A Neural Network-Based Estimation of Tire Self-Aligning Torque

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***Abstract*—Virtual sensing has attracted the interest of car makers and automotive service providers, owing to its cost-effective advantages, capacity to extract valuable insights from car data and its significance in enhancing the reliability of Advanced Driving Assistance Systems (ADAS). For instance, accurate virtual sensing of tire forces and torques can help adapt and improve the control strategies embedded in the vehicle's active safety systems. This paper deals with tire Self-Aligning Torque (SAT) estimation, an inherent parameter for identifying the limits of the vehicle at an early stage to prevent skidding. We present a data-driven approach to estimate the right and left front SATs, using a Neural Network (NN) model. The estimator takes directly existing in-vehicle signals and does not rely on expensive and unpractical sensors, which makes it cost-efficient and fast. Simulation results based on a high-fidelity vehicle model show a good performance of the chosen NN to estimate the SATs while considering the combined slip and road friction change.**

***Index Terms*—Tire Self-Aligning Torque, Estimation, Neural Network, Simulation.**

I. INTRODUCTION

To improve vehicle handling and ensure passenger safety, current research trends of Advanced Driving Assistance Systems (ADAS) and Automated Driving (AD) are focusing on monitoring the vehicle states, computing the road friction conditions, and adapting the control outputs according to the identified situation. Since the physical interaction between the car and the road occurs through the tire, estimating the forces and the moments applied at the contact surface of the tire in real-time is essential for developing advanced, performance-oriented, and safe driving assistance or automated driving systems [1]–[3]. For active safety systems, real-time identification of the maximum grip μ on the road is a critical task. Estimating the tire self-aligning torque (SAT), *i.e* the torque that a tire creates as it rolls along its vertical axis, allows to detect when the vehicle reaches its maximal lateral and longitudinal force capacity before the skid: it peaks at a lower slip angle than that corresponding to the maximum of the lateral forces (FY) (Figure 1). However, only a few contributions are harnessing this physical characteristic of the SAT. Current SAT estimation can be classified into two categories: the estimation based on an analytical model and the model-less estimation. Estimations based on analytical models use a physical or empirical tire model to infer the SAT. On the other hand, the model-less approach does not need an explicit tire model to build the virtual sensor.

The present study belongs to the second category and proposes using a Neural Network (NN) model to directly and cost-effectively estimate SAT with the aid of already existing sensors, along with left and right suspension deflection sensors. The latter has gained popularity in various applications such as vertical parameter estimation [4], [5], and skyhook control due to its cost-effective nature.

The structure of this paper is as follows: in Section II, we review existing methods for estimating the SAT and evaluate their performance. In Section III, we introduce the NN-based approach that we use for SAT estimation. Section IV presents the results of our simulations and provides an interpretation of the NN model. In Section V, we discuss the potential applications of SAT estimation. Finally, in Section VI, we outline future work to enhance the robustness of our observer and validate it on real data, before concluding with a summary of our findings.

II. RELATED WORK

Concerning the analytical model approach, Lenzo et al. [6] successfully estimate the SAT from a Brush tire model. First, their method uses the TRICK tool (Tyre/Road Interaction

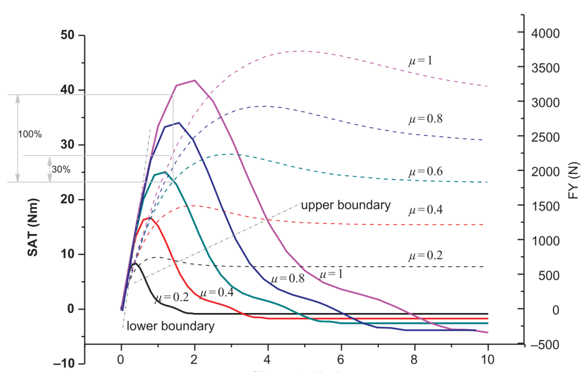

Fig. 1. SAT and Lateral force (FY) vs slip angle at different friction coefficients μ; (SAT: solid line , FY: dashed line).

