Hardware-in-the-Loop Test of an Open-Loop Fuzzy Control Method for Decoupled Electrohydraulic Antilock Braking System

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Abstract—To verify the functionality of an intelligent open-loop fuzzy-logic-based antilock braking system control method for four on-board motor drive electric sport utility vehicle, a hardware-in-the-loop experiment is conducted in this article. The experimental facility includes a novel decoupled electrohydraulic brake test bed characterized by highly nonlinear dynamics and time-varying behavior. It reproduces real pressure dynamics of the brake circuit allowing for simulation of various tire–road adhesions conditions and brake blending scenarios. To cope with degradation of antilock braking system performance induced by unexpected changing environmental conditions, such as road surface, the developed fuzzy control features a very simple yet effective and robust road surface recognition tool with estimation of the peak braking demands. Thus, the fuzzy logic serves as a controller and road surface estimator simultaneously allowing for complex mathematical modeling and feedback control avoidance not sacrificing safety system’s performance. The results indicate that the control method manages highly nonlinear and time-variant dynamics of the brake system and offers significant feasibility for optimal slip control at regenerative braking, ensuring fuzzy control's potentiality for real-time application.

Index Terms—Antilock braking system, electric vehicles, electrohydraulic actuator, fuzzy control, intelligent control.

I. INTRODUCTION

In addition to transportation, vehicle technology must ensure safety of occupants, goods, and environment, which has higher priority than time or cost. For example, an excessive braking torque leads to wheels’ lockage, what deteriorates vehicle steerability and significantly reduces braking force: the vehicle is able to neither turn and avoid collision nor decelerate as fast as practicable. To solve this problem, an active safety technology promoted from aerospace industry, antilock braking system (ABS), was applied to ground vehicles. The ABS aims at decelerating a vehicle as fast as possible along with simultaneous maintaining steerability during an emergency braking maneuver. Its superior goal is to enhance the braking, steering, and driving stability. Today, the ABS is a mandatory safety system in almost every country in the world [1].

The challenge of controlling an ABS for electric sport utility vehicle (e-SUV) is provoked by

1) system’s high nonlinearity and significant time delay;
2) controller’s instant response capability and robustness to continuously varying system’s states and environment;
3) uncertainties and lack of knowledge about the plant;
4) electric motor and electrohydraulic brake (EHB) actuators efficient blending strategy for maximum energy recuperation.

Despite continuous response, the robust control methods, such as sliding-mode (SMC) [2], [3], model predictive [4], [5], non-linear proportional-integral-derivative (PID) [6], linear matrix inequality [7], fail to operate such complex systems as ABS for e-SUV due to fundamental lack of robustness to ill-defined variables and vagueness, and their inability to consider several system binding aspects simultaneously. Consequently, fuzzy set theory, which is capable of overcoming abovementioned problems, found its effective application in ABS control [8]–[10].

For instance, a Mamdani’s fuzzy logic controller (FLC) was applied to electric vehicle [11], for an FLC combined with PID controller [12] and for a quasi-SMC accompanied with fuzzy-neural network estimator applied to a conventional passenger car [13]. In [14], Chen et al. developed the ABS FLC that provides optimal slip for varying road conditions. Recently, another solution consisting of SMC and FLC cooperation was presented [15]. In [16], the fuzzy logic was used in road surface detection, and additional FLC—for pressure control that holds optimal wheels slip. The control method was first tested against a quarter-car hardware-in-the-loop (HIL) simulation. Later, road type recognition was enhanced with an artificial neural network and validated in simulation and real vehicle experiment [17]. Finally, a complex control method based on fuzzy logic, which required three inputs and a state observer to detect road

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friction coefficient and to decide upon an optimal wheel slip, was developed and tested in simulation and on a real car [18]. An FLC in combination with SMC [19], [20] or $H_{\infty}$ [21] led to significant improvement in electrohydraulic servomechanism control via rapid adaptation to dynamic system’s states variation and robustness to plant–environment correlation uncertainties. In [22], the scholars utilized ratio of wheel equivalent linear acceleration to drive motor torque to detect and control vehicle skidding. Again fuzzy logic was applied in this instance to handle a balanced tradeoff between antiskid control and vehicle acceleration performance.

Development and verification of safety systems on real vehicles is often expensive and time consuming. On the other hand, computer simulation does not always guarantee realistic environments for testing vehicle safety systems, such as ABS, traction control systems, electronic stability programs, etc. Consequently, in recent years, the researchers have extensively used HIL simulation tests that replicate vehicle subsystems, such as the braking system, suspension, and steering rack, while the rest of the vehicle is represented as a numerical model. The HIL testing provides real-time behavior of the studied vehicle system and enables significant cost and time reduction in development and testing stages [23], [24].

