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Vincenzo Maria Arricale; Andrea Sammartino; Guido Napolitano Dell' Annunziata; Francesco Timpone

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RIDElab: Advanced Calibration Tool for a Real-Time MF-Based Multiphysical Tire Model

Vincenzo Maria Arricale,[1] Andrea Sammartino,[1] Guido Napolitano Dell'Annunziata,[2] and Francesco Timpone[2, a)]

[1)] *MegaRide applied vehicle research, Naples, Italy .*
[2)] *Department of Industrial Engineering, University of Naples Federico II, Naples, Italy.*

[a)] *Corresponding author: francesco.timpone@unina.it*

Abstract. In an increasing number of vehicle dynamics applications, from virtual prototyping and on-board control systems to real-time simulations, a tire-road interaction model is essential to obtain reliable results in reality's representation. In the recent years, an advanced multiphysical tire model, called adheRIDE, has been developed to take advantage of the accuracy and quite low computational cost offered by the underlying tire Magic Formula dynamic model, also including the effects linked to tire thermal and wear conditions, compound viscoelastic properties, and road roughness characteristics, making use of auxiliary multiphysical formulations, modifying the parameters of the original MF model in runtime. The necessity to parametrize the advanced MF model has led in the development of an interactive tool RIDElab, able to identify the miscellaneous model parameters on experimental data acquirable in outdoor or indoor testing sessions. The RIDElab tool is presented highlighting the methodological steps and the smart features introduced. The goodness of the model parameterization and the potential of the RIDElab methodology is validated on a real case-study, employing the experimental data acquired in outdoor handling session with a motorsport partner.

Keywords: Advanced MF-Model, Tire Multi-Physics, Data Pre-Processing

INTRODUCTION

Nowadays, the use of reliable simulations and model-based analyses is widely adopted in the development of real prototypes and the motorsport racing preparation scenarios with the aim to minimize the on-track testing and the connected costs [1, 2, 3]. This hybrid approach allows reducing the number of configurations to be physically tested, pre-selecting only the ones achieving satisfactory results in simulations, lowering time and costs, and avoiding possible risks connected to the real environment. A reliable vehicle dynamic model can therefore represent a valid tool for the development of both performance and safety as long as it can reproduce the same stresses that a driver would experience when driving a real vehicle; in this perspective, tire-road interaction models cover a critical aspect in the vehicle's system modeling since not only the forces responsible for traction and cornering arise within the tire-road contact patch [4, 5], but they also show non-linearity and dependencies on different interconnected multiphysical phenomena that make the tire a particularly complex component to be described through mathematical expressions, without a high computational effort [6, 7].

In the literature, the tire modeling approaches and research activities [8, 9, 10] vary from analytical semi-empirical models up to full finite-element-based (FEM) models [11, 12, 13, 14]. Although the latter are able to provide a more accurate modeling of the tire structure, they require the knowledge of some materials' physical characteristics achievable only through specific tests [9, 15, 16]. On the contrary, the strength of analytical semi-empirical models is the low computational effort that makes them the optimal solution in real-time automotive simulations and on-board advanced control logic for safety and performance [17, 18, 19]. They don't require the knowledge of physical properties but are based on a series of numerical parameters that must be appropriately calibrated, in order to faithfully reproduce tire behavior and its high non-linear dependencies with several factors. Among them, Pacejka's Magic Formula model (MF) [4, 15] is certainly one of the most used in automotive applications due to the robustness and accuracy it offers in simulations with a reduced computational cost, once it has been appropriately parameterized on the experimental data. In its standard formulation, however, it allows to reproduce the response of the tire only to inputs such as the longitudinal and lateral slip values, the camber angle and the vertical load, but is not affected by other thermal and wear factors, not negligible in automotive applications.

The approach presented in this article consists in adopting a multi-physical tire model based on the semi-empirical Pacejka's Magic Formula model and enriched with analytical multi-physical formulations, thus introducing in the simulation loop additional variables concurring to tire-road interaction, not covered by the standard Pacejka's formulations. An advanced multiphysical MF-based real-time tire model, called adheRIDE, has been conceived by the

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Vehicle Dynamics UniNa research group and its academic spin-off company MegaRide [20], which covers the variation of the forces exerted by the tire on the ground not only towards the typical kinematic and dynamic factors, but also towards tire thermal and wear conditions [21, 22, 23], viscoelastic properties [24] and road roughness [25], employing auxiliary polynomial functions of the standard MF micro- and macro- coefficients to varying of these boundary phenomena. As a result, the modeled tire will be characterized by properties that are no longer constant, but variable point by point in a multi-dimensional space featured by these additional co-simulated tire states.

The adopted approach indeed offers a remarkable compromise between accuracy and robustness in reality's representation and quite low computational request, which makes it suitable for both real-time driving simulations and for offline performance optimization algorithms. Nevertheless, since it is based on analytical formulations, model's robustness and reliability are achievable only after it has been properly calibrated on the experimental data.

In the literature, several methods have been proposed to calibrate the Magic Formula model on experimental results: in [26] the authors proposed an approach based on the identification of the Pacejka's micro-coefficients only on indoor tests and then of the sole scaling factors on outdoor track tests; in [27] a method based on genetic techniques has been used to identify the MF parameters; in [28] the authors show the achievable identification results with different algorithms. Several tools, conceived for the calibration of Pacejka's model and the evaluation of its quality comparing Pacejka's curves and the experimental tire-road interaction characteristic, have also been proposed: in [29] a tool for tire data analysis was presented, which allowed the manual identification of the MF parameters; in [30] TRIP-ID tool (Tire Road Interaction Parameters IDentification), providing a procedure to identify the MF micro-coefficients both trough manual modifications and optimization algorithms, has been described; in [31] propose the cascading methodology combining the strengths of both the Genetic Algorithm and Nelder-Mead Simplex (NMS) algorithm for the tire model fitting process applied for the parameterization of the standard MF model.

A data-processing and model-calibration tool, called RIDElab, has been developed to provide a series of guided steps and smart features for a reliable identification of the multi-physical adheRIDE model [20] parameters on the experimental data, offering a solution to the problem already addressed in the literature, namely the identification of the MF micro-coefficients, and also extending the validity of the MF dynamic model on several factors not foreseen in the standard Pacejka's formulation.

