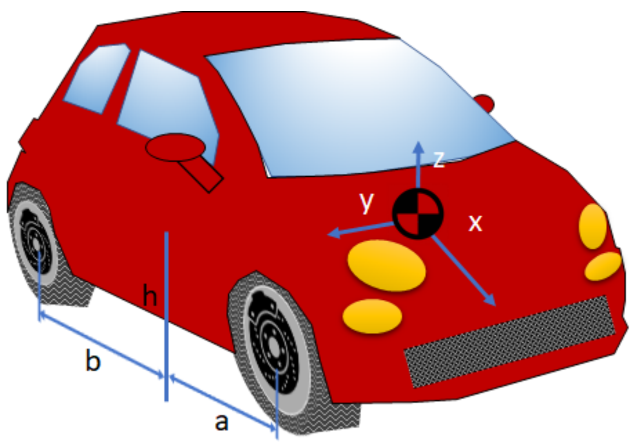

Fig. 1. Vehicle UC: Fiat 500e.

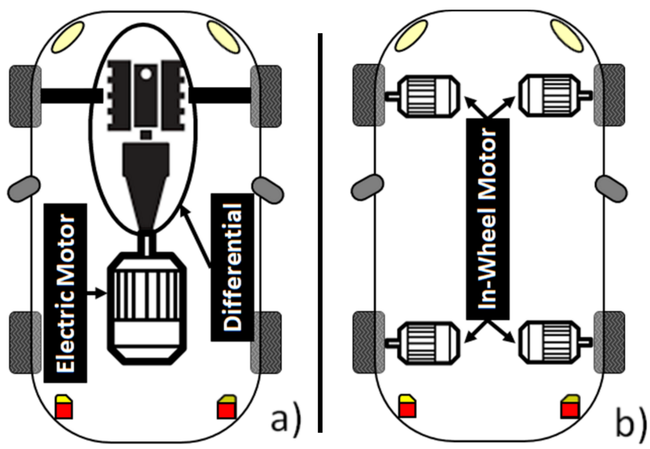

Fig. 2. Investigated EV powertrain architectures: a) FWD with one EM and a differential mechanism; b) 4WD with independents IWM.

The main UC parameters are summarized in Table I, which are freely available online. It is important to note that the gathered experimental data has allowed to estimate the the number of cycle which the battery has already experienced, based on our model. It has been found that the battery has performed about 25 equivalent cycle before tests starts. These results are in agreement with the ones arise from the real vehicle.

B. Fuzzy Brake Blending Controller

Fuzzy logic can be considered as a simplified neural network whose primary benefit is to approximate systems behaviour when analytic functions or numerical models don't exist, are poorly structured [14] or object of high level of measurement uncertainty [15]. This solution is a widely adopted tool for the control of complex system which involves several devices and components belonging to quite different physical fields [3]. Is the case of the BB, in which is fundamental a prediction of the states evolution to avoid undesired situations, while assuring the fully exploitation of the EM torques availability. Indeed, conventional controllers cannot handle driving scenario in some specific condition, when non-linear effect occurs and predominate the system's states evolution, as they are often restricted to linear ranges of variables.

TABLE I
MAIN VEHICLE PARAMETERS: FIAT 500E

Vehicle Parameters		
Name	*Symbol*	*Value [unit]*
Vehicle Mass	m_V	1355 [kg]
Front Wheelbase	a	0.989 [m]
Rear Wheelbase	b	1.311 [m]
Vertical Dist. Ground to COG	h	0.65 [m]
Electric Motor Power	P_{EM}	83 [kW]
Battery Capacity	C_{batt}	64 [Ah]

Proposed Fuzzy Inference System (FIS) logic controller, whose block diagram is represented in Fig.3, aims at the controlling of the blending strategy of the available braking actuators: RBS and disc brake. For doing that, accounts multiple variables in the process, listed above.

1) Driver demand: establish the requested torques on each wheel. As already pointed out, when battery State Of Charge (SOC), defined by (1), is lower than a certain value, it is recommended to prioritize electric braking, in order to ensure the maximum regeneration. Otherwise, when battery is almost completely charged a de-rating of the EM brake performances should be applied. For medium SOC value instead, regenerative brake is still desired, but it achieves its maximum value of 1 only if the entity of the requested brake exceeds a threshold, corresponding to an acceptable level of regeneration. Indeed, if the brake command is smaller than this established value, the reduced amounts of recovered energy doesn't justify the increased complexity in the system management. The *Driver demand* is then fuzzified through three different Mothership Function (MF)s, respectively *full*, *derate* and *no* for low, medium and high SOC values.