Despite complexity and inherent nonlinear characteristics, the electrohydraulic systems, due to their effectiveness, precision, and fast response, are widely used in automotive industry (i.e., braking system, suspension, etc.) [25], where advance regulation strategies are necessary for high-performance of motion, force, or positioning control [26]. However, most of these systems are featured with additional challenges caused by flow–pressure relationship, like dead-zone due to valve spool overlap, oil leakage, oil temperature variation, etc. Hence, fuzzy set theory was successfully applied as a control method for multiple electrohydraulic systems, what allowed for avoidance of difficult time- and environment-dependent mathematical model of a plant [27]–[29].

In the previous study, the adaptability of the intelligent feedforward fuzzy control method for ABS for e-SUV with four independent in-wheel motors powertrain to dynamically changing and ill-defined environment conditions was investigated [30]. Although the simulation results proved control method’s positive impact on ABS performance, it does not guarantee success on real system. Hence, testing the control method on HIL set up is an essential intermediate step before applying it to a real system. The main contribution of this article is experimental verification and results demonstration of practical applicability of the previously proposed open-loop FLC against HIL platform. The HIL setup consists of a novel decoupled EHB test bed developed by the ZF TRW Automotive (Koblenz, Germany) [31] and interconnected with a high fidelity vehicle dynamic software IPG CarMaker (Karlsruhe, Germany), which runs experimentally validated e-SUV. The complexity of the HIL system under investigation is as follows.

1) Separate control of each of the four wheels, whose performance influences each other and the overall system.

2) Separate control of each of the four wheels via two fundamentally distinct actuators, i.e., decoupled EHB and electric motors.

3) Collaboration between two actuators for ultimate goal of ABS performance and energy recuperation maximization.

4) The delay of the EHB system induces significant loses in ABS performance.

The remaining of the article is structured as follows. In the next section, the open-loop fuzzy-logic-based ABS control method for e-SUV is introduced. Section III is devoted to the decoupled EHB system and HIL setup description. The experimental results on low-$\mu$ and varying road conditions are presented in Section IV. Section V concludes this article.

II. ANTILOCK BRAKING SYSTEM CONTROL METHOD

The main task of the ABS is fast vehicle deceleration by keeping vehicle handling stability and steerability. Additionally, for the EVs, the ABS must guarantee maximum energy recuperation from the braking process. The feedforward FLC-based ABS control method (see Fig. 1) recognizes road surface and holds optimal wheel slip deceleration on various road adhesions as well as in complex braking maneuvers for each wheel contemporaneously. It is managed by a single open-loop FLC, which serves as a road surface identifier and a controller concurrently. Hence, complex mathematical modeling and set point-oriented control are avoided without sacrificing ABS’s functionality. Efficient recuperation is provided by applying the maximum possible braking torque from the electric motors $T_{RB}$, and adding braking torque from a conventional EHB $T_{FB}$ only when the torque generated by the electric motor is not sufficient to attain an optimal wheel slip $\lambda_{opt}$ [30].

A. States Estimation

1) Road Surface Estimator $\mu^*$: A simplified schematic drawing of a braked wheel is depicted in Fig. 2. The tire–road
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The adhesion coefficient $\mu$ is a ratio of the applied longitudinal $F_x$ and vertical $F_z$ forces on a tire, and considering wheels’ uniform adhesion, it is expressed as follows:

$$\mu = \frac{F_x}{F_z} = \frac{mV \cdot aV_x}{mV \cdot g} = \frac{aV_x}{g}$$  \hspace{1cm} (1)

where $mV$ and $aV_x$ are mass and longitudinal deceleration of a vehicle body, respectively, and $g$ is the gravitational acceleration.

To estimate road surface under the tires $\mu^*$, the peak longitudinal deceleration value of the sensor is tracked. Moreover, during the braking process, $\mu^*$ is reset with a certain frequency. While the variable is reset, the ABS is turned off allowing maximum requested braking torque on the wheels. In this period, a peak $aV_x$ is measured again. If the road surface remains unchanged, the same peak $aV_x$ is detected as in the previous step. However, if the road surface changes, the value of $\mu^*$ is updated according to the road profile.