The identification procedure occurs both through smart scrolls and editable parameters and through minimization algorithms that can be properly customized by the user; besides, it follows a preliminary data processing, consisting in the elimination of inaccurate samples deriving from measurement or estimation errors, the filtering of signals to remove measurement noise and a discretization phase. In fact, considering that model's robustness depend on the accuracy of model's parameterization, which is strictly linked to the quality of the dataset employed and to the operating conditions explored during the tests, the pre-processing steps are meant to avoid that model calibration could be misdirected by acquisition errors and noise, or intrinsically weighted on the frequency of the different tire operating conditions.

In order to validate the reliability of the adheRIDE model and the robustness of the RIDElab calibration procedure, the data provided by a motorsport research partner, in which neither thermodynamic effects nor wear can be neglected, have been used as a case study; for this reason, due to confidentiality agreements, the scales in the all the following figures are non-dimensional. The procedure guided by the RIDElab tool led although to a reliable multiphysical tire model that demonstrates not only a good correspondence between the model outputs and the experimental data on which it has been calibrated, but also a predictive capability to simulate tire behavior on different tracks, characterized by different operating kinematics and dynamic quantities, and under different thermal and wear conditions.

THE RIDELAB TOOL

The identification of the adheRIDE model [20] parameters on the only experimental data is not trivial because the available data are often misleading, characterized by measurement errors or estimation errors, and often don't cover all the operating tire conditions or don't represent them in equal measure. A series of pre-processing steps results fundamental for the parameterization of the tire model, in order to better characterize kinematic and dynamic quantities and discerning the effects of different heterogeneous phenomena within the large amount of data available.

The RIDElab tool has been conceived to provide a smart and user-friendly procedure to identify the characteristic parameters of the physically enriched MF model, and a set of features and panels useful for the user to evaluate the goodness and robustness of the process. In particular, the guided procedure provided by the RIDElab tool pass through three steps: the first step consists in pre-processing the experimental data on which the model will be calibrated in order to ensure reliability and robustness; the second step aims at identifying the standard Pacejka MF micro-coefficients on the pre-processed data corresponding to the nominal thermodynamic range of tire; the third one aims at the calibration of the physical formulations providing tire performance on the basis of a thermally enriched dynamic state, both regarding the maximum exploited grip and tire stiffness.

Data pre-processing module

A model parameters' identification could be automated, in order to ensure robustness and repeatability, by using a minimization algorithm acting on the difference between measured (or estimated) forces and the forces obtained from the model, changing the parameters governing how tire responds to the different physical stresses and conditions included in the tire model. The minimization algorithm, however, finds the minimum of an error measure, so it is actually blind to the correctness and the physicality of the data itself; thus, a preliminary pre-processing phase on the data by which the MF-evo model is tuned must precede the identification and should involve two steps which allow, respectively, to eliminate inaccurate data and to select a dataset that provides consistent and complete information on tire's behavior.

Data cleaning

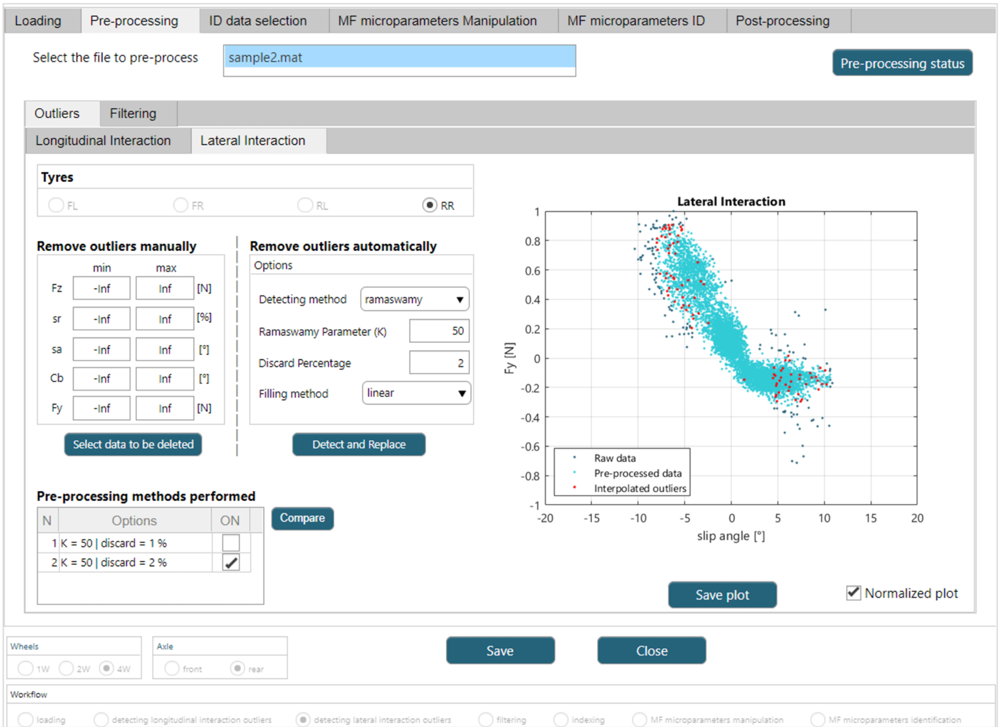
During acquisitions on track or on test benches, incorrect samples may occur and replacing or deleting them by means of an accurate process of data cleaning is crucial and challenging whereas the purpose is to find a way to maximize a dataset's accuracy without deleting information.

Several outliers' detection methods exist and each one is particularly suitable for a specific applications due to its features: while statistical methods ensure that computational effort grows only with the model complexity and not with the data size, data-mining related methods do not require any prior assumption about the data distribution and they are also very simple to implement, but they are often computationally expensive. Among the latter, distance-based methods may be the most suitable for tire-road interaction data application, since forces arising in the contact patch are indeed influenced by many variables and show complex multi-physics dependencies and a distance measure could therefore be used to quantify the similarity between objects in feature spaces, such us longitudinal and lateral interaction characteristics, where objects that are far from others, under the same working conditions, could be regarded as outliers. Samples detected as outliers should then be replaced with more consistent values, in order to ensure the total number of samples remains unchanged, without gaps in a time-based view; the signals should no longer present spikes but a filtering phase may still be necessary to eliminate the measurement noise that overlaps them.

The RIDElab tool enables the user to display samples in both lateral and longitudinal interaction plots and to remove outliers both manually, on the basis of a visible inconsistency with the macroscopic trend of data, and automatically, allowing to test different outliers' detection technique, its feature parameters and the filling method for replacing outliers, comparing the different solutions and choosing the one that best suite the specific dataset.