2) EM shaft speed: essential for the evaluation of the available torque by the electric powertrain and the avoidance of shaft overrunning. Fully exploiting of the EM characteristics is achieved making sure the delivered torque closely trace the ideal traction/braking curve. To realize this assumption in the FIS, we build a 2 MFs variable dependency: the *start* function, used to avoid vehicle going in reverse direction, and the *stop* function, which turns off the regenerative braking above the maximum admitted shaft speed. Indeed, when the vehicle is approaching 0 speed, regenerative braking is not suggested, since applying negative torque to wheels when the car is in stationary conditions can cause the vehicle going backward. The Iso-Torque and Iso-Power curve are implemented by the signals arising by the MCU.

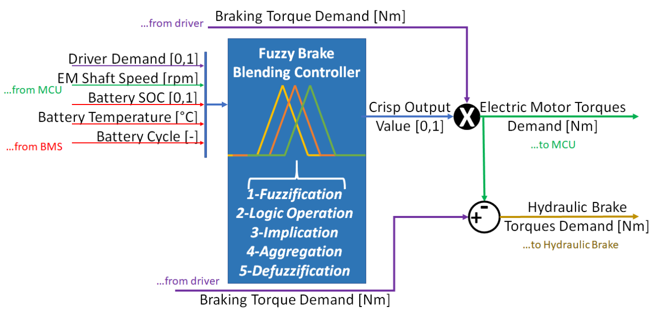

Fig. 3. Fuzzy Brake Blending controller.

3) Battery SOC: fundamental for averting dangerous condition of the storage system. Regenerated power should be limited at high SOC to prevent battery over-charging, while electric braking should be prioritize at low SOC to avoid under-discharing. Viceversa during traction phases. State of Charge is a key parameters to ensure a safe behaviour of the battery and to guarantee its reliability respect to some limit conditions. The power constrains are implemented by 3 MFs named *low*, *medium* and *high*, reflecting the corresponding SOC states defined by (1), where *Cnominal* is the battery capacity.

$$SOC = 100\left(1 - \frac{1}{Cnominal}\int_0^t i(t)dt\right) \tag{1}$$

This variable is essential to avoid fast performances degradation due to high level of requested Depth of Discharge (DOD), as pointed out in [19], where DOD is defined by (2).

$$DOD = 1 - SOC \tag{2}$$

4) Battery Temperature: it is recommended to reduce the power flowing in the battery when low or high temperatures condition occurs. Similarly at the previous case, temperature effects increase the ageing rate of the battery [16], [19]. So it is advisable to limit the battery C-rate when operating at temperature that differs from the nominal. We adopt a Gaussian MF in function of the battery temperature to reduce the current.

5) Battery ageing: used to implement energy limitations of storage according to capacity fade effects. As the battery ages its capacity decreases, so it is recommended to limit the amount of power recovered during regenerative braking scenario. Otherwise we could accelerate the decay performances law.

According to [16], automotive battery are considered at End of Life (EoL) when their capacity drops below 80% of the Beginning of Life (BoL) capacity value C_{BoL}. For the reference UC we assume an equivalent number of full charge-discharge cycle of N_{EoL}=2000. However, in EVs applications, only in a restricted number of case batteries are object of full cycles. So, to account the effect of partial cycles we define the battery ageing using the *Ampere-hour throughput* model [19], a framework for the battery lifetime prediction. The battery nominal Ampere-hour throughput is calculated by (3), supposing a DOD of 100% and an ambient temperature of 20°C.

$$Ah - throughput_{\mathrm{nominal}} = \int_0^{t_{\mathrm{EoL}}} |i_{\mathrm{nom}}(t)|dt \tag{3}$$

Where $i_{nom}(t)$ is the nominal current of the battery and t_{EoL} the instant in which battery capacity reaches the EoL value.

To quantify the ageing effects we consider the severity factor σ, an indicator of the battery degradation respect to the nominal number of admitted cycle N_{EoL}. In particular, the severity factor, at a given *DOD* and temperature T_{batt}, is defined by (4), with *i(t)* the current actually flowing in the battery.

$$\sigma = \frac{Ah - throughput_{\mathrm{nominal}}}{\int_0^{t_{\mathrm{EoL}}} |i(t)|dt} \tag{4}$$

TABLE II
FUZZY CONTROLLER IMPLICATION RULES

Implication Rules: Statements						
n°	***Brake$_{CMD}$***	***EM$_{rpm}$***	***SOC$_{batt}$***	***T$_{batt}$***	***Cycle$_{batt}$***	***output***
1	full	start	low	cycle	T	max
2	derate	start	medium	cycle	T	max
3	no	start	high	cycle	T	min
4	stop	/	/	/	/	min