The method of road estimation proved to be very efficient in combination with fuzzy logic. In this case, it is necessary to know neither the peak deceleration rates nor the wheel optimal slips for every possible road surface. As to the limited available data about the wheel slip curves, computational intelligence methods based on fuzzy set theory, artificial neural networks, etc., can be used as an artificial decision-making system to approximate the e-SUV’s behavior for varying road surfaces from already known ones. In Table I, the presented data are experimentally collected on different road surfaces and are true only for the studied vehicle and particular tire. These data are utilized in control method design. Conventional controllers, unlike soft computing methods, are not suitable for dealing with this type of stochastic and ill-defined information [32].

For instance, when the peak $aV_x$ is between wet and damp to any degree of certainty, it is not efficient to hold the $\lambda_{\text{opt}}$ precisely for wet or for damp road. The $\lambda_{\text{opt}}$, according to the tendency (see Table I), lays somewhere between those two road surfaces. The fuzzy system processes this vague information using linguistic reasoning understandable for human. For example, fuzzy inference may be expressed in the modus ponens (If premise Then consequence) form as follows: If road surface value is between wet and damp and wheel slip ratio is high for damp road, then decrease torque to obtain wheel slip ratio between optimal for wet and damp roads.

2) Longitudinal Wheel Slip $\lambda$: In braking mode, the longitudinal wheel slip $\lambda$ expressed in percentage is calculated as follows:

$$\lambda = \frac{vV_x - vW_x}{vV_x} \times 100\%$$  \hspace{1cm} (2)

where the longitudinal vehicle velocity $vV_x$ is an integration of $aV_x$

$$vV_x = \int aV_x \, dt$$  \hspace{1cm} (3)

and longitudinal wheel velocity $vW_x$ is derived from the measured wheel speed $\omega_W$ and radius of deformed tire $r_W$

$$vW_x = r_W \cdot \omega_W.$$  \hspace{1cm} (4)

The radius of the deformed tire is a relation of the stationary wheel ground contact force $F_{c0}$ to the tire stiffness $k_T$ in accordance with [33]

$$r_W = r_{W0} - \frac{(F_z - F_{c0})}{k_T}$$  \hspace{1cm} (5)

where $r_{W0}$ is the radius of undeformed tire and the wheel vertical load is approximated using a quasi-static longitudinal weight transfer approach [33]. In case of pure longitudinal driving without lateral acceleration, tire vertical forces for front ($f$) and rear ($r$) wheels are computed as follows:

$$\begin{cases}
F_{z(f)} = mV \left( \frac{l_r g - h_f aV_x}{l_f} \right) \\
F_{z(r)} = mV \left( \frac{l_f g + h_r aV_x}{l_r} \right)
\end{cases}$$  \hspace{1cm} (6)

where $l_r$, and $l_f$ are rear and front semi-wheelbase, $l$ is the wheel base, $h_c$ is the center-of-gravity height.

The friction (FB) and regenerative (RB) brake FLCs receive $\lambda$ and $\mu^*$ as inputs. The corresponding requested regenerative $T_{RFB_{\text{req,in}}}$ and friction $T_{FB_{\text{req,in}}}$ braking torques are generated to keep an optimal slip for each wheel.

Remark 1: Pertinent sensors available in modern cars measure pressure of the EHB $p_{eb}$ and current of the on-board motor $i$, which are proportional to friction $T_{FB}$ and regenerative braking torques $T_{RFB}$, respectively. Hence, in this article, the controller’s corrective variables are RB torque for the motor and FB braking pressure for the EHB.

Remark 2: To reduce the noise in the sensors’ signals, which is particularly important for the wheel longitudinal slip estimation (2), a linear Kalman filter [34] was applied.

B. Fuzzy Logic Controller

An FLC is composed of four main elements: fuzzification interface, inference engine, rule base, and defuzzification interface. FLC takes a numerical value (“crisp”) and transforms it into a linguistic variable in the fuzzification interface. Using

Fig. 2. Simplified drawing of a braked wheel.

| TABLE I | OPTIMAL WHEELS’ SLIP RATES AND VEHICLE’S BODY PEAK DECELERATION VALUES FOR COMMON ROAD SURFACES FOR STUDIED VEHICLE |
|----------|------------------------------------------------------------------------------------------------------------------|
|          | icy | Wet | Damp | Dry |
| Font wheels $\lambda_{\text{opt}}$ [%] | 2.55 | 5.21 | 7.87 | 9.91 |
| Rear wheels $\lambda_{\text{opt}}$ [%] | 2.76 | 6.11 | 8.89 | 11.57 |
| Peak $aV_x$ [m/s²] | 2.69 | 5.09 | 7.62 | 10.10 |
Fig. 3. FLC MFs and fuzzification procedure for randomly picked \( \lambda = 2.45 \) and \( \mu^* = 4.2 \): \( \mu(\lambda/\mu^*) \) — degree of certainty of an FLC input.

a predefined rule base (a set of “If–Then” rules), the mapping between the input and output linguistic values is conducted by the inference engine. Finally, the defuzzification interface turns consequent linguistic output back into its crisp value [32].