Characterization & Knowledge) [7] to estimate the lateral forces. Then, the parameters of the Brush model are optimized to fit the estimation and are used to compute the SAT. The effectiveness of this approach depends on the accuracy and convergence speed of the TRICK tool.

Model-less estimation is mainly a data-driven method based on dedicated sensors such as force transducers, tie rod forces sensors [8] or sensors mounted on the kingpins [9]. Pasterkamp and Pacjeka [9] present a 3-layer NN fed by the steering wheel angle, the suspension inclination angle, the forces on the kingpins and the force in the steering link to estimate the forces and the SAT. Despite accurate results, the training and validation test cases were not extensive. In addition to that, sensors used to map the non-linearities are not commonly mounted on commercial vehicles. Luque et al. [8] employed a 2-layer NN (NN) to estimate the front right and left SATs in their study. The input to the NN consisted of tire longitudinal and lateral forces inferred from a Random Walk Extended Kalman Filter (RW-EKF), along with front axle vertical forces, steering wheel angle, and steering tie-rod forces measured by extensiometric sensors. However, one major drawback of this approach is that the error in the estimated forces from the RW-EKF, due to non-Gaussian noise, can be propagated to the outputs of the NN, resulting in decreased accuracy of SAT estimation.

III. Self-Aligning Torque Estimation

A. Data Acquisition and Context of Study

In our case, we use a high-fidelity vehicle model from AMESIM software, equipped with Electric Power Assisted Steering (EPAS) system and two suspension deflection sensors mounted on the front right and left.

To extract sufficient and reliable data and to map our entries to different regions of the SAT, the simulation was done on different open loop handling maneuvers, as depicted in Table I.

TABLE I
Open loop manoeuvers done in simulation.

ISO Maneuver	Longitudinal velocity range (Km/h)
Free steer	20 – 80
Steering pulse	20 – 80
Double lane change	40 – 120
Circular maneuver	40 – 80
One transient	40 – 80
Random swept sine steer	40 – 80
Braking in a turn	40 – 120
Fishhook	40 – 80
Sine with dwell	40 – 120
Steady brake/acceleration command	40 – 120

It is worth mentioning that the maneuvers were simulated with high repeatability on dry asphalt and other grip surfaces ranging between 0.7 (wet) to 0.2 (ice). Moreover, this evaluation did not consider active safety systems such as the Anti-lock Braking System (ABS) or the Electronic Stability Program (ESP).

We consider some measurable inputs related to the steering system [10] and other vehicle dynamic-related signals: The first part consists of choosing the steering wheel angle, the steering torque, and the assist torque according to the equation (1) of a second order steering system model. These measurements are available if the car has EPAS.

$$J_{eff}\,\ddot{\delta} + b_{eff}\,\dot{\delta} = \tau_{SAT} + \tau_{SW} + \tau_{assist} - \tau_f \qquad (1)$$

where J_{eff} is the effective moment of inertia, b_{eff} is the effective damping of the steering system at the road wheels, and δ is the steering wheel angle. τ_{SAT}, τ_{SW}, τ_{assist}, and τ_f represent the Self-Aligning Torque (SAT), the steering wheel torque, the assist torque, and the frictional torque at the road wheel, respectively.

The SAT observed from the previous equation is different from the real one. The main reason is the complexity of the tire behavior [9] due to the variation of the load, the couplings between longitudinal and lateral slips, and the non-linearities due to suspensions. To take this into account, additional measurable signals are considered such as the longitudinal and lateral accelerations, the longitudinal velocity, the yaw rate, the wheels speed, the wheel torque, and the compression/decompression of front right and front left suspensions. In total, 12 inputs are used to train the neural network to estimate the front right and the front left SATs. Specifications of the input and output data are listed in Table II.

TABLE II
Input & output data.

