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# Use of Naturalistic Driving Studies for Identification of Vehicle Dynamics

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**ABSTRACT** This paper discusses the feasibility of data captured in a long-term Naturalistic Driving Study (NDS) for identification of vehicle dynamics. Driving data were captured for over a year. In this data capture, there was minimal effort to define or control everyday driving practices. While the use of real-world data for model parameter identification is a well-known method, NDS are commonly used to explore the behavior of drivers or to analyze real-world traffic situations. Data from NDS have not yet been used for the purpose of parameterizing vehicle dynamics models since everyday drives commonly do not reflect the full range of vehicle dynamics. This leads to the question if the data from an NDS contains the needed information to describe vehicle dynamics accurately. This paper shows that data captured from long-term everyday vehicle usage is sufficient to characterize vehicle dynamics models. It uses lateral vehicle dynamics as an example to show how the data quantity changes the model accuracy and robustness. There is a point where any further data capture produces redundancy and does not add to the overall information. The well-known single-track model serves as the modeling example which offers options to simply compare the derived model behavior with a reference.

**INDEX TERMS** Driving data, information growth, naturalistic driving study, identification process, vehicle dynamics.

## I. INTRODUCTION

Modern passenger vehicles are equipped with multiple systems that rely on taking measurements of the vehicle's internal states, drivers activities, and the vehicle's environment. All these new systems rely on sensor data or additional external information from infrastructure and other vehicles. It has become an accepted fact that vehicles take measurements and exchange information with other vehicles or infrastructure [1]. While collecting more measurements was mainly driven by introducing new functions, the manufacturers and third-party companies have become interested in exploring the additional possibilities that these data offer. On the one hand, there are direct economic benefits, and companies are trying to make the best use of them. Studies by Capgemini estimate that the market volume of data taken from vehicles ranges from 80 – 800 bil [2]. McKinsey & Company come to similar conclusions and state that vehicle data could have a market volume of 450 – 750 bil [1]. On the other hand, the collected data can be used to further optimize existing functions or the product.

Modern passenger vehicles offer the option to send and receive data via modems which makes the access to measurements a lot easier if it needs to be analyzed outside of the individual vehicle. Any company with access to the data is also interested in defining mechanisms to leverage it for business advantages. There are three major areas for value creation based on vehicle data [1].

- Increasing revenue: many ideas and first business models exist. The question, therefore, is how to best monetize available data.
- Reducing cost and
- Increasing quality.

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Opportunities to reduce cost or increase quality both rely on a deep understanding of a product under real-world conditions. Data sets from system usage can be used for that purpose. Technical research and development departments are attempting to analyze the data mainly from these optimization points of view. When doing that, it becomes evident that the data collection process on modern passenger vehicles during everyday drives, to a great degree, meets the demands of so-called Naturalistic Driving Studies (NDS).[1] This type of study is useful to explore the behavior of drivers in real driving scenarios. For that purpose, NDS capture data during a realistic drive situation (best during everyday drives) where there is very little control of the actual experiment. The vehicle captures data during a drive without any visible evidence that it is happening. NDS data capture allows realistic vehicle use but demands a long study duration to capture all effects of interest since they are not triggered intentionally. These studies allow for research on what happens with a vehicle over its lifetime or a drive cycle. This information leads to the optimization and understanding of technical requirements in more detail, considering actual world usage.

Many steps during the development of modern motor vehicles need models describing the vehicle dynamics. This ranges from studies early in development to first calibrations of control systems. Furthermore, models are also an integral part of many vehicle control systems. However, analyzing the vehicle dynamics is out of the usual scope of NDS. A different approach for this area of interest is commonly used– short but clearly defined experiments (e.g., lane change, steering angle steps, slalom, etc.) that do not mimic real driving situations, but excite certain states of a vehicle, work well for this purpose. These extreme driving situations are rarely found in actual world drives since they are defined to bring the vehicles' abilities to an edge of its performance.

Well-defined stimulation of the car allows for precise measurements. Specific sensor setups are used for these tests. Even with the vast number of onboard sensors and the ability to collect data from actual world driving, only a few research projects have attempted using NDS-like data for vehicle dynamics analysis or the parameter identification for vehicle models.

1. NDS (Naturalistic Driving Study) is an experimental measurement method to observe naturalistic (real) driving situations. It is often used to study the behavior of the driver or the traffic. Some common properties of NDS are the following.

- The driver uses her/his own vehicle (or a known vehicle) for regular uses cases.
- Sensors and data-logging devices are inconspicuous so that the driver becomes unaware of being monitored.
- There are no additional researchers in the vehicle.
- Data are taken continuously over a drive.
- The driver, the vehicle and surrounding traffic is observed For further information on NDS and its usual use refer to: [3], [4], [5] or [6].

The results of the research project Dreams4Cars (2017) [7] show that identifying parameters for a vehicle dynamics model is possible based on data taken from regular (everyday) drives on public roads. Many other studies have used measured data for model parameter identification before and this method is well known. The main question for vehicle dynamics therefore is whether the information, which can be captured during everyday drives allow for accurate models over the entire range of vehicle dynamics.

Compared to NDS, the study performed in Dreams4Cars was minimal since it used a specific 50km long track and only two rounds were measured. The drivers were test engineers and the drives where performed for measurement purposes. It therefore cannot be counted as a practical implementation of NDS. The data taken in this project and used in [8]–[10], and [11] to identify controller parameters of an autonomous vehicle cannot fully be compared to field data taken during private vehicle use. It still indicates the potential for similar approaches. James *et al.* [10] notes that data from everyday driving do not meet the requirements for identification (full range of excitation). However, the paper does not investigate what information can be collected in everyday driving, how the information growth proceeds. Additionally, the researchers did not study the completeness of information to be gained from the captured data nor did they discuss limits of the approach in a wider sense.