1) Fuzzification: The first input of the FLC is the wheel slip \( \lambda \). It has seven symmetrically dispersed and overlapping membership functions (MFs) over the whole universe of discourse (UOD) with a set of linguistic values {“slip equals to 0” (\( S_0 \)); “slip equals to 3” (\( S_3 \)); “slip equals to 6” (\( S_6 \)); “slip equals to 9” (\( S_9 \)); “slip equals to 12” (\( S_{12} \)); “slip equals to 15” (\( S_{15} \)); “slip equals to 18” (\( S_{18} \))}. Its UOD is bounded inside of \([0 18]\) limit, which provides the range of values the \( \lambda \) can assume. The second crisp input is the estimated road surface \( \mu^* \). It has five equal span and overlapping triangular MFs with linear fuzzy rule. The set of MF values is {“Zero”; “Icy”; “Wet”; “Damp”; “Dry”}. The UOD is restricted inside \([0 10]\).

Symmetrical dispersion of the MFs over the UOD is responsible for equal MFs’ sensitivity. Due to simplicity and fast response, all the inputs’ MFs have triangular shape. The UOD limits are chosen based on the information about the plant, i.e., experimentally validated tire model (see Table I).

In Fig. 3, the fuzzification process for the designed MFs for the FLC inputs is presented. The crisp inputs are fuzzified with a singleton (blue) function. As a result, two arrays \( a \) and \( b \) are obtained. Each position of the array corresponds to an appropriate MF linguistic value, and it contains a rate of its degree of membership (a value between 0 and 1) for a given input. When the input singleton does not intersect an MF, its array position value equals to zero. Thereafter, a dyadic product of two arrays is calculated resulting in matrix \( C \) [35]

\[
C = a \otimes b = ab^T.
\]  

2) Rule Base and Inference Mechanism: A rule base captures the expert’s knowledge about how to control the plant. Because a finite number of input MFs are designed, there is only a finite number of fuzzy rules. When there are not more than three inputs, a conventional way to list all possible sets of linguistic relations is to use a tabular representation [32].

The output of the RB FLC is the requested torque \( T_{RB}^{req.in} \). In total, it has 11 possible values starting from 0 to 200 with equal step of 20 between each variable. Its fuzzy rule base is presented in Table II for front and rear wheels. The requested FB pressure \( p_b^{req.in} \) is limited to 150 bar. Therefore, its consequent values from 0 to 150 form 16 output options with a fixed step of 10 between each other. Input–output mapping of the FB FLC for front and rear wheels is introduced in Table III. Each FLC has 35 rules.

All the rule bases were obtained with a trial and error method, where the main criterion was to keep wheel slip as close as possible to its optimal rate. A linguistic quantification for one of the front wheels in regenerative braking may be expressed, for example, as follows: If wheel “slip equals to 9” and road surface is “Wet” then request from the electric motor regenerative braking torque equal to “100” N-m.

For inference engine, every rule base is converted into a matrix \( R \). In Fig. 4, this transformation for RB front wheels FLC is shown. The same principle is applied to other rule bases. Finally, fuzzy inference is done via Hadamard product of two matrices of the same dimensions: \( C \) from the fuzzification interface, and
\[ R \text{ from the rule base [35]} \]
\[ D = C \circ R. \] (8)

3) Defuzzification: The final element of every FLC is a defuzzification interface, where a resultative crisp output is obtained. Here the derived matrices \( C \) and \( D \) are converted into a single number. In this article, a weighted average of the matrix elements is found. To this effect, a sum of elements in matrix \( D \) is divided by a sum of elements in matrix \( C \). The calculation is shown for the RB requested torque on the front wheels [32]
\[ T_{\text{req, in}}^{\text{RB}(f)} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} d_{ij} c_{ij}}{\sum_{i=1}^{M} \sum_{j=1}^{N} c_{ij}}, \quad i = 1, 2, \ldots, N; \quad j = 1, 2, \ldots, M \] (9)

where \( d_{ij} \) is an element of the \( i \)th row and the \( j \)th column of matrix \( D \) and \( c_{ij} \) is an element of the \( i \)th row and the \( j \)th column of matrix \( C \).