Inputs		
Longitudinal acceleration Lateral acceleration	A_x (ms^{-2}) A_y (ms^{-2})	
Longitudinal velocity	V_x (ms^{-1})	
Yaw rate Steering angle Steering torque	$\dot{\psi}_z$ (rads^{-1}) $\alpha_{steering}$ (rad) $\tau_{steering}$ (Nm)	 from EPAS
Assist torque	τ_{assist} (Nm)	from EPAS
Motor torque	τ_{motor} (Nm)	
Compression/Decompression of the suspensions	$coslad_{left}$ (m) $coslad_{right}$ (m)	from front left sensor from front right sensor
Wheel speed	ω_{left} (rads^{-1}) ω_{right} (rads^{-1})	from front left sensor from front right sensor
Outputs		
Self-Aligning torque	τ^l_{SAT} (Nm) τ^r_{SAT} (Nm)	front left front right

From the previous remarks and due to the variation of the pressure distribution in the tire, the use of a physical tire model such as the Brush model is disregarded. Thus, we choose to label our data using the Pacjeka tire model or the Magic Formula [11]. This semi-empirical model fits best the

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measured data and takes into account the couplings between longitudinal and lateral slips. The details of SAT formula from Pacjeka 97 tire model can be found in [11].

In the first step, the correlation between all variables is performed to assess the dependency between the inputs and the outputs, as shown in Figure 2. The assist torque has the highest correlation value since it is linearly related to the SAT, as described in the steering system model equation (1). In addition, we also notice a medium dependency on suspension deflection sensors, highlighting the relation between the load variation and the SAT.

The data were sampled at 20 Hz, giving us an input matrix of (45000x12) and an output matrix of (45000x2).

The next part of this section will focus on the choice of the network model, the tuning of its parameters, and the definition of the performance metrics for evaluation.

B. Proposed Model

A static feedforward neural network or Multi-Layer Perceptron (MLP) is considered in this study. The goal is to use the MLP as a non-linear function approximator to map the entries to the SAT. In general, an MLP is composed of one input layer, one or more layers called hidden layers, and one output layer. The inputs of each layer are combined in a weighted sum and subjected to an activation function. Then, the result of this combination is propagated to the next layers. A backpropagation learning mechanism allows finally to adjust weights with the goal of minimizing the cost function.

The design of the NN model and the tuning of the hyperparameters was done in an iterative manner using the Grid Search library in Python. This tool enables us to find the optimal hyperparameters by evaluating different combinations of values based on a defined performance metric. To assess the score of our predictor, we choose to use the R-squared metric defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{\sum_{i=1}^{n}(y_i - \bar{y})} \tag{2}$$

where n is the total number of measurements, y_i is the true measured value, $\hat{y}_i$ is the predicted value and $\bar{y}$ is the average of all measures. The best possible score for R^2 is 1.

The optimal model has 2 hidden layers with 32 and 12 neurons, respectively. We use the hyperbolic tangent activation function for non-linear mapping and the Adam optimization [12] for training. Table III summarizes the set of the chosen hyperparameters and the estimation structure is presented in Figure 3.

TABLE III
OPTIMAL PARAMETERS FOR THE MLP.

Parameter	Optimal
Hidden dimensions	[32,12]
Learning rate	Adaptive
Optimizer	ADAM
Activation function	Hyperbolic tangent
Data pre-processing	Robust Scaler

IV. SAT ESTIMATION RESULTS

A. Simulation results

To test the performance of our model, the recorded data were randomly split into 70% for training and 30% for testing. The optimal NN model yields an R-squared score of 0.986 for the first and 0.982 for the second. The Mean Absolute Error (MAE), which is less sensitive to the outliers caused by software compilation errors, is found to be 2.4 (Nm) in training and 2.59 (Nm) in the test phase.

To appraise the extrapolation ability of our NN model, we run the same vehicle model on the Magny-Cours race track. This sort of track is available on Simcenter AMESIM and is generally used to simulate severe maneuvers. The reference trajectory, the longitudinal velocity, and the steering wheel angle of the simulation are depicted in Figure 4.

The car does two rounds, the first one on a dry surface (μ=1) and the second on wet asphalt (μ=0.7). The results of estimation on dry asphalt presented in Figure 5 show that our NN model predicts accurately the front wheels SATs with an MAE of 3.1 (Nm). The blue line represents the true value and the red one is the NN estimation. On the wet road though, the MAE increases to 8.1 (Nm) and the NN does poorly to extrapolate the peak of the SAT. The results of this second case are plotted in Figure 6. Table IV summarizes all simulations' values of MAE and R-squared.