This paper shows that the NDS method can be used to identify parameters for vehicle dynamics models accurately and it proves that the captured data is sufficient to be used for vehicle dynamics modeling. The scope of the work is lateral vehicle dynamics using the single-track model as an example. The model parameters can be quantified using the data captured during the NDS and the resulting parametrized model can be used to accurately describe the vehicle dynamics beyond the range, which has been observed during the study. All in all, this implies that modeling based on NDS data is possible. Furthermore, even artificial neural networks of similar approaches could also be based on NDS since the needed information is captured in the data. Early parameter identification can lead to many new considerations, especially with continuously taking measurements during passenger vehicles' actual use. The vehicle models could be continuously parametrized during operation. Continuous updating could show changes in the vehicle dynamics that might indicate wear but could also be used to individually parametrize controllers. In some cases, using actual data potentially allows for a further reduction of specific tests on a test track. One interesting aspect also seems to be that non-OEM research groups, which often lack some of the physical parameters to model a vehicle and might also not have the ability to perform standard dynamics tests on test tracks, can use real-world driving data for modeling purposes.

This paper is divided into the following sections.

- Description of the process of data collection during NDS compared to standard vehicle dynamics tests.

- Considerations of information growth during an NDS with respect to vehicle dynamics.
- Description of the NDS setup and the captured data used for this study. The data is compared to theoretical vehicle dynamic boundaries and expected values for everyday drives to evaluate its completeness/adequacy.
- Use of the data and data subsets to characterize the vehicle dynamics model.
- Evaluation of the model with different parameter-sets to show how the measurement duration affects the accuracy and robustness of the resulting model. This leads to a rating of data sufficiency.
- A final discussion of the results and limitations of the approach.

## II. PROCESS OF NDS FOR IDENTIFYING VEHICLE DYNAMICS

Identification of model parameters requires experimental investigations and measurements. The recorded experimental data influence the identification process and are of great importance. As described in [12], the commonly used process for identification consists of five consecutive steps. In the case the validation results are not acceptable, previous process steps can be repeated and needed changes for experiment design or measurements can be implemented. The option to jump back to an earlier step and run multiple iterations makes the overall method highly flexible. Any new iteration uses the experience that was gained during preceding iterations. With increasing complexity of a test fewer iterations are usually accepted due to time and cost considerations.

NDS are very time consuming which limits the option to repeat them as a whole. It is however possible to change the design of the experiment during the measurement phase. The data needs to be analyzed continuously and changes are implemented. The data analysis in parallel to the measurement phase can also be used to define an end of the data capture process. Changing the set-up while performing the study will add complexity to the later analysis since the captured data are not consistent. Changes of the set-up therefore need to be limited to a minimum. Furthermore, NDS do not have a predefined termination, since it is unclear when enough data will be captured. The endpoint is usually defined by a project duration but could also be coupled to specific criteria. Therefore, the classic process steps for parameter identification need to be adjusted when attempting to use NDS as part of the method. The identification process for NDS is presented in Fig. 1. The most significant differences are:

- A large amount of data due to long measuring duration → need to use a proper database and analyze large sets of data.
- A growing database as well as continuous data analysis and evaluation.
- Impractical option to rerun the entire test due to long duration.

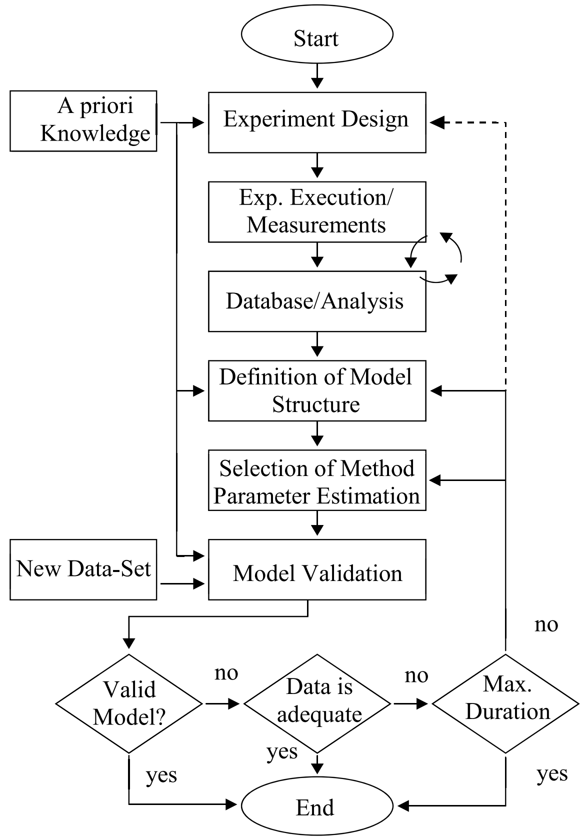


**FIGURE 1.** Identification process for NDS based on [1].

- NDS are exploratory, and the properties of the database are not known a priori → the achievable model quality is not known in advance, and reasonable termination criteria must be defined. The achievable model quality depends on the interaction of the chosen model structure (e.g., number of model degrees of freedom) and the database.