Value of σ higher than 1 corresponds to more severe operating conditions respect to the baseline. In [19] the severity factor is mapped respect to DOD and T_{batt}, highlighting that at higher temperature and depth of discharge the severity factor is increased, as the ageing rate. So, is recommended to reduce the flowing current when the effective battery Ampere-hour throughput is approaching his EoL value. To implement this functionalities we use a single MF respect to the performed equivalent cycles. The severity factor σ is used as adjusting coefficient for the calculation of the effective battery *Ah-throughput$_{eff}$*, according to (5).

$$Ah - throughput_{\text{eff}} = \int_0^t \sigma(t)|i_{\text{batt}}(t)|dt \qquad (5)$$

At this point the *Ah-throughput$_{eff}$* is used to establish the equivalent number of performed cycles *N$_{eff}$*, subdividing it by the nominal *Ah* consumed during a cycle in nominal condition, which is double the nominal capacity of the battery supposing a cycle composed by a full charge and discharge process.

6) Output: the fuzzy logic requires the definition of proper output MFs to fulfill the implication phases. Those are *max* and *min*.

Once established the inputs fuzzy values using the corresponding MFs during the fuzzification process, the fuzzified input variables, whose degrees of membership are comprised between 0 and 1, have to be processed according specified rules. Adopted implication rules, summarized in Table II, have the objective to join model-based constrains with poor structured reliability aspects of the electric powertrain, while maximizing the regenerated energy. The resolving of those statement is done according to AND operator logic (min).

For each rule a single degree of membership is obtained using an OR operator between fuzzified input and corresponding output MFs, during the implication phase. The aggregation stages conjugated the previously described rules, while the defuzzification process returns a single crisp final value using a Small Of Minimum (SOM) logic. The FIS controller uses a *mamdani-type* inference method and the output signals are continuous (instead of discrete for the *sugeno-type*). This final value corresponds to the desired EM brake ratio that can be exerted by the electric powertrain, respect the maximum requested braking torque. The remaining effort should be burden by the hydraulic brake system. The disc brake desired torque is calculated by (6), subtracting from the requested braking torque, provided by the driver and subsequently modified by the EBD controller, the electric deliverable torque, visible also in 3.

$$Tq_{\text{disc}} = Tq_{\text{req}} - Tq_{\text{EM}} \qquad (6)$$

Summarizing, all this recommended specification are integrated by a proper design of the fuzzy controller rules, along with the BB controller developed in [6]–[9], whose functionalities are not reported here for brevity reasons. It is sufficient to know that the crisp value arise by the fuzzy controller constitute a correctional gain, variable between 0 and 1, which is multiplied to the EM torques command. The presence of redundant braking systems make appear the vehicle over-actuated, so the coherence with the commands in braking condition is ensured by the hydraulic brake plant, which can compensate the RBS unavailability. This solution concretized the attempt to reproduce a model-based concept in a fuzzy controller. Electric powertrain protections should be considered also during traction, so the fuzzy controller functionalities have been extended in order to implement EM and battery constrains, both during deceleration and acceleration phases. However, to ensure the execution of maneuvers according to the pilot's request, the traction fuzzy controller output is used to reduce the torque constrains, not the command.

The above mentioned input and output MFs are visible in Fig.4.

III. SIMULATIONS RESULTS

For evaluating the performances of the proposed FBB controller, the models of the investigated EV (the *FIAT 500e*) has been implemented in *MATLAB Simulink* environment, according to the scheme of Fig.5, in order to execute some simulation campaigns. As already pointed out, output results concerns two different powertrain architectures: the conventional FWD architecture and an hypothetical 4WD layout.

Performed tests can be grouped in two branches:

1) Reference Manoeuvres: consist in the execution of straight line deceleration at fixed boundary condition, i.e. battery temperature and initial vehicle speed, varying the corresponding initial charge. In this way it is possible to show the influence of *Brake$_{CMD}$* and *EM$_{speed}$* Membership Functions on the blending strategy.

During these full braking manoeuvres the blending controller prioritizes the RBS when available. Initial vehicle speed *V_i=27.78 m/s* and battery temperature *T_{batt}=20 °C* are supposed constant, while consecutive simulation have been performed at different battery initial charges *SOC$_i$*. Outcomes of the tests, for the FWD vehicle UC, are the torque references summarized in Fig.6.