TABLE IV
SUMMARY OF SIMULATION RESULTS.

Simulation test	R^2 score	MAE (Nm)
Training phase	0.986	2.4
Test phase	0.982	2.59
Magny-Cours dry asphalt	0.971	3.1
Magny-Cours wet asphalt	0.931	8.1

One last thing to highlight is the good accuracy of our NN model to estimate the total aligning moment of the front axle *i.e.* the sum of the front right and front left SATs, as shown in Figure 7.

This observation proves that our NN model would be accurate to target mainly the front axle maximum grip estimation. However, it will do less to predict a μ-split case for example.

B. Interpretation of the model

To boost our model transparency, we will provide its interpretation based on SHapley Additive exPlanations (SHAP) [13]. SHAP was introduced as a unified framework for interpreting predictions. It is a game theoretic approach that assigns each feature an importance value. Two types of explanations are accessible via SHAP: A global one where the SHAP values show how much each predictor contributes to the target variables. And, a local one dedicated to a specific observation.

In this paper, we will provide only global interpretability based on the test set data. Figure 8 is a bar plot that lists the most influencing features in descending order and the average impact on the SAT magnitude is shown on the x-axis. On the

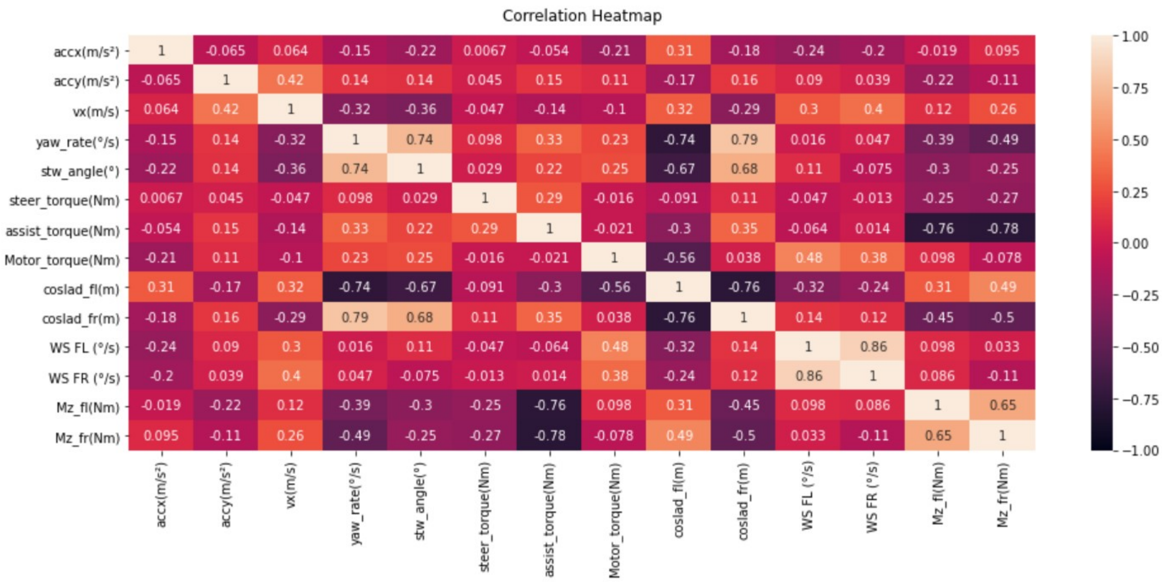

Fig. 2. Correlation matrix of input and output data.