In total, four different FLCs are designed for the e-SUV: two RB FLCs (i.e., for front and rear wheels), and two FB FLCs (i.e., for front and rear wheels). At last, the nonlinear three-dimensional (3-D) surfaces for every FLC are generated (see Fig. 5). Representation of the FLC controller with 2-input three-dimensional (3-D) surfaces for every FLC are generated (see Fig. 5). The surfaces represent the outputs of the FLCs against their own inputs \( \lambda \) and \( \mu^* \) inside of the universe of discourse limits.

4) Stability Analysis: The proposed open-loop FLC does not involve a set-point reference inputs. Therefore, traditional stability analysis approaches, like Lyapunov’s direct or indirect methods [32], [36], are not feasible. In this article, the trajectory phase-plane analysis is used to refine the FLCs control surfaces (see Fig. 5). It gives a visual assessment of the local stability and performance of studied nonlinear plant. It allows for analyzing the ability of the controller to prompt convergence to an equilibrium point taking into consideration the following stability condition [37]: if the control is capable to stabilize the error and its derivative around the origin, then the control is locally stable. The method is especially efficient for nonlinear systems whereby analytical solutions for the proof of stability does not exist.

Time differentiation of (2) leads to the following statement:
\[ \dot{\lambda}v_{V_x} + \lambda \dot{v}_{V_x} = \dot{v}_{V_x} - \omega_W r_W. \] (10)

Taking into account torque balance during the straight-line braking, the longitudinal wheel slip dynamics are expressed as follows:
\[ \dot{\lambda} = \left( \frac{T_b - F_x (\lambda) \cdot r_W}{J_W} \right) \cdot \frac{r_W}{v_{V_x}} + \frac{\dot{v}_{V_x}}{v_{V_x}} - (1 - \lambda) \] (11)

where \( J_W \) is the moment of inertia of wheel. The equilibrium point of (11) is characterized by \( \dot{\lambda} = 0 \), where the condition below is true
\[ T_b = -v_{V_x} \cdot (1 - \lambda) \cdot \frac{J_W}{r_W} + F_x (\bar{\lambda}) \cdot r_W. \] (12)

In Fig. 6, the experimental results are represented on of the stability trajectory phase-plane analysis for front left wheel. The designed FLCs are activated. The arrows show the magnitude and direction of the wheel slip variation. The wheel slip is calculated applying (2), while the wheel slip rate is found in accordance to (11). In additional, the performance of the e-SUV without ABS activation is also shown.

With no ABS activated (gray), the wheels are locked, what leads to unstable behavior. Although the system reaches its stable equilibrium point, the FLC controlling the EHB (blue) takes significant time to reach the equilibrium. On the contrary, thanks to fast dynamics, the RB actuator (red) allows for a faster convergence of the system to the equilibrium. Despite the difference in convergence speed, both actuators operate inside of the safe wheel slip area, what has a higher priority in the framework of vehicle safety and steerability in emergency braking situation.

C. Torque Blending Strategy

The torque blending strategy is designed to prioritizing usage of electric motor for maximum energy recuperation for a given road surface. The EHB system is activated if the maximum motor torque for a certain speed is requested, and the tire slip value is lower than its optimal one for a given road. Furthermore, the strategy it also accounts for the battery’s state of charge (SOC) switching between electric motors and EHB.

For this reason, the torque blending strategy is classified of series type, as the EHB is only activated when the request exceeds the motors performance. The outputs are the resultative
RB and FB torques, $T_{RB}^{req\_out}$ and $T_{FB}^{req\_out}$, requested from the actuator. A schematic flowchart is shown in Fig. 7.

1) The algorithm checks the velocity of the vehicle: If the vehicle longitudinal speed $v_{x\_min}$ is smaller than the fixed minimum threshold $v_{x\_min}$ (e.g., 8–15 km/h), the ABS control is deactivated considering the difficulties of estimating the wheel slip [1].

2) When the SOC reaches the maximum allowed threshold SOC$_{\text{max}}$ (e.g., 90%), the braking switches to pure FB mode.

3) The blended ABS considers the motor’s peak performance: when peak torque $T_{\text{cl}}^{\text{max}}$ of the SRM is requested by the FLC, the block supplies the peak torque request to the motor and calculates additional torque for the FB actuator to ensure optimal deceleration.

4) When none of the previous conditions are true, the EV decelerates only with motors as the ABS actuators. At last, the braking torque $T_b$ of the e-SUV is a sum of regenerative and friction torques (see Fig. 1)

$$T_b = T_{RB} + T_{FB}.$$  \hspace{1cm} (13)

III. HARDWARE-IN-THE-LOOP SET-UP

A. Vehicle Configuration

An experimentally validated 14 degree-of-freedom vehicle model is provided by the IPG CarMaker 6.0. The vehicle under investigation is an e-SUV equipped with decoupled EHB. Each wheel contains an electric drive connected through a half-shaft transmission that enables independent wheels control. The Pacejka’s “Magic Formula” 6.1 is applied for tire modeling. The e-SUV configuration is introduced in Table IV.