## III. CRITERIA TO TERMINATE NDS

As the flowchart from Fig. 1 shows, the overall process is stopped when one of three stopping criteria is fulfilled.

- The goal of the study is achieved. For this example, this is creating a valid model. Validity of the model is a criterion that is specific to the task and must be derived from the intended application.
- The data is adequate, which means that no more information with respect to the underlying task can be gained when continuing.
- The maximum NDS duration is reached. This maximum duration is often determined by non-technical restrictions (e.g., budget constraints or development cycles).

If either the data is adequate or the max. study duration is reached without the data being sufficient to create a valid model, the overall approach would prove not useful for a given task. Adequacy as well as sufficiency of the data are complex to be evaluated and are discussed further in the following section.

The captured data is sufficient if it allows to solve the task. For this example, the sufficiency is proven once the modeling task results in a valid model for the intended application. This means it is not evaluated on the data itself but implicitly shown while creating and validating the model. The modeling scope and needed accuracy, however, need to be defined beforehand.

The adequacy of data describes whether or not all information that could be gained from the measurement set-up is captured. This can only be answered on an individual basis and for specific properties that are analyzed. Information is an attribute of data that provides new knowledge. When taking additional data without gaining new knowledge, there is no information extracted from it. In case of frequent repetition of the same experiment, the expected information gain for further trials decreases. Whenever additional measurements during an NDS do not add other knowledge concerning the underlying task, the collected data are adequate and the NDS can be stopped at that point. For NDS, this is an intriguing fact. The researchers often start a measurement to investigate unknown systems/behaviors. Therefore, it is unclear what situations or states are possible and need to be part of an experiment. The experiment itself is also explorative and, hence, indeterminate leading to the need to introduce criteria for adequacy.

These criteria are mainly based on the probability for further gain of information. One option to judge upon this probability is the use of statistical methods to examine the database. Furthermore, knowledge can be used to define expected values or even to state physical boundaries. In case there is not enough *a priori* knowledge for a property under investigation, the termination criterion can solely be made on statistical measures. In Liu and Zhu (2019) [12], Liu *et al.* (2018) [13], and Wang *et al.* (2017) [14], a method based on the information criterion of Kullback-Leibler [15] is presented. The information growth of the data set is investigated and serves as the termination criterion of the NDS. No system knowledge is required for this approach. However, it does not allow any direct conclusions to be drawn about the achievable model quality after the identification. In this paper, descriptive methods are used and combined with knowledge about the measured variables. A statement can then be made about the expected information growth of the data set and its adequate size. Both approaches are options to make a statement about an adequate data set. A combination of them is presented in Reicherts [16] and leads to similar results. The following section shows what this means using the example of vehicle acceleration.

## IV. NDS CAPTURED DATA AND DATA ADEQUACY

The data presented and analyzed for this paper has been captured in a study at the University of Duisburg-Essen. A 2013 Ford C-Max Energi Plug-In-Hybrid vehicle was used for the period 7/1/2019 to 6/30/2020. Any employee of the Chair of Mechatronics at the university could use the vehicle for transportation during that period. The drivers did not have any specific task related to this study nor were they asked to follow any specific rules or processes.

**TABLE 1.** Driving data of the study over a study over a study period of 12 months.

| | All Data | Drives [3] > 2km | Validation Data |
|---|---|---|---|
| Study period | Jul. 2019 – Jun. 2020 | | Jul. 2020 |
| Number of single drives | 360 | 273 | 26 |
| Total distance (km) | 9,030 | 8,800 | 491 |
| Total duration (h) | 148 | 140 | 8 |
| Average distance (km) | 25 | 32 | 19 |
| Average duration (h) | 0.42 | 0.52 | 0.3 |
| Average velocity (km/h) | 61 | 63 | 61 |

Table 1 summarizes drive data captured during the study. A drive is defined by a key cycle and a traveled distance greater than 2km. A total of 273 individual drives is used for further analysis.[2] The collective sum of traveled distance is 8,800km with a total duration of 140 hours. The measurement setup and signal access parameters are described in [17]. The data presented in Table 1 is a highly diverse set that includes the entire possible range of vehicle speeds, varying travel distances and duration (a few km to several 100km), and a variety of roads.

The total distance of approximately 9,000km over the year is about 65% of the average mileage for a vehicle in Germany in 2019. The reduced travel distance recorded in the first half of 2020 can be attributed to the impact of the Covid pandemic. Comparative statistical data for Germany covering 2020 are not yet available [18]. For Germany, average highway usage is estimated at 30%-40%. This estimate is based on data from Metz *et al.* [19] and Tewiele [20]. The data set of this study contain a high percentage of highway mileage of almost 60%. It follows that a higher average speed and greater distance than German average traffic as a whole is observed [21]. This is not astonishing when analyzing the area that the vehicle was mainly used in. There is a very dense highway net that is used for most travels. Compared to the average vehicle use, this nuance is not an obstacle for its use during the analysis of the data with respect to vehicle dynamics. The complete range of speed is captured as well as other needed dynamic properties.

2. Drives with less than 2km have been neglected for further analysis. The vehicle has its own parking spot with a charging station which means that the starting point for many drives is the same one. Meaning that the first traveled distance is observed in many drives. Additionally, this criterion was used to sort out parking maneuvers etc. The expected maneuvers, traffic and road type are also seen in any longer drive. The assumption is that these very short drives do not add information. By using that definition almost 1/4 of the total drives cut be neglected which at the same time did only decrease the traveled distance by 2.5%. Increasing the analysis time by using theses short drives therefore seems to be unnecessary.