Figure 2(a) shows an example of outliers' detection by means of the Ramaswamy algorithm, which uses the distance between each point and the kth point nearest to it as outlier-measure and requires the k-parameter, which controls the smoothing effect, and the rate of points to discard as user-specified inputs.

Furthermore, the tool offers the possibility to apply a filter on the telemetry channels in order to remove measurement noise, providing features to design the filter to be used, display the frequency response (Bode diagram) and compare signals resulting from different filters (Figure 2(b)).

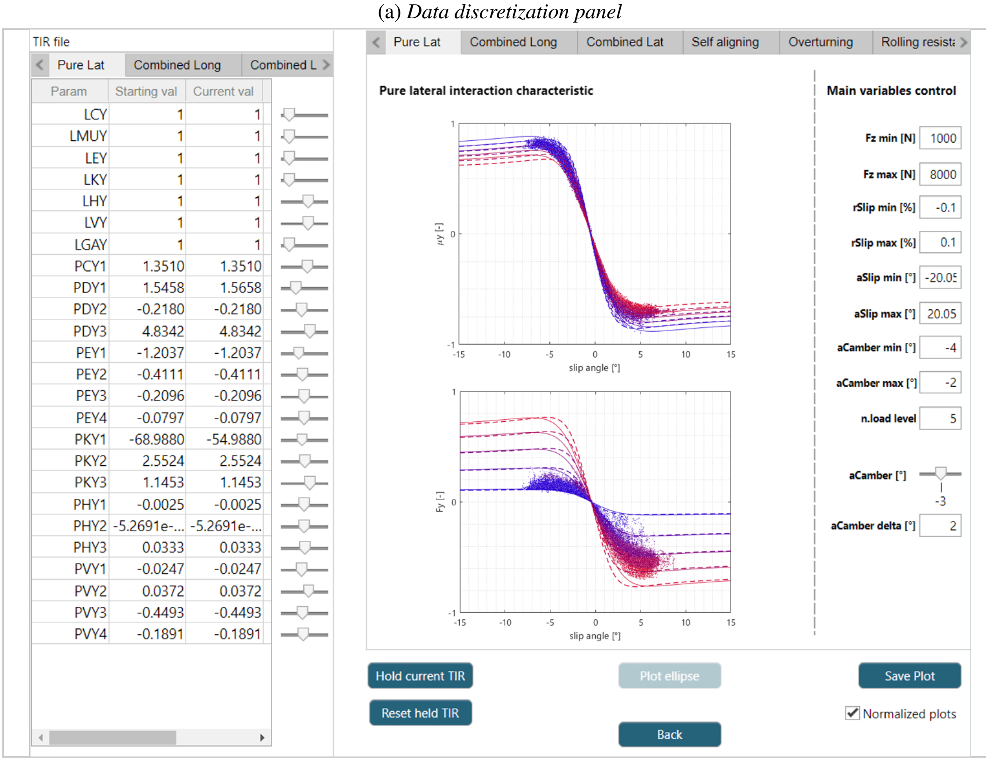


(a) *Outliers removal panel*

(b) *Filtering data panel*

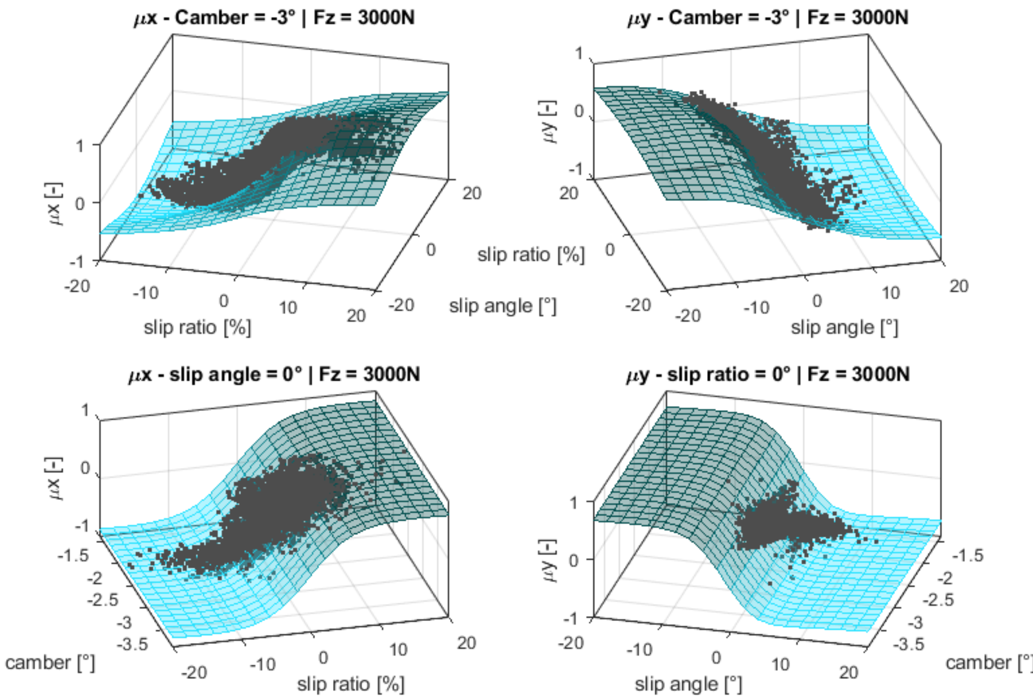
FIGURE 1: RIDElab - pre-processing steps (part 1)