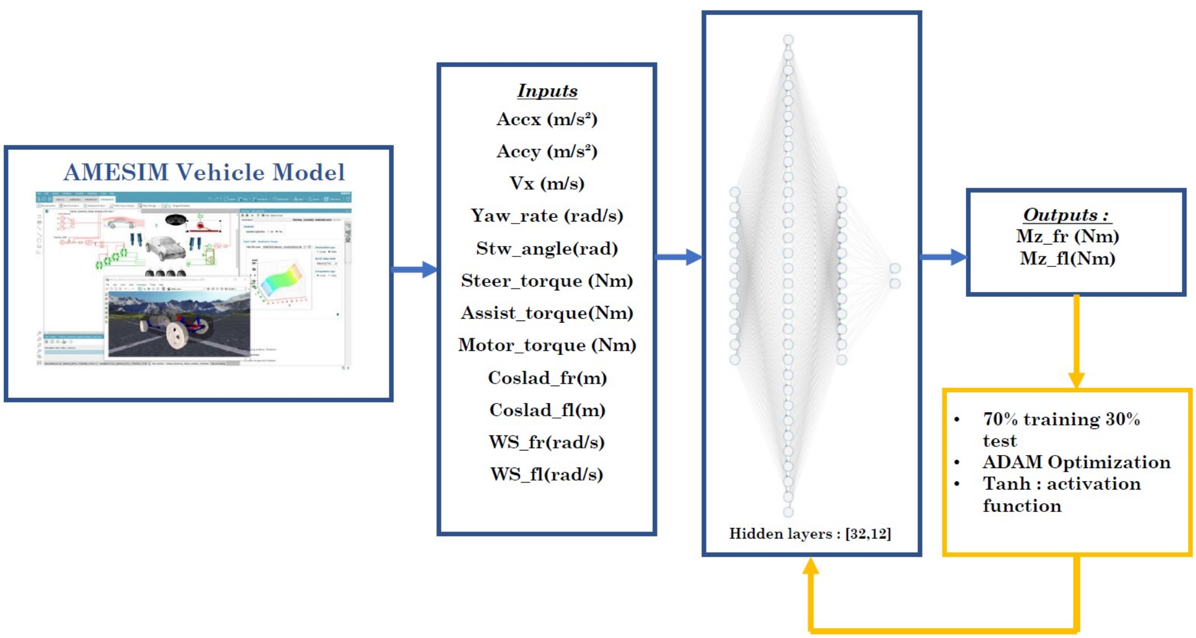

Fig. 3. SAT estimation structure, adapted from [8].

other hand, the dependence plot depicted in Figure 9 explains the marginal effect between the top 3 features and the front left SAT. From the latter, we observe a negative linear relationship between the assist torque and the front left SAT. While for lateral acceleration and the steering wheel angle, the effect on the SAT is non-linear.

V. Discussions

A. SAT dependency on inflation pressure

Tire inflation pressure has an influence on the quasi-static generated forces and moments, most importantly, the SAT. From a physical perspective, the SAT is generated because of the distance between the contact patch center and the point of lateral force application, this distance is called the pneumatic trail and it is linearly dependent on the contact patch.

An investigation on the effect of pressure change on SAT was carried out using an extended version of the Pacjeka tire model in AMESIM environment. This model called SWIFT-Tyre has been developed at Delft University of Technology and TNO Automotive [14] and includes the most recent developments such as inflation pressure effects. We observe from Figure 10 that the amplitude of SAT decreases when

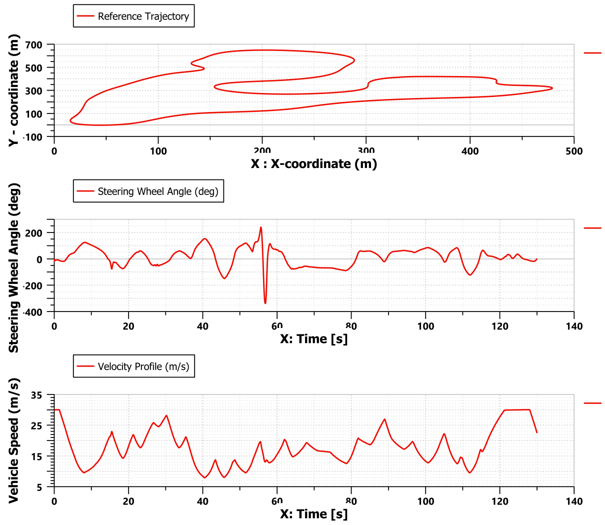

Fig. 4. Reference trajectory (top), steering wheel angle (middle), and velocity profile (bottom) for Magny Cours Track.