To reproduce real dynamics of the brake linings coefficient of friction, the Ostermeyer’s model [33] is used. The model allows for an improved fidelity of the HIL platform, because it accounts for the brake linings’ coefficient of friction dependence against speed, pressure, and temperature. It assumes that the friction coefficient is proportional to the total area of contact patches. The resulting patches area is determined by the equilibrium between the flow of growth (i.e., temperature related) and destruction (i.e., wear related). The model relies on two differential equations in the friction $\mu_b$ and temperature $\tau$ states

$$\dot{\mu}_b = -\alpha \cdot \{\mu_b \cdot \omega_b \cdot F_{cl} + \beta \} - \gamma \cdot \tau$$

$$\dot{\tau} = \varepsilon \cdot r_b \cdot \omega_{\text{w}} \cdot F_{cl} - \delta \cdot (\tau - \tau_0)$$ \hspace{1cm} (14)

where $r_b$ is the effective braking radius, $\tau_0$ is the initial temperature of brake disc, and $F_{cl}$ is a brake clamping force found as follows:

$$F_{cl} = A_p \cdot p_b$$ \hspace{1cm} (15)

where $A_p$ is the piston area of caliper.

Remark 3: The term $r_b \cdot \omega_{\text{w}} \cdot F_{cl}$ embeds the combined effect of clamping force and sliding speed, whilst the constant parameters $\alpha, \beta, \gamma, \delta, \varepsilon$ are attributable to the pad chemical formulation:

1) $\alpha$ is a time constant ruling the growth / destruction rate of the contact area and its current value;

2) $\beta$ is correlation parameter between the change rate of the contact area and its current value;

3) $\gamma$ correlates the change rate of the contact area to the temperature;

4) $\varepsilon$ rules the frictional power dissipated as heat on the contact patches;

5) $\delta$ refers to a brake cooling factor and rules the convection effect.

B. HIL Testbed

The decoupled EHB system shown in Fig. 8 is based on the slip control boost technology developed by the ZF TRW Automotive. The EHB system finds wide use in EV, because it ensures smooth coordination between FB and RB without the driver noticing it. Such a system also ensures faster response time, more flexible packaging, and better integration with other chassis and powertrain control systems.

The hardware setup consists of the EHB and its control unit. The brake calipers are mounted on two discs, fixed with respect to the structure frame. The main task of the HIL is to reproduce real pressure dynamics of the brake circuit. The sensor measures the brake line pressure in the four brake calipers in a range from 0 to 20 MPa with a cut-off frequency of 1 kHz.

The core HIL test rig is based on dSPACE (Paderborn, Germany) modular platform with several hardware components responsible for data input/output, the control of the EHB and the communication with the vehicle simulator in IPG CarMaker.
The EHB does not require the actuation of the brake pedal since the pressure request can be generated directly from software and sent via controller area network (CAN) bus to the EHB control module. For this task, one of the four CAN interfaces of the DS4302 is used. To configure the CAN network and to combine dSPACE boards with CAN networks, the real-time interface multimessage blockset is used. The control on the EHB unit uses the direct digital synthesis board DS2302. This board can generate waveform signals and is required for the operation of emulators of wheel angular speed sensors. This latter is particularly important to account for the sensors’ white noise.

The transfer function of the decoupled EHB system is experimentally assessed to be equal to

\[
\frac{T_{FB}}{T_{req\_out}} = \frac{1}{0.00075s^2 + 0.037s + 1}e^{-0.026s} .
\]  

(16)

\[
\frac{T_{FB}}{T_{req\_out}} = \frac{1}{0.00021s^2 + 0.045s + 1}e^{-0.015s}.
\]  

(17)

Finally, the electric motor is represented as a mathematical model. It is run in the multibody vehicle model. Considering the transmission gear ratio, the maximum torque applied directly to the wheel achieves 2100 N·m. The motor dynamics are described by the first-order transfer function [30]

\[
\frac{T_{RB}}{T_{req\_out}} = \frac{1}{0.0022s + 1}e^{-0.002s}.
\]  

(18)

IV. HARDWARE-IN-THE-LOOP EXPERIMENTAL RESULTS

To evaluate the developed control method on robustness to changing environmental conditions, the HIL experiment is conducted on multiple road surfaces and their transient combinations. In this article, braking performance on low-μ and transient (i.e., from high-μ to low-μ) road surfaces are discussed in details. In all experiments, the vehicle is accelerated to 100 km/h, and then the maximum braking torque is requested.