To analyze the data with respect to it being adequate, the vehicle physical boundaries and expected dynamics range are analyzed. Physics limit the longitudinal and lateral acceleration of any vehicle. For a regular passenger vehicle, the maximum tire vector force at the contact patch allows for approximately 1g of horizontal acceleration. The tire forces are limited by the downforce (in the absence of aerodynamic elements, this is the weight) and the road-to-tire coefficient of friction. Therefore, a circle can be drawn representing the maximum acceleration (see Fig. 2), the so-called Kamm's Circle [22]. The longitudinal acceleration in positive x-direction could also be limited further by the drivetrain's power [23].

A further part for consideration is that regular drive situations and the average driver will not push the vehicle to exercise its physical limits. To achieve high lateral accelerations, aggressive evasive maneuvers are required. Only full ABS braking events might show the full deceleration capability. Both are typically avoided where possible and therefore unlikely to be seen in NDS data. Previous studies have shown what accelerations are to be expected for everyday use of a passenger vehicle. In 1973, Rice [23] described the expected range without using statistical distribution.

Fig. 2 overlays the physical boundaries and expected values based on system knowledge with the measured acceleration data from the NDS discussed in this paper. The statistical distribution of the measured data is particularly interesting since it allows judgment of the information stored in the data.

Fig. 2 shows the measured data and the quantities for measurement points. The measured data match the expected area for the type of drive scenarios that are mainly observed. Its distribution density is relatively high for small accelerations $[a_x,\ a_y] \approx [0, 0]$. For rising distance to the origin, the density is decreasing exponentially. Acceleration values above $4 \mathrm{m/s^2}$ are rarely observed since the vehicle dynamics for high lateral accelerations are unlikely to be seen in everyday use. There is no information about high lateral acceleration close to the physical vehicle limits. The distribution density is almost zero. A very similar distribution for a large driving study is presented in Liu and Zhu [24]. The distribution indicates that it is very unlikely to measure higher accelerations when continuing the study without changes. The data therefore indicate that it is adequate with respect to acceleration.

Especially when discussing lateral acceleration, the environment conditions are of interest. The maximum tire force depends on the coefficient of friction $\mu$ between tire and road. It varies for different road surfaces and is also influenced by weather conditions (wetness, snow). Since these conditions where not captured over the course of the NDS they cannot be used as an additional input for further analysis. With the help of the established tire model of Pacejka (Magic Formula, [25]), the influence of the coefficient of friction $\mu$ on the transmissible tire force and potential influences to this study can be estimated. Two very

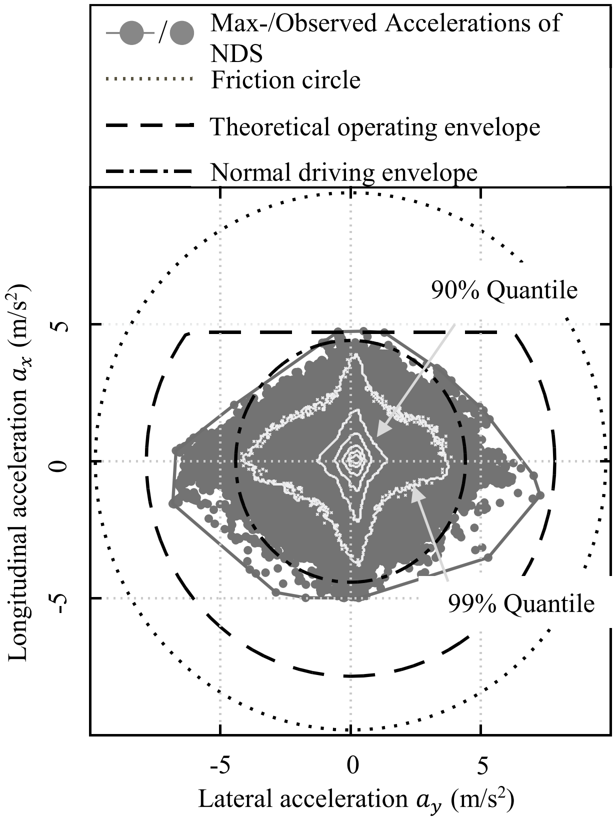


**FIGURE 2.** gg diagram: Acceleration data of the driving study. Comparison of the observed acceleration with the acceleration value to be expected for everyday driving.

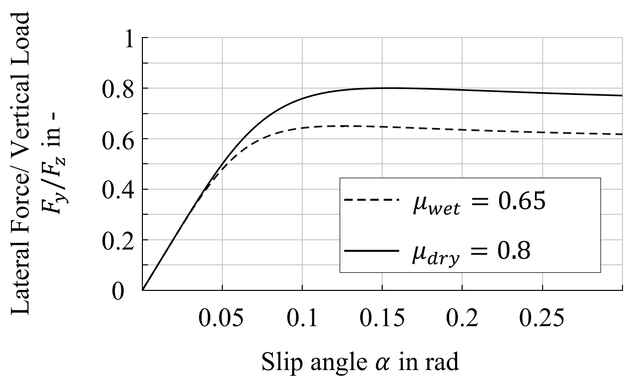


**FIGURE 3.** Typical characteristics for side force vs normalized vertical load and slip angle on dry and wet road.

different tire-to-road contacts are compared to show how the data could be influenced by this aspect. In Pacejka [25], a friction value of $\mu_{\mathrm{dry}} = 0.8$ is assumed for a new tire on a dry road and $\mu_{wet} = 0.65$ for a worn tire on a wet road. In the figure both variants are shown.