(a) *Data discretization panel*

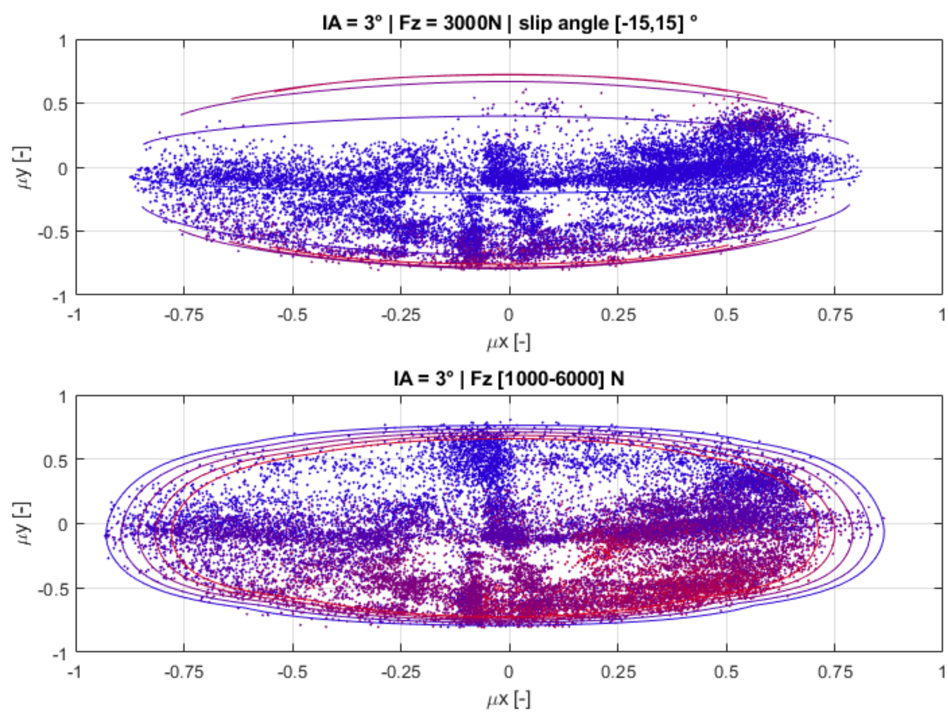


(b) *MF-parameters manipulation panel*

FIGURE 2: RIDElab - pre-processing steps (part 2)

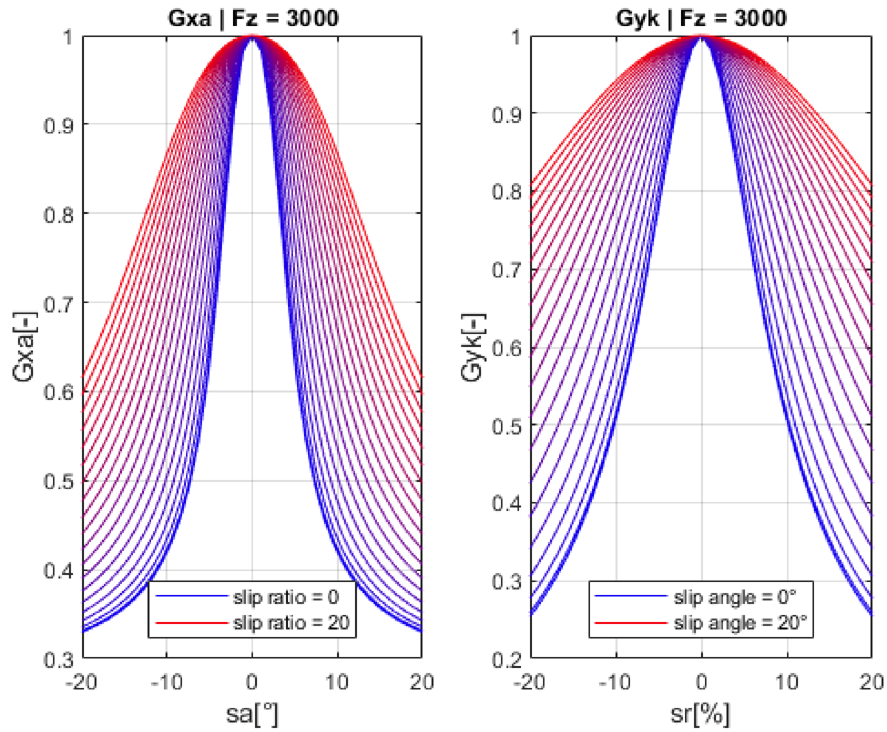


(a) *3D plots*

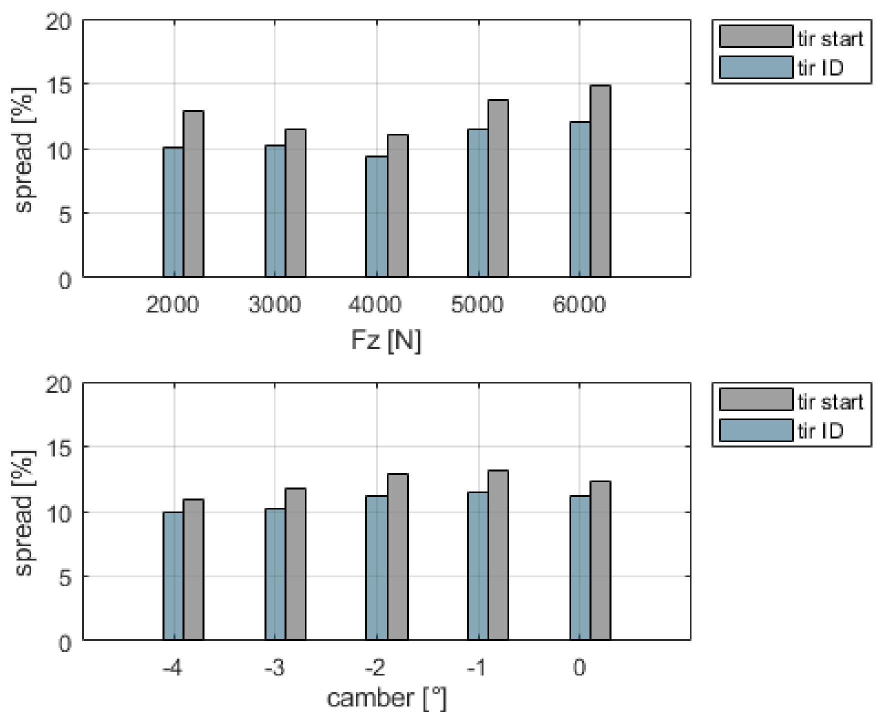


(b) *Adherence ellipse*

FIGURE 3: RIDElab - additional plots (part 1)



(a) *Hill function*



(b) *Model spread*

FIGURE 4: RIDElab - additional plots (part 2)

Furthermore, binning data allows to count the number of actual operating conditions explored in the different thermal phases, lacking in samples that do not give additional information in terms of tire response. In this way it is possible to identify the nominal thermal operating range of the tire, reasonably assumed as the range with the highest number of observations, and fit the corresponding points with the standard Pacejka MF model. In this view, the tool provides a section for data screening(Figure 2(c)), designed for the selection of a reference thermal range in which to identify the standard MF model's parameters, employing multi-dimensional heat maps, coloured with respect to the amount of working conditions explored for each dimension of interest (temperatures, pressure, wear, ...).

adheRIDE model calibration module

Once acquired data have been properly pre-processed, the RIDElab tool guides the user in a series of steps for a proper model parameterization on the resulting dataset. The identification of the several parameters typifying of the model could occur by a minimization algorithm, which needs several inputs to proceed:

- the experimental data on which tire model's features must be customized;
- the starting parameters' set, which is required as starting point for the minimization algorithm (leading to a significant improvement of the solution and a faster identification);
- the objective function, which is the error function to be minimized by the algorithm;
- the research domain, i.e. the region in which the solution must be found; it is defined by means of linear and non-linear constraints on the macro-parameters which result by combining the micro-parameters to be identified (since they are associated with a physical tire property and they should vary within a certain range to ensure a physical sense).