A. Low-μ Surface Experiment

High-performance ABS is essential on low-μ surfaces (e.g., icy, wet), because on a slippery road the vehicle loses control very quickly. In this section, the results of heavy braking on a low-μ road surface (μ ≈ 0.25) with blended braking control (see Fig. 10) are presented, and are compared to the conventional FB (see Fig. 11). The notations FL, FR, RL, and RR refer to the front left, front right, rear left, and rear right wheels, respectively.

1) Regenerative Braking: In Fig. 10(a), the wheel speeds and vehicle longitudinal velocity diagrams for RB are plotted. The braking torques are generated by the electric motors only. Thus, the vehicle decelerates in full regenerative mode, as the FBs are not applied. Each wheel rotates almost with the same speed because the optimal wheel slip ratios are approximately the same for both the front and the rear wheels, roughly equal to 3% (see Table I). Thanks to its fast dynamics, the controller is able to maintain the optimal slip value for each wheel [see Fig. 10(b)].

In Fig. 10(b), the optimal wheel slip is also depicted as a black dashed line. Every two seconds peaks in the slip signals

(see Fig. 9). The latter runs the multibody e-SUV model parameterized according to experimental data. The dSPACE unit converts signals from analog to digital form and vice versa for real-time experiments.

The DS1006 board is the main element of the HIL platform. It is capable of distributing computing tasks between four core processors that guarantee real-time simulation. This board communicates via user datagram protocol with a local host personal computer (PC). Analog input signals information from the sensors of the brake system are digitalized by multichannel A/D board DS2002. The DS2002 features a total of 32 A/D channels at 16-bit resolution with an ADC conversion time of less than 5 μs. The dSPACE Control Desk software coordinates the test rig and allows for separate control of each actuator.
are observable. These are the results of the reset, which is used to understand whether the road surface is changed or not during the braking maneuver. Within this period, the road surface estimator applies the maximum braking torque [see Fig. 10(c)] and concurrently the road recognition is reset to null [see Fig. 10(d)].

In Fig. 10(c), the wheel RB torques are represented. The motors respond very fast allowing for precise and smooth control of the vehicle. Finally, in Fig. 10(d), the vehicle longitudinal deceleration $a_{Vx}$ curve is shown along with a road recognition variable $\mu^*$, which represents the maximum braking potential. At the beginning of the heavy braking maneuver (i.e., at around 2 s), the controller detects maximum possible deceleration rate. Thereafter, the FLC addresses this variable to an appropriate road surface (see Table I), whose linguistic value is “Icy.” As a result, thanks to optimal wheel slip control, a constant vehicle deceleration is maintained during the whole braking process. Therefore, high efficiency of a braking process is deemed with an enabled steerability.

2) Friction Braking: In Fig. 11(a), the wheels’ speeds and vehicle velocity are presented for the conventional FB case. In this experiment, the vehicle decelerates only by applying the FB torques supplied by the EHB. The difference between RB and FB results is easily noticeable. The wheel slip tracking of the FB [see Fig. 11(b)] has significant lower performance than the RB [see Fig. 10(b)]. This phenomenon is attributable to the EHB (16) and (17) slower dynamics compared to the motor (18). Indeed, the FLC for the FB was tuned to optimize the optimal slip tracking performance (see Table I) and avoid controller output oscillation detrimental to the EHB actuators. Therefore, the FLC FB efficiency is sensibly decreased.

In Fig. 11(c), the FB torques for each wheel are revealed. Comparing to RB [see Fig. 10(c)], the HIL system entails a slower but markedly oscillating dynamics that take a toll on the driving comfort. Nevertheless, both FLCs are requesting similar torque values for the front and rear wheels.

In Fig. 11(d), road detection together with vehicle body deceleration curve are presented. The vehicle deceleration rate is considerably lower than for the full RB scenario [see Fig. 10(e)]. The tracking of a slip value lower than its optimal value still ensures steerability but to the detriment of the braking force, which accordingly leads to efficiency losses.