For everyday driving the quotient of $\frac{a_y}{g} \approx \frac{F_y}{F_z} < 0.4$ and the tire behavior is approximately identical for different tire-to-road conditions. Seasonal influences like weather conditions cannot be detected. This finding represents a limitation of the approach. NDS are not/ poorly suited to identify the influence of the friction coefficient on vehicle dynamics, since the needed range of vehicle dynamics are not excited properly. The observation of highly dynamic situations is not excluded by the study design, but it is very rare in everyday driving. The data set and the method seem unsuitable for the identification of these events. Well known standard maneuvers are the better choice to perform studies explicitly for that type of condition.

An additional aspect when discussing general data quality and its implications for other studies is that this small-scale study, with only one vehicle and a limited group of drivers, has a risk that the data collection is biased with respect to car/driving behavior/driving context. Comparisons with other studies show that the distribution of speed and acceleration are similar. The driving dynamics of the test vehicle to be identified are independent of the study design. However, the study design has influence on the type of system excitation. To ensure that the bias can be neglected, it was investigated whether all expectable conditions were observed and thus a typical and representative stimulation set is gained. For a detailed analysis, please refer to Reicherts [16].

The observations allow for the following considerations.

- The data cover the range that would be expected and have a distribution observed in other studies.
- The data taken show regular drives and the vehicle dynamics to be observed.
- The measurement duration has been long enough.
- The data are adequate with respect to horizontal vehicle dynamics since new measurements are unlikely to show new acceleration values.
- The data are improper to identify tire characteristics for different environmental influences.
- The data is unsuitable for studies on highly dynamic vehicle behavior.

Further considerations of the data being adequate are drawn based on vehicle dynamics model parameters in the next section. Additionally, the sufficiency of the data with respect to vehicle dynamics is discussed based on the model validity.

## V. VEHICLE DYNAMICS MODELS USING NDS DATA

In the previous chapter, the hypothesis of an adequate data set is investigated based on previous experience on driving physics. It can be shown that the entire expected dynamic range is covered, and consequently, further information gain is unlikely. A further confirmation of this hypothesis can be provided by the parameter identification for a vehicle model. Using the example characteristic dynamics properties from the model, it is shown that they do not change with additional data after a certain point and that, consequently, adequacy is achieved. This method is also used to discuss how much data has to be captured to be adequate.

Fundamentals regarding the identification of models can be found in [26]–[28], and [29]. An overview of different aspects is given in [30]. Using real-world measurements for model creation and parameter identification is a known method.

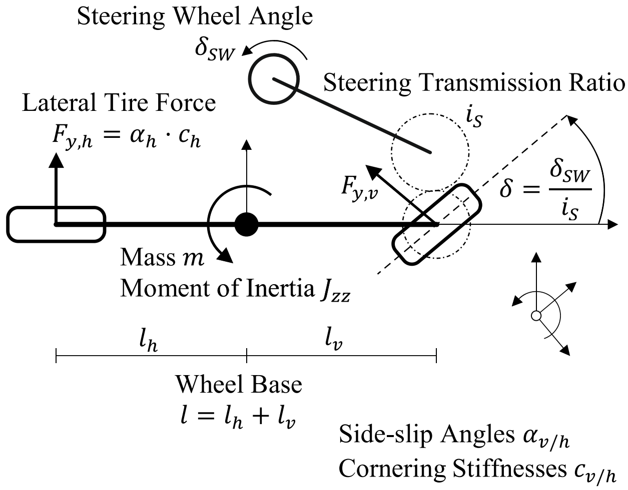


**FIGURE 4.** Single-Track Model.

Deriving a valid vehicle model based on large amounts of data can generally follow two different patterns. The first is using the data to train an artificial neural network. This approach is discussed widely in multiple research areas and is also part of the research that this contribution is based on. The second approach is to use a physical vehicle model that describes the physics of a general vehicle and then to identify the model parameters of that model. The difference is that the second approach demands knowledge of the physics before starting the experiment. At the same time, however, it is easier to interpret and validate the identified parameters. This contribution uses a physical model to effectively discuss adequacy and sufficiency of the collected data. This idea can be leveraged to prove sufficiency for data before using it for non-physical modeling methods (e.g., neural nets). Please refer to [16] for further and more detailed information about either one of the modeling methods.

Further discussion regarding the results uses the well-known single-track model (bicycle model), which is widely used to describe any passenger car's lateral dynamics [22]. It uses the physics of the vehicle to describe the behavior. The representation of the model as well as its parameters are given in Fig. 4.