Standard MF model calibration module

After the experimental data have been properly pre-processed and a reference working range has been selected (Figure 2(c)), the identification of the MF micro-coefficients therefore follows and consists of three steps: pure MF model identification, combined model identification and model set refinement. Pure model parameters are identified considering the working conditions characterized by low slip ratio values for the lateral interaction, and low slip angle values for the longitudinal interaction (within a user-defined limitation range); combined model identification is carried out keeping pure interactions parameters constant; model refinement can occur only after the first two steps and is obtained by means of convergence criteria (also editable by the user) to improve both pure and combined conditions accuracy.

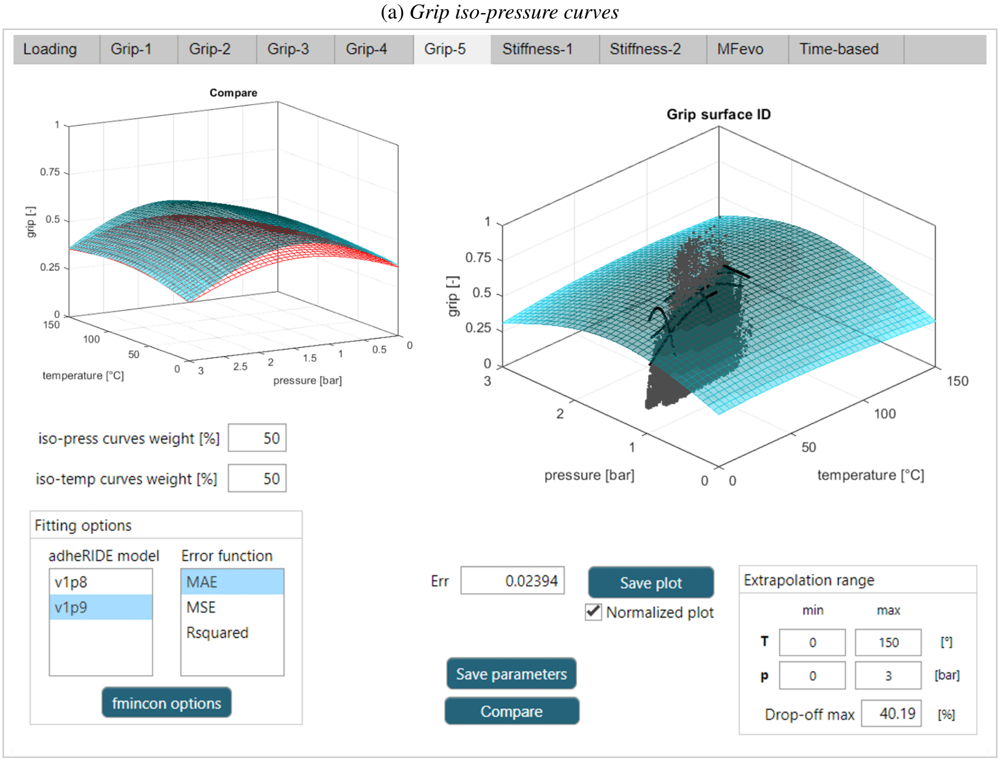
The user has at his disposal a series of features to customize the process and visualize the results step by step. Within the process customization, it is possible to define the range of pure interactions, load a set of micro-coefficients provided or previously identified, choose the optimization algorithm and the convergence criteria for the model refinement, modify the micro-coefficients by means of scrolls and items to obtain the initial conditions for the identification algorithm and to test the sensitivity of the different parameters on the interaction characteristics by displaying the resulting curves in comparison with those obtained from a reference set (Figure 2(d)). A series of additional plots, such as those shown in the Figure 4, allow the user to view the dynamic response of the tire model considering all the variables covered, as well as to display the mean relative spread between the experimental data and the model resulting from the starting parameters' set and the edited one, as a reference to modify the parameters and to find a better new starting set to be used in the following identification process.

Advanced MF model calibration module

To achieve a complete calibration of the adheRIDE model for a given tire, the next step consists in parameterizing the formulations that enrich the MF model, including a series of coefficients to be identified on the basis of the sensitivity exhibited by the tire towards the embedded multiphysical phenomena.