3) Regenerative and Friction Braking Performance Comparison: Although the difference between the FLCs’ performance for RB and FB is clearly visible in Figs. 10 and 11, the main ABS performance indexes are presented in Table V. The average deceleration rate for RB braking is higher comparing to the FB.
Accordingly, the braking distance $s_{\text{braking}}$ of the RB is smaller than FB by almost 20 m, which is a significant result in vehicle safety. Furthermore, the ABS index of performance $ABS_{IP}$ is considered to evaluate the system’s efficiency. The variable is a ratio between the mean vehicle body decelerations achieved respectively with enabled controller and with locked wheels when no ABS control is applied

$$ABS_{IP} = \frac{a_{\text{ABS}}}{a_{\text{lock}}}$$

(19)

### B. Varying Road Conditions (From High-$\mu$ to Low-$\mu$)

The road surfaces are rarely homogeneous. Hence, the results stemming from a heavy braking maneuver on changing road surface are reported. Particularly, the vehicle starts decelerating on a high-$\mu$ ($\mu \approx 1$) surface and continues toward low-$\mu$ ($\mu \approx 0.25$). For this test, the RB requires additional torque from the EHB, because the torque generated by on-board motor is not enough to reach optimal wheel slip.

1) **Regenerative Braking (Blended):** In Fig. 12, the vehicle deceleration results in regenerative mode on a changing road surface are presented. The vehicle decelerates with higher wheel slip values at the beginning of the maneuver. Whilst the slip of the rear wheels is close to its optimal value (see Table I), for the front wheels the value is much lower. This phenomenon is because the peak brake torque for the front wheels exceeds the motors’ limits [see Fig. 12(c)]. Consequently, the controller activates the FB to supply the brake torque gap [see Fig. 12(d)]. The slow EHB dynamics deteriorate the wheel slip tracking performance on the front wheels causing efficiency losses.

The road estimator successfully detects transient road conditions [see Fig. 12(e)]. At the beginning, the peak deceleration is around 10 m/s$^2$, which refers to high-$\mu$ surface (see Table I). After 4 s, the vehicle drives on a low-$\mu$ road, the control method resets $\mu^*$ and measures peak $a_{V_x}$ again. As the road surface has changed, the new value of $\mu^*$ is recognized. Thereafter, the controller reduces the braking torques [see Fig. 12(c) and (d)] to maintain the wheel slip rates close to their optimal values for a low-$\mu$ road surface (see Table I).

2) **Friction Braking:** Friction braking performance results are presented in Fig. 13. The difference in optimal slip control is easily noticeable [see Fig. 13(b)]: the EHB does not reach $\lambda_{\text{opt}}$ for high-$\mu$ surface and nor keep its value on significantly lower percentage. The road estimation [see Fig. 13(d)] worked similar to the RB experiment. However, this time the vehicle deceleration rate is much lower.

3) **Regenerative and Friction Braking Performance Comparison:** A comparison of the main ABS performance indexes in the case of transient road surface conditions for RB and FB experiments is reported in Table VI. The mean vehicle decelerations in the regenerative mode are higher in comparison to the FB for both the high-$\mu$ and low-$\mu$ phases. As a result, the controller requires around 3 m shorter distance with electric motors to bring the vehicle to a full stop. Furthermore, the ABS index of performance is higher for the RB as compared to the FB for all changing road conditions tested in this experiment.

**Remark 4:** The wheel slip oscillations at low speeds [see Figs. 10(b) and 13(b)] are the common problem, if the “Magic Formula” is parameterized by the experimentally obtained characteristics. Overall tire–road adhesion is a complex challenge, because its behavior is influenced by multiple parameters: speed,
mass displacement, environmental conditions, tire characteristics (i.e., new, worn), etc. However, tire modeling is out of the scope of the presented work.

V. CONCLUSION

In this article, the development and experimental verification of an open-loop fuzzy-logic-based control method with road surface recognition feature for a novel decoupled electrohydraulic ABS is presented. The HIL set-up consists of an EHB connected to a host PC through a dSPACE electronic platform. The PC runs the IPG CarMaker software containing an experimentally validated model of e-SUV. The HIL system is capable of reproducing real pressure dynamics in the brake circuit, whereas the vehicle dynamics are rendered by the e-SUV numerical model.

The EHB’s slower comparing to the on-board electric motor dynamics take a toll on the controller tracking performance: in case of pure conventional FB utilization, the controller exhibits significant lower performance. Despite, identical FLC design for both FB and RB actuators, fast dynamics of the motor allow for more accurate tracking of the optimal wheel slip. As a result, the mean vehicle decelerations in full RB mode are higher in comparison with the decoupled EHB system for both high-μ and low-μ surfaces. Furthermore, the ABS index of performance also proves that the controller in case of full braking regeneration performs better than in the case of pure FB utilization. In the future, the FLC-based ABS control method will be tested on an experimental e-SUV.

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