The model inputs are the longitudinal vehicle speed, $v_x$, and the steering wheel angle, $\delta_{SW}$. The model output analyzed for this contribution is the lateral acceleration, $a_y$. The used single-track model is a relatively simple and linear vehicle model. There are more complex and nonlinear models available that describe the physics of a vehicle in more detail. This is especially true for extreme states. The single-track model is, however, well suited for this study for multiple reasons. As already described above, the NDS type data collection rarely measures lateral accelerations above $4\text{m/s}^2$. For these accelerations, the tire forces are linear and can be represented based on the linear combination of their

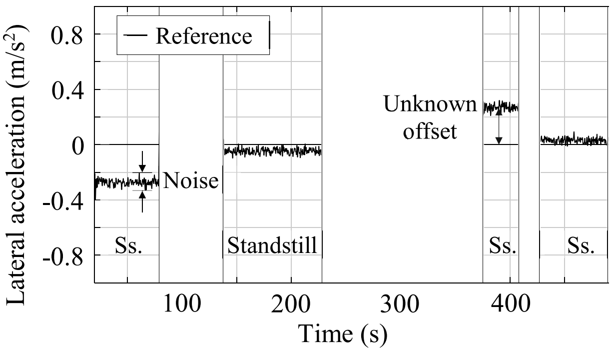


**FIGURE 5. Visualization of the measured lateral acceleration for a drive for standstill situation. Areas for not standing still are covered. Legend: Reference, measured lateral acceleration.**

cornering stiffness and the side-slip angle ($F = c_\alpha \alpha$). The vehicle state is therefore in the range of validity that holds for this model [22]. Vicente *et al.* [11] state that, especially with limited *a priori* knowledge, a model with high complexity can suffer from poor model quality. This indicates that the single-track model is a good choice for this study. Nonlinear models would only differ from this behavior for higher lateral acceleration. Knowing that these states are rarely stimulated during regular driving, it is questionable whether parameters describing the non-linearities could be appropriately identified [11].

One limitation in the measurement setup is the rolling motion of the vehicle. The roll angle cannot be detected by the vehicle's own sensors and the single-track model cannot represent it either. It's evident that during standstill, the lateral acceleration would be $a_y = 0$ m/s$^2$ and the vehicle speed is $v_x = 0$ km/h. The measurements for $a_y$ often show a constant value (see Fig. 5). These values do not result from a measurement offset (error) but are caused by road inclination. Therefore, the lateral acceleration for different standstills is not the same and cannot be estimated based on the given model inputs. Without considering this, the measurements could lead to erroneous conclusions. The standstill can be filtered out for parameter identification purposes.

A similar observation can be made when looking at curved trajectories. A real vehicle will roll to some degree, which adds to the measured lateral acceleration (due to gravity then showing in the measurement) since the vehicle's sensor will roll with it and hence change its orientation. This is a similar effect to the road inclination but is caused by vehicle dynamics. The roll angle and the overlay of gravity on the vehicle lateral acceleration increase with the lateral acceleration. As shown, regular drives are usually in the area of $|a_y| < 4$m/s$^2$. The effect as described can be neglected here. The maximum expected error is about 6%.[3]

For this paper some well-known quantities are used to show how the information growth over the NDS change the resulting model parameters, the model accuracy, and robustness. The change of modeling parameters with a growing amount of data allows for a discussion on the adequacy of the data. No further change of modeling parameters with more data indicates that there is little additional information to be gained with respect to these parameters. Given a reference, the model can be checked for validity to also prove sufficiency for the data. This portion is discussed in the next chapter.

The so-called self-steering gradient, *EG*, is a vehicle property that can be used to express the lateral dynamics of a vehicle in a single value. It shows how close the needed steering wheel angle, $\delta_{sw}$, is to the pure kinematic Ackermann steering angle, $\delta_a$

$$\frac{\delta_{sw}}{i_s} = \delta_a + EGa_y = \delta_a + \frac{m}{l}\left(\frac{l_h c_h - l_v c_v}{c_v c_h}\right)a_y. \tag{1}$$

The data taken during the study is compartmentalized to create independent modules. Starting from the finest possible split, single drives (SD), to only one set containing the full 140h of driving data (AD). This leaves 273 single drives, 31 independent sets of 5h drive data each, 7 sets of 20h, 2 sets of 70h, and one set containing all the drives (called H5, H20, H70, H140/AD). The sets consist exclusively of complete drives, so they vary in size. The individual drives are randomly assigned to the sets. The use of these different sets shows how the information growth during the study influences the model parameters.

Every data set can be used to identify the parameters for the single-track model ($m$, $J_{zz}$, $l_v$, $l_h$, $c_v$, $c_h$, $i_s$) as well as *EG*. Error is reduced when the boundaries for the identification are based on datasheets. For this contribution, only publicly accessible knowledge is used. E.g., the wheelbase can be found on a data sheet. Knowing that the wheelbase is the sum of rear and front distances to the center of mass ($l = l_h + l_v$) $l_h$ and $l_v$ are no longer independent parameters (which reduces the parameters to be identified). Initial values for the vehicle mass, $m$, as well as for the steering ratio, $i_s$, are taken from datasheets. The moment of inertia initial value and the cornering stiffnesses are derived based on the methods from [31], [32]. The parameter optimization is performed with the initial values using the measured data.[4] The cost function used for this is a least squared error approach with $e_k$ being the residual error at the k$^{th}$ step. It is the difference of the measured lateral acceleration $a_{y,ref,k}$ and the value

3. The max. error for the measured lateral acceleration due to increased roll angles has been estimated based on the roll gradient of the vehicle. For 4m/s$^2$ it reaches about 6%.