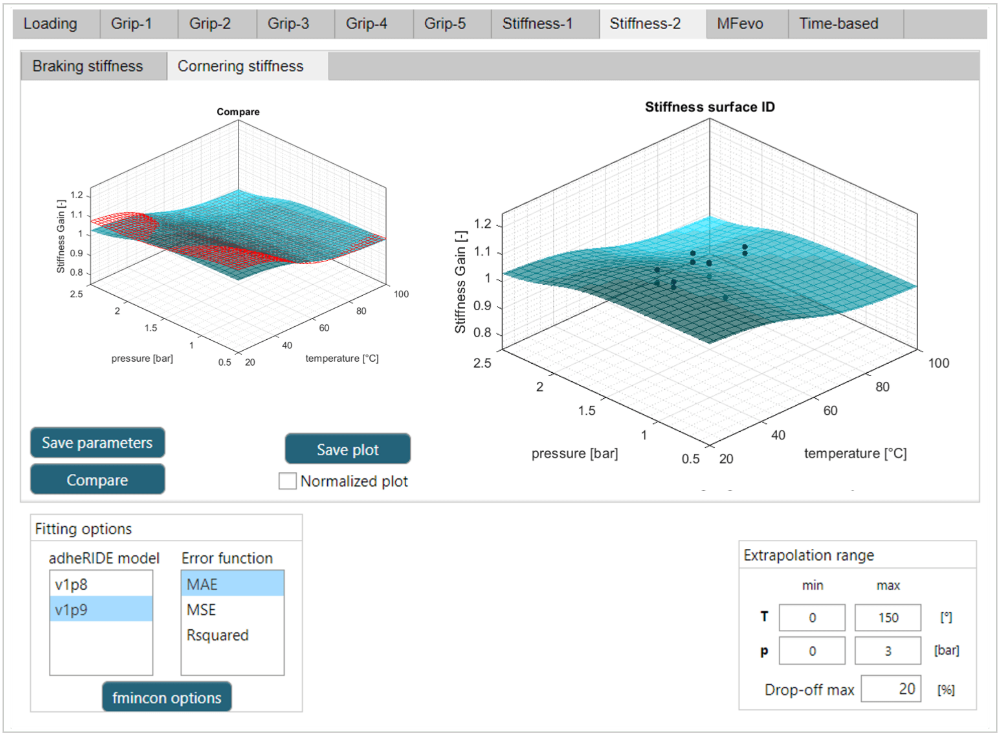
N	p min	p max	p mean	Err	w [%]
1	1.2699	1.4106	1.3403	0.1249	19.1747
2	1.4106	1.5564	1.4835	0.0768	42.2063
3	1.5564	1.7423	1.6493	0.0333	38.6190

(a) *Grip iso-pressure curves*

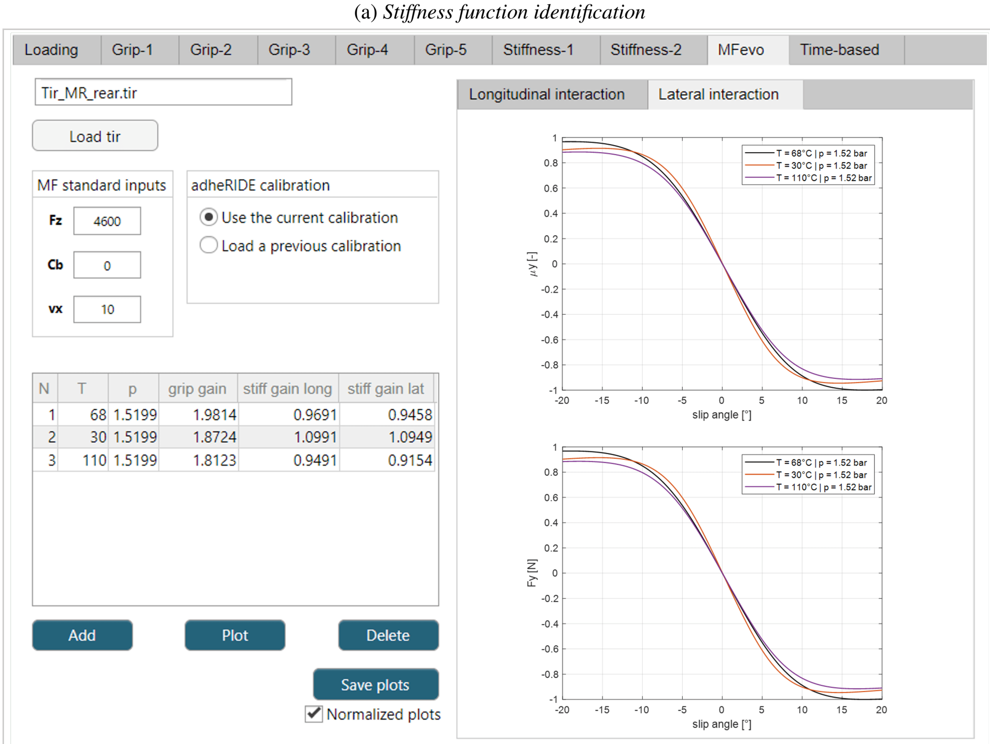


(b) *Grip function identification*

FIGURE 5: RIDElab - adheRIDE calibration (part 1)



(a) *Stiffness function identification*



(b) *adheRIDE model outputs*

FIGURE 6: RIDElab - adheRIDE calibration (part 2)

The additional adheRIDE functions act on MF micro-coefficients and ensure that the surfaces resulting from the envelope of forces for each combination of temperature, pressure and wear show the characteristics proven by experimental evidences, both regarding the maximum exploitable grip and tire stiffness; for a specific wear level of tire compound, the MF-evo model provides an optimal window of tire temperature and inflation pressure where the maximum amount of friction performance is exploitable, while the stiffness of the tire exhibits a decreasing trend as both temperature and pressure increase; moreover, the amount of grip available decreases due to wear phenomenon, as well as tire tends to become stiffer.

The RIDElab tool presents a series of guided steps for the calibration of the grip and stiffness surfaces resulting from the envelope of the interaction forces in the so featured multiphysical space, providing intermediate steps to first identify grip and stiffness iso-temperature curves as a function of pressure and iso-pressure curves as a function of temperature, for different levels of wear (Figure 6(a)), in order to create a network of points and curves on which the actual whole multi-physical model can be calibrated (Figure 6(b) and (c)). Also in this case an error minimization algorithm can be used to automatically handle the identification of a significant number of coefficients that act on different dimensions and a series of constraints can be set to guarantee the looking for a feasible solution. The user can also compare the resulting law with a previously identified one and to verify how the interaction characteristics will react to changes in thermal and wear factors due to the embedding of the identified law in the tire model (Figure 6(d)).

CASE STUDY

A motorsport case study is presented in this section to show the enchanced reliability of the adheRIDE model compared to the standard MF model, parameterized with the described methodology and the advantages offered by the RIDElab tool. The data employed came from outdoor on-track tests, conducted with instrumented wheels for the acquisition of kinematic and dynamic signals, used to obtain the experimental tire interactions characteristics. Compound and carcass temperatures, inner air pressure and wear level certainly could not be neglected in motorsport application (Figure 8), both in terms of the maximum available grip and tire stiffness; these channels were provided by specifically calibrated thermodynamic [21] and wear [22] real-time models, able to evaluate in run-time all the necessary additional physical quantities, without causing singularities within the stress-strain distribution and therefore affecting the thermal state of the tire, as it could happen using additional sensors.