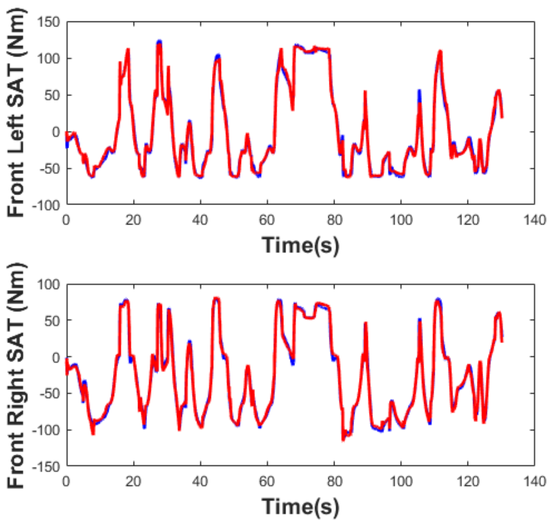

Fig. 5. Estimation results of SAT on dry asphalt; Blue (True) and Red (Estimated with NN).

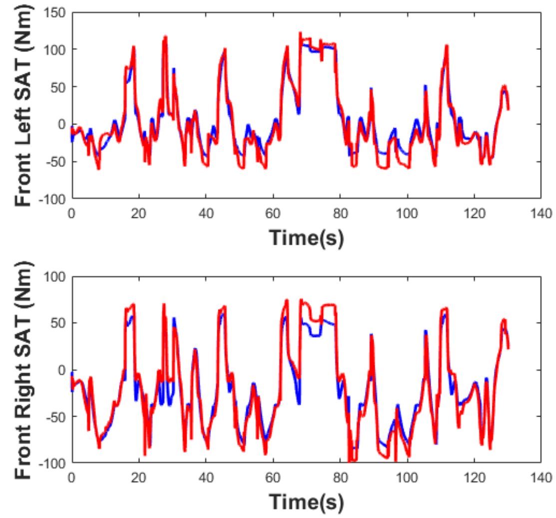

Fig. 6. Estimation results of SAT on wet asphalt; Blue (True) and Red (Estimated with NN).

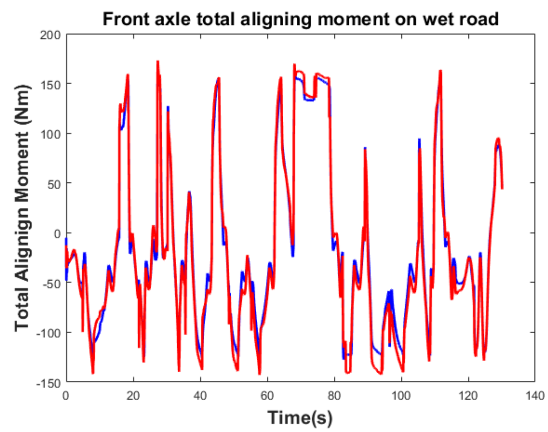

Fig. 7. Estimation of front axle total aligning moment on wet asphalt; Blue (True) and Red (Estimated with NN).

inflation pressure increases. This is logical because higher pressure reduces the contact length, thus the pneumatic trail decreases and eventually also the SAT. This leads us to consider in a future study the tire's inflation pressure acquired from Tyre Pressure Monitoring Systems (TPMS) as an input of our NN model to enhance the performance and robustness of our estimator. Or in a simpler way, consider a corrective term that will compensate for the effect of the pressure.

B. Applications of SAT estimation

What motivates most the SAT estimation is the early detection of tire friction coefficient. Unlike other traditional approaches that reach a good estimate near the critical region of the tire, the SAT is viable for limits detection at low excitation levels. Owing to this, the knowledge of friction conditions is prior to the intervention of advanced active safety systems.