4. The global particle swarm optimization method followed by a local gradient-based algorithm has been used during the studies presented here. The initial values which have been set based on the described a priori knowledge and their boundaries are

$$\mathbf{p} = \begin{bmatrix} m_{min} & J_{z,min} & \mathrm{c}_{\alpha,\mathrm{v,min}} & \mathrm{c}_{\alpha,\mathrm{h,min}} & l_{v,min} & \mathrm{i}_{\mathrm{s,min}} \\ m_{max} & J_{z,max} & \mathrm{c}_{\alpha,\mathrm{v,max}} & \mathrm{c}_{\alpha,\mathrm{h,max}} & l_{v,max} & \mathrm{i}_{\mathrm{s,min}} \end{bmatrix}$$
$$= \begin{bmatrix} 1,800\mathrm{kg} & 2,200\mathrm{kgm}^2 & 65\frac{\mathrm{kN}}{\mathrm{rad}} & 110\frac{kN}{rad} & 1.0\mathrm{m} & 14.2 \\ 2,000\mathrm{kg} & 3,200\mathrm{kgm}^2 & 90\frac{\mathrm{kN}}{\mathrm{rad}} & 135\frac{kN}{rad} & 1.3\mathrm{m} & 15.3 \end{bmatrix}$$

This leaves 6 independent parameters to be optimized based on least square errors.

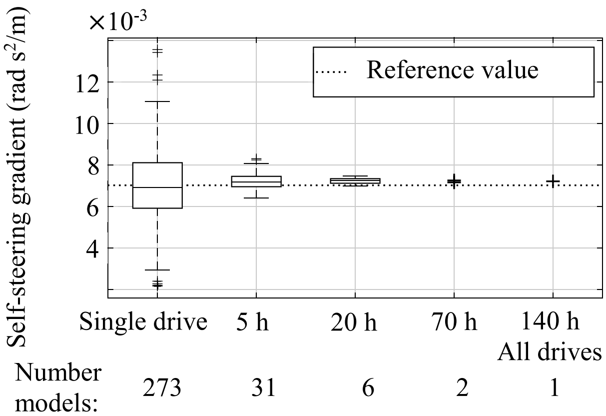


**FIGURE 6.** Dependence of the identified self-steering gradient on the amount of data. The reference line shown is taken from a Ford CMax Diesel 2.0. The reference serves as an orientation value and cannot be taken as an absolute target value. Deviations are due to differences between the diesel and hybrid, the tire used, as well as aging and wear on the vehicle.

from the single-track model $a_{y,LSM,k}$.

$$e_k = a_{y,ref,k} - a_{y,LSM,k} \tag{2}$$

$$V_{RMSE}(\mathbf{p}) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} e_k^2} \tag{3}$$

$$\widehat{\mathbf{p}} = \min_{\mathbf{p}} V_{RMSE}(\mathbf{p}) \tag{4}$$

The choice of Least Squared errors was taken since this function is well suited for optimization and a large data set if its noise is Gaussian [27].

An independent simulation run is performed for each drive within a set. The residual for each timestep, $e_k$, over the different drives is inserted into the cost function (4). The parameters, $\boldsymbol{p}$, are adjusted according to the optimization routine. The simulations of each drive are run again, and the residua are calculated and are fed back to the cost function. The process of optimization continues until the termination criterion of the optimizer is reached.

Fig. 6 shows the distribution of *EG* derived from the different sets of the same kind. The entire set of 140h obviously does not have a distribution since there is only one single set of that type. The variance for *EG* rapidly decreases with an increasing amount of data within one set. For sets of 20h, the distribution already shows no outliers and for the 70h sets the deviation between the *EG* values is 1%. After the first 70h of measurements, there seems to be little potential to change the *EG* and, hence, to gain more information with respect to the steering behavior. The independent data sets are approximately similar since they do not store different information. From this perspective, the data set can be considered adequate. Fig. 6 allows for similar conclusions based on the overall model behavior.

The variance of the identified parameters or model properties can be used to judge the data's adequacy. As described above, this does not necessarily mean that the derived parameters correctly describe the physics of the real system. The derived model can only be valid if the data fits to the needs of the identification task. This discussion is continued below with respect to the lateral dynamics of the vehicle.

**TABLE 2.** Quality of the identified models for the validation data.

| Data amount | RMSE | | | |
|---|---|---|---|---|
| | min | max | median | mean |
| 140h | 0.2226 | - | - | - |
| 70h | 0.2225 | 0.2227 | - | 0.2226 |
| 20h | 0.2224 | 0.2235 | 0.2226 | 0.2228 |
| 5h | 0.2215 | 0.2268 | 0.2231 | 0.2233 |
| Single drive | 0.2215 | 0.2864 | 0.2247 | 0.2281 |

## VI. MODEL VALIDATION AND DATA SUFFICIENCY

Validity of a model can only be proven for a specific use case. Numerical criteria can be used to show how well the model matches a given reference. A single-track model describes the lateral vehicle dynamics below an acceleration of about $4\text{m/s}^2$. The low model complexity does not include rolling nor any nonlinear behavior of tires etc. The modeling of these effects would add additional degrees of freedom and therefore add uncertainty to any identification. Fortunately, these effects are relatively unimportant for low speeds and low lateral accelerations. With a set of physical parameters, the model is called valid if it matches the reference drives for these low accelerations.

This reference must be independent of the model or the data that was used during the parameter identification. There are two options that are often used. The model can be validated using independent additional measurements or a second more accurate and already validated model can be used as a reference. Both options are used for different aspects in this paper.

### *A. VALIDATION WITH NDS DATA*

For validation purposes a set of data has been taken after the NDS period (see Table 1, third column). To compare the quality of different sets of parameters, numerical error values are defined in the following paragraphs. They allow for one single scalar value representing the quality over one or many drives but also bring some level of lost information. The Root Mean Squared Error (RMSE) is chosen. The RMSE is also used as the optimization criterion (3) during identification. TABLE 2 lists the RMSE values for the identified models with respect to the validation data.

In view of the above discussion, the quality of the resulting models has been demonstrated to be high. Even the model with the highest RMSE values resulting from an identification using only one single drive deviates from the value of the model from all drives only in the second decimal place. One of the lowest RMSE values of 0.2215 is reached using a single drive for the parameter identification. The reason for this is intuitive. One of the many single drives also seems to be the best identification drive. However, the probability of picking this is low. The parameters and the model quality

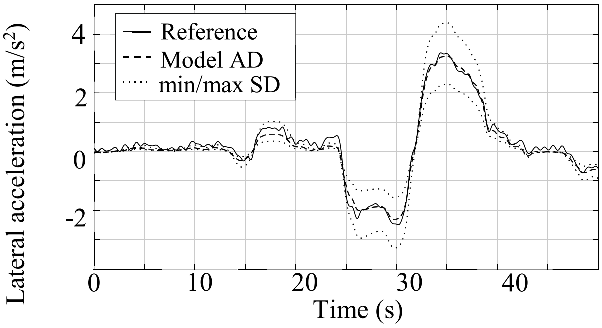


**FIGURE 7.** Comparison of the measured and simulated lateral acceleration for a validation run for cornering events. Legend: Reference, measured lateral acceleration; Model AD/SD, simulated lateral acceleration. Model identified based on All Drives (AD)/ min/max for models identified based on Single Drives (SD).

show a relatively wide distribution when using single drives. The larger data sets ensure a smaller parameter distribution and hence, a more robust model.

It also becomes evident that adding more data does not increase the model quality beyond a certain point. The RMSE scores of H20 onwards change only marginally. The *EG* approaches a final value that changes only minimally with further driving. This value is approximately the median of the distribution of the H5 data sets. Since this value is unknown in advance and can only be reliably determined with adequate data, the study must not be terminated prematurely. The median over all data sets remains approximately unchanged.

Fig. 7 shows a partial drive from the validation data which is superimposed with the model results for the same inputs. Furthermore, the figure includes the possible band of models if single drives would have been used to identify the model parameters. The reference and the model are almost identical. The lateral dynamics can be described extremely well up to $|a_y| < 4\mathrm{m/s}^2$. The band defined by models based on single drives additionally shows the influence from using a large amount of data instead of single drives.

The comparison of the model with the drives from the validation data implies that the vehicle's lateral dynamics are described very well. Regardless of which data set is used for parameter identification, the RMSE remains above 0.2. Deviations between model and measured drives can partially be explained by the modeling assumptions that do not allow for some of the effects to be shown. The model does not use all of the real-world influences (inputs) to change the outputs.

### B. VALIDATION USING COMPLEX VEHICLE MODEL

To prove the validity of the identified model and, hence, sufficiency of the data, an already validated complex vehicle model can be used as an additional method. This has the advantage that there is no measurement noise or external influences such as road inclination, changing road friction, wind, etc., to the reference data. Especially the option to generate a roll compensation for the reference data is to be mentioned here. Furthermore, the validation can be extended to dynamics ranges that are not part of everyday-drives. A validated ADAMS/Chassis model of a Ford CMax Diesel 2.0l as used during the development process serves as a reference for this discussion. The assumption is that this vehicle and the models are very similar to the test vehicle (Ford CMax Energi).

A typical maneuver to determine *EG* is a steady-state circular drive with a radius of 60m and a velocity starting at 10km/h and increasing to 70km/h [33]. The steering wheel angle needs to be controlled in a way to stay on the circular track. A constant radius with increasing velocity then results in increased lateral acceleration $a_y$, hence allowing for calculation of *EG*.

Fig. 8 compares the reference model and the single-track model with parameters based on the different data sets. The figure additionally shows the variance that the parameterized models have. The reference maneuver allows for lateral accelerations up to $8\mathrm{m/s}^2$. Higher accelerations are not to be expected for a regular passenger vehicle under normal conditions as described above. The shown quantiles for the underlying measurements show that the vehicle has been mainly used with low lateral accelerations, as was expected. 75% of all measurements were below $1\mathrm{m/s}^2$. $2\mathrm{m/s}^2$ already accounts for more than 90% of all the measured data points. Measurements that show higher lateral accelerations are rare. The measured data indicate that accelerations in the range below $5\mathrm{m/s}^2$ contain more than 99% of any measurement. This implies that the single-track model is suitable to describe the lateral acceleration for the measured data. It can be used for low and medium lateral accelerations. For higher lateral accelerations the linear combination of the Ackermann-angle and the self-steering coefficient is no longer valid, and the single-track model then becomes inaccurate.

The figure contains the median value of the derived models and the minimum and maximum for a certain data set. The models are compared to the Ford reference model (solid line). This reference shows the typical curve for the steering (wheel) angle. $\delta_{SW}$ increases linearly over the lateral acceleration.

As already stated in previous chapters the data seems to be adequate for lateral vehicle dynamics when analyzing sets of 20h and above. Less data (5h sets or SD) lead to a high variance of resulting models. How much data are sufficient for a valid identification is a function of required accuracy and the applicable acceleration range. Very low accelerations seem to already be modeled well even with any 5h data set. 20h measurement sets lead to an excellent representation of the reference model for the entire area that the single-track model is valid for. The error for higher accelerations results from different effects. On the one hand the error results from little data for high acceleration and on the other hand from the fact that the used single-track model is not capable of correctly describing higher accelerations. Effects from non-linearities and effects due to increased roll angles are more important for these inputs. As stated at the beginning of the