Case study - processing

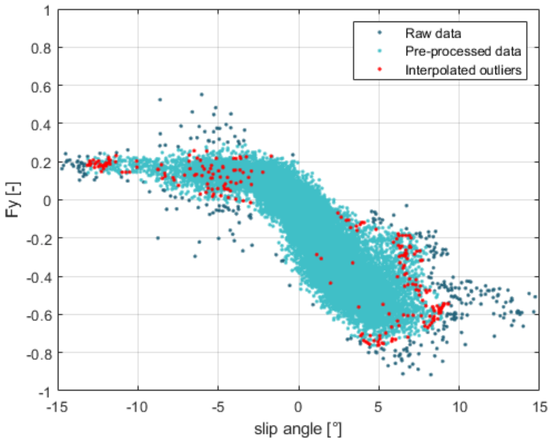
The data collected during outdoor on-track tests inevitably involve outliers, measurement noise and non homogeneous frequency of observation of the different operating conditions of tire; thus, the pre-processing steps provided by the RIDElab tool are fundamental to get a reliable multiphysical tire model that is not deviated by incorrect information and is representative of the real behavior of the tire in equal measure for each operating condition.

The Figure 7 represents the fundamental steps for the identification of the Pacejka micro-coefficients governing the dynamic behavior of the tire: the elimination of data generated by inaccuracies and measurement noise (Figure 7(a)), the discretization of the available dataset to obtain the smallest number of samples strictly necessary for the characterization of all the operating conditions of the tire (Figure 7(b)), the identification of a nominal thermal range in which to characterize the response of the tire to those variables contemplated by the basic MF model, such as pure and combined longitudinal and lateral dynamics, camber angle and the vertical load (Figure 7(c)).

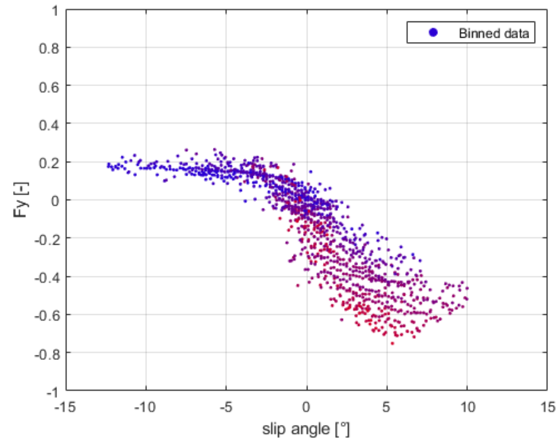
Once the MF micro-coefficients have been identified, the tire model thus allows to reproduce tire dynamics but exhibits constant performance characteristics. Their dependencies on tire thermal and wear conditions is covered in the adheRIDE model by means of additional formulations based on physical evidence and featured on experimental evidence (Figure 8(a) and 8(b)), therefore leading to obvious improvements in the tire model correlation towards experimental data in all its thermodynamic conditions (Figure 8(c)).

Case study - results

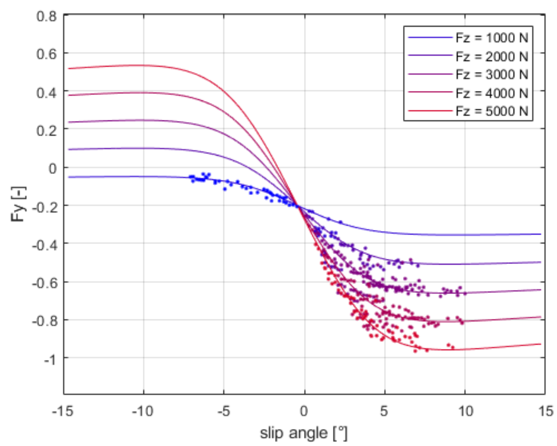
The resulting advanced MF-based adheRIDE model can be employed in co-simulation with thermodynamic and wear models in software-in-the-loop, hardware-in-the-loop or driver-in-the-loop scenarios, allowing to reproduce tire's



(a) *Outliers removal*



(b) *Binning data*



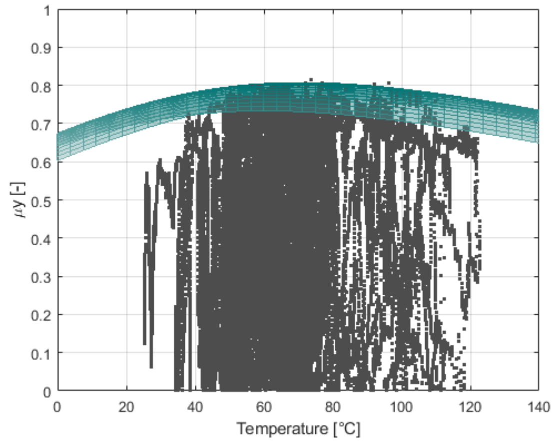
(c) *MF calibration*

FIGURE 7: RIDElab procedure steps for a motorsport case-study

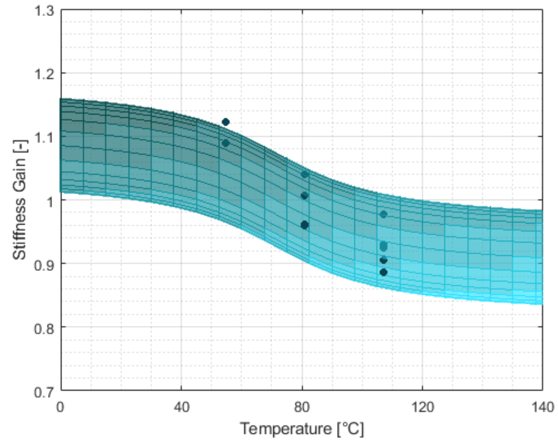
behavior and driver's feeling in all the possible operating conditions concerning the vehicle handling frequency range. As shown in figure 9, a dynamic model such as the standard Magic Formula always provides an equal level of available grip for equal steering, camber angle and speed, while the adheRIDE model provides consistent levels of grip with the tire internal temperature and pressure, in correspondence of the same curve along a longrun, thus reproducing in simulation the sensations of the driver during the different phases of heating the tires.