The knowledge of SAT can also improve the lateral control [15] and particularly the Steering Wheel Angle (SWA) control in EPAS systems [16]. While it is considered a disturbance to be overcome in most controllers, a precise estimation can prevent generating inefficient control gains and cancel its effects in some situations. Moreover, it can be useful to return to the center position of the SWA after a change in direction.

To wrap up, real-time estimation of SAT is inherent to guarantee safety by providing the available grip at an early stage and also enhancing the performance of some lateral controllers.

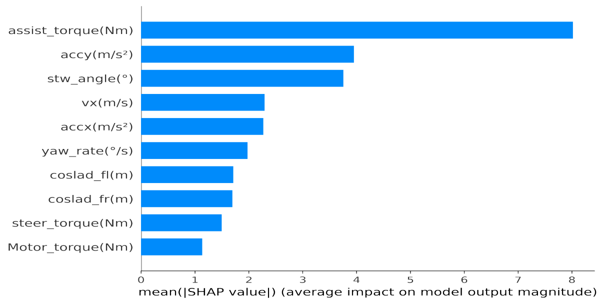

Fig. 8. Feature Importance based on SHAP.

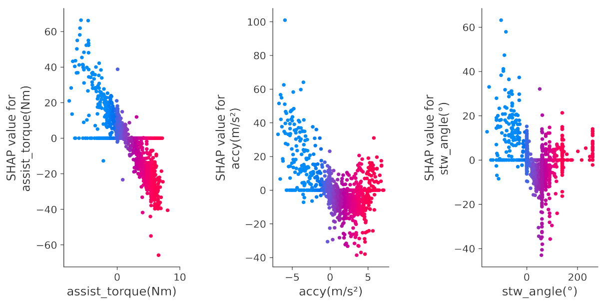

Fig. 9. Dependency plot of the top 3 features.

VI. Conclusion and Future Work

In this paper, we presented and outlined a real-time data-driven approach for SAT estimation. This quantity is inherent for friction coefficient prediction at low excitation levels and for enhancing some lateral controllers' performance e.g (SWA control).

The proposed neural network model and the methodology followed distinguish themselves from the previously reported methods in terms of the following features: 1) The NN is fed directly by in-vehicle sensor signals and does not rely on estimated inputs nor uncommon expensive sensors. 2) It is trained and tested on a wide range of maneuvers with different road surfaces to improve its extrapolation ability. 3) Labeling the data uses a semi-empirical tire model (Pacjeka tire) that considers combined lateral and longitudinal dynamics and can fit the measured SAT on a real test drive. 4) A global interpretation based on SHAP values is provided. It gives us the most important features and the nature of their relationship with the estimated SAT. We investigated also the effect of inflation pressure on SAT by using an extended version of the same tire model, and we deduced that for more robustness and precision, the pressure acquired from TPMS can be considered as an additional input in our model.

The graphs and regression metrics show a good performance of our NN model to estimate the front right and front left SATs, especially for tests on dry asphalt. As the error increases for the wet road test, enriching the dataset with repeatable maneuvers on other grip surfaces may resolve this problem.

Future work will be oriented towards generating larger data sets in different friction coefficients and considering the inflation pressure as an input, in order to refine the generalization of our estimator. Besides, this estimator will be used for friction estimation in a subsequent paper. Finally, a real test drive is planned with GROUPE RENAULT for validation and evaluation.

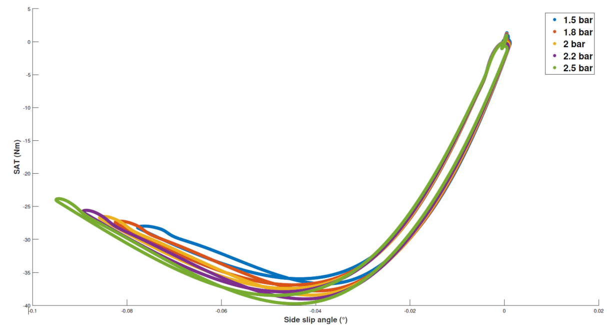

Fig. 10. Inflation pressure effect on SAT for a triangle-shape steer command.

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