2) Driving Cycle: making the vehicle perform specific driving cycles at different initial battery temperature *T$_{batti}$*, in order to account the effect of the FBB controller on storage reliability aspects. The simulations campaign consists in the execution of specific speed references over time. In particular the New European Driving Cycle (NEDC). Though more significant driving cycles are available and frequently used, e.g. Worldwide Harmonised Light Vehicles Test Procedure (WLTP), which better replicates real driving conditions by involving a wide spectrum of acceleration and speed ranges, we still opted for the NEDC. This is due to the fact that experimental data have been made available by CRF concerning this cycle, useful for the model and controller design.

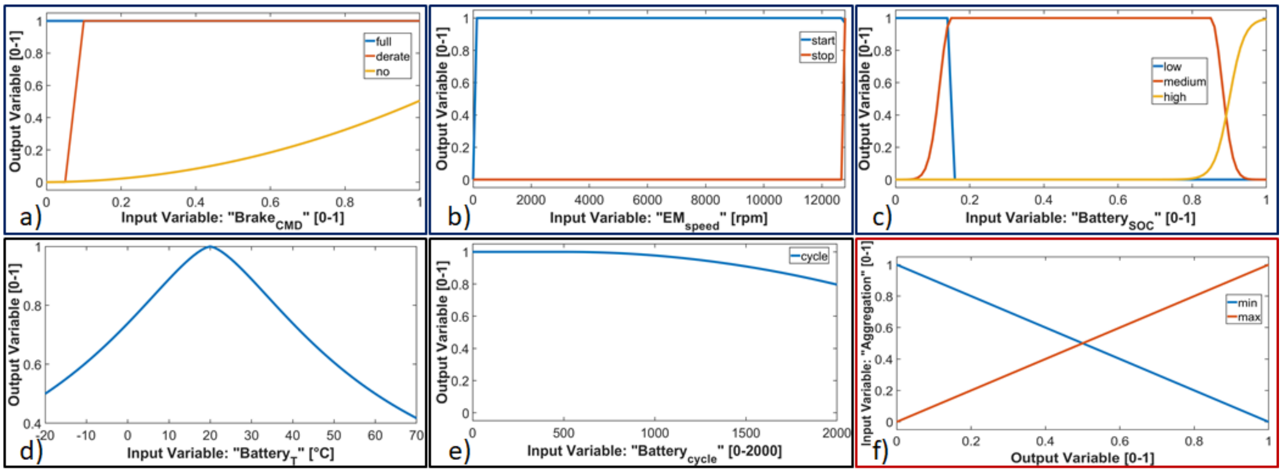

Fig. 4. Membership Function for: a) Brake Comand; b) EM shaft speed; c) Battery SOC; d) Battery Temperature; e) Battery Cycle; f) Aggregation.

Tests are repeated, for both the electric powertrain configurations of Fig.1, supposing the unavailability and availability of the FBB controller in order to metrical asses its performances. Interesting output are regenerated energy respect to the consumed one, final SOC_f and effective Ah-throughput impact on one equivalent performed cycle (7), visible in Table III, which show the effect of the FBB on above mentioned variables, assuming the data arise from simulation performed with conventional BB as a reference baseline for the improvement evaluations.

$$Ah - throughput_{\text{impact}} = \frac{Ah - throughput_{\text{eff}}}{2C_{\text{nom}}} \quad (7)$$

Concerning the first simulations, results of Fig.6 show how the proposed controller correctly assign the EM torque references, according to the battery SOC and motor shaft speed: when high level of charge occurs the blending strategies reduces the RBS effort to avoid over-charging. Viceversa, for low and medium level of charge the algorithm prioritize electric braking to ensure a maximum energy recover.

Regarding the driving cycle simulations, we expect a faster performances degradation when the BB strategy do not account thermal and ageing phenomena. Data of Table III are in agreement with these assumptions, since more severe operative conditions accelerates the performances decay: the equivalent performed cycle are higher. Indeed, according equation (4)-(5) and [19], the impact in the battery ageing of cycles performed at temperatures which differs from the nominal, is greater. Nevertheless, energy performances are reduced in potentially dangerous scenario. Important consideration about the proposed controller could be done observing that the amount of energy regenerated is minor for higher battery temperatures. A first look at this output could suggest some error in the simulations activities, since we expect a less significant decrease of the energy recovered ratio by the RBS, when the tests are performed at severe temperature conditions.

However, these results are justified considering the limited vehicle's accelerations involved by the NEDC. The constrains limitation imposed by the fuzzy controller during acceleration phases are not overcomes by the driver request, which require negligible torques, so the consumed energy remain the same. During braking instead, the performances are reduced, since are applied directly to the driver command, unlike during traction, in which are applied to the e-powertrain limits.