CONCLUSIONS

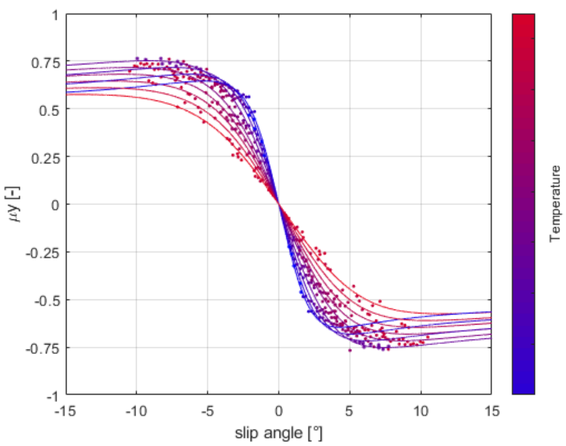
Considering that modelling and simulation have become fundamental tools in research and development fields on multiple levels and market areas, the models employed in simulation need both to be accurate, robust and faithful to reality, and also to guarantee a low computational burden to be employed in real-time and offline simulations, virtual prototyping software and on-board safety control logic. The use of the adheRIDE multiphysical model suits well both requests, since it is based on the analytical semi-empirical Magic Formula model, which requires low computational cost and provides reliable modeling of tire dynamic behavior over a certain thermal operating range, and enriches it with the co-simulation of further states of the tire by means of physical thermal and wear models and the use of multiphysical formulations that make the model's parameters sensitive to them. This indeed offers a



(a) *Maximum grip surface calibration*



(b) *Stiffness surface calibration*



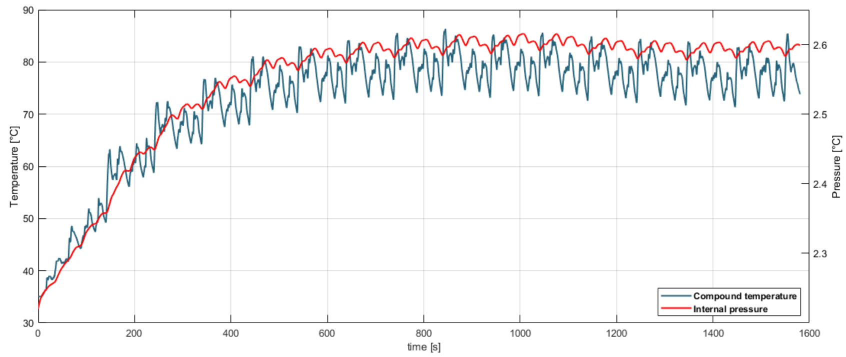
(c) *adheRIDE model curves*

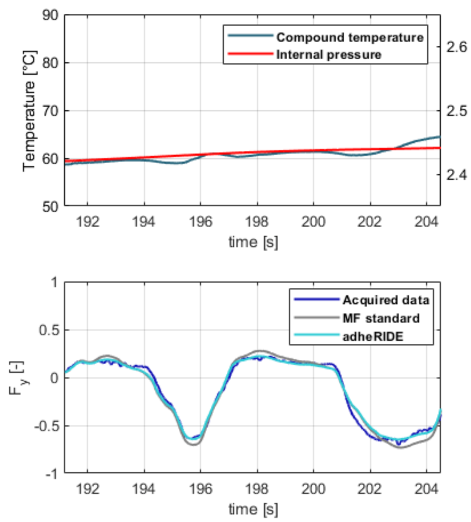
FIGURE 8: adheRIDE model calibrated on a motorsport case-study

remarkable compromise between accuracy and robustness in the whole tire's behavior representation and quite low computational request, which makes it suitable for both real-time driving simulations and for offline performance optimization algorithms. Furthermore, since the proposed model is based on analytical formulations, it results strictly sensitive to the quality of the data on which the parameterization is carried out.

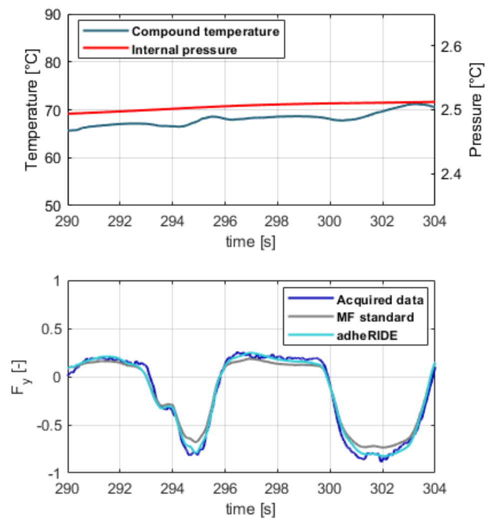
Hence, the RIDElab tool presented in this paper offers the necessary tools and procedures to properly calibrate the multi-physical model starting from the only acquired data, which might come from both outdoor and indoor testing routines, so that it ensures a faithful, predictive and realistic real-time simulation of tire's behavior in all its operating conditions.

A case study, provided by a motorsport research partner, was therefore used to show the advantages in using the RIDElab tool to get a proper parameterized multi-physical adheRIDE model. The case-study procedure illustrated started from outdoor acquisitions on track, where incorrect samples, which may hinder the identification process or provide inaccurate results, easily occur. The available dataset was therefore cleaned of measurement errors and noise and a more compact representative dataset of tire's behavior was achieved, on which it was possible firstly to identify the parameters of the standard Pacejka's model in a precise thermodynamic range and then calibrate the additional formulations governing the variation of those parameters with temperature, pressure and wear. It was therefore highlighted the achieved fitting as well as predictive results in simulating the tire-road interaction forces taking into account all the variables and tire's states concurring in defining their magnitude and shape.

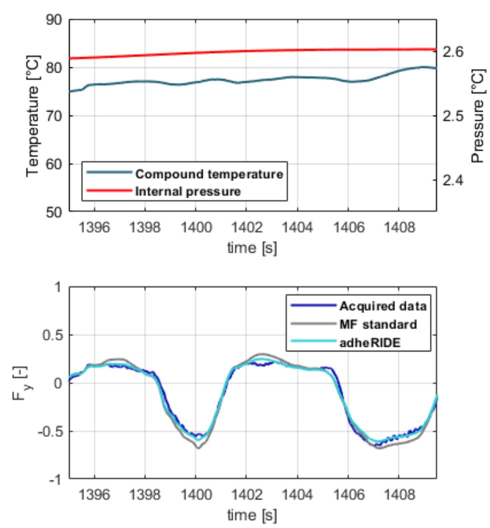




(a) *Warm-up*



(b) *Mid temperature*



(c) *Thermal steady-state*

FIGURE 9: Comparison of the MF standard and the MF-evo outputs towards the experimental data for three different thermodynamic conditions

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