IV. Conclusion and Future Developments

Most significant results of the simulations are the energy performances and reliability improvements obtained. Supposing different powertrain layouts allows to comparatively evaluate the outcomes, as well as the assessment of scalability and portability properties of the developed control strategy.

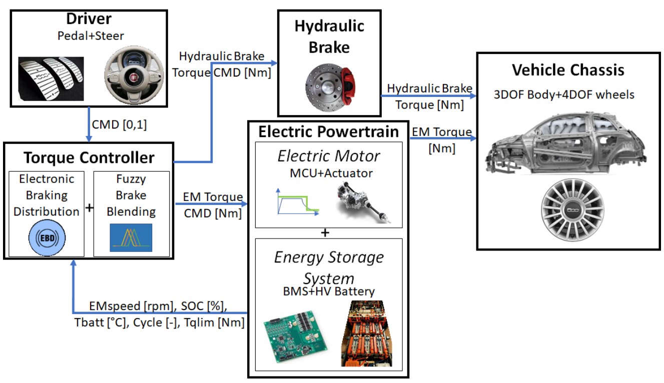

Fig. 5. Simulation layout implemented in MATLAB Simulink.

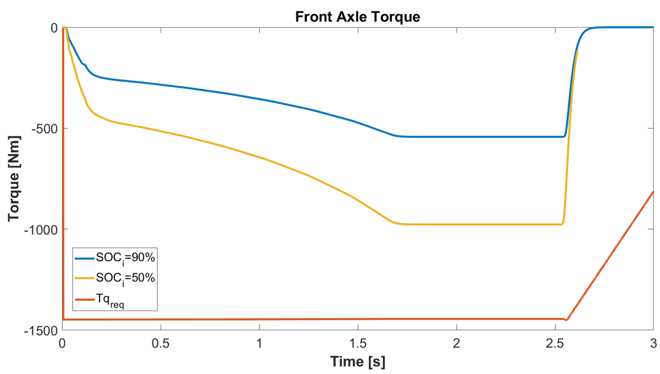

Fig. 6. Straight line deceleration: regenerative torques at different SOC_i

TABLE III
NEDC SIMULATION RESULTS AT SOC_i=85% *and DOD=5%*

Initial Condition: T_{batt0}=20°C; $\sigma = 1$				
Layout	***Fuzzy BB***	***SOC_{battf}[%]***	***E_{reg}/E_{cons}[%]***	***$Cycle_{impact}$[%]***
FWD	ON	80.1	16.24	3.24
	OFF	80.2	16.28	3.45
4WD	ON	80.5	21.72	3.40
	OFF	80.5	21.76	3.61
Initial Condition: T_{batt0}=45°C; $\sigma = 1.5$				
Layout	***Fuzzy BB***	***SOC_{battf}[%]***	***E_{reg}/E_{cons}[%]***	***$Cycle_{eff}$***
FWD	ON	79.9	10.87	4.93
	OFF	80.2	16.28	5.17
4WD	ON	80.0	14.47	5.09
	OFF	80.5	21.76	5.41
Initial Condition: T_{batt0}=60°C; $\sigma = 2$				
Layout	***Fuzzy BB***	***SOC_{battf}[%]***	***E_{reg}/E_{cons}[%]***	***$Cycle_{eff}$***
FWD	ON	79.7	8.14	6.42
	OFF	80.1	16.23	6.90
4WD	ON	79.9	10.85	6.57
	OFF	80.5	21.71	7.22

In conclusion, to ensure the maximum flexibility of the controller, we have developed an algorithm which owns important scalability and portability properties. This conclusion is due to the fact that the FBB strategies applies effectively to different electric powertrain architectures. In addition, improvements in the driver dynamic feedback are achieved: conventional blending policies could generate abrupt accelerations when passing from the usage of a braking actuators to another. A smoother dynamic instead, as the one proposed in this paper, can reduce the passengers perception.

Results highlight how the proposed fuzzy controller could increase battery reliability and lifespan, selecting more conservative power constrains when limit conditions occurs. However, adopt FBB reduce the overall energy which could be recovered for the RBS in those scenarios. This strategy, attempt to find an optimal comprise between energy regeneration and energy storage system preservation.

Possible future developments concerns the refining of the models and the further calibration of the Fuzzy BB controller, making it capable to regenerate a greater amount of energy, e.g. by modifying the ideal EM Torque vs Speed curve, or by accounting more input variables in FIS design process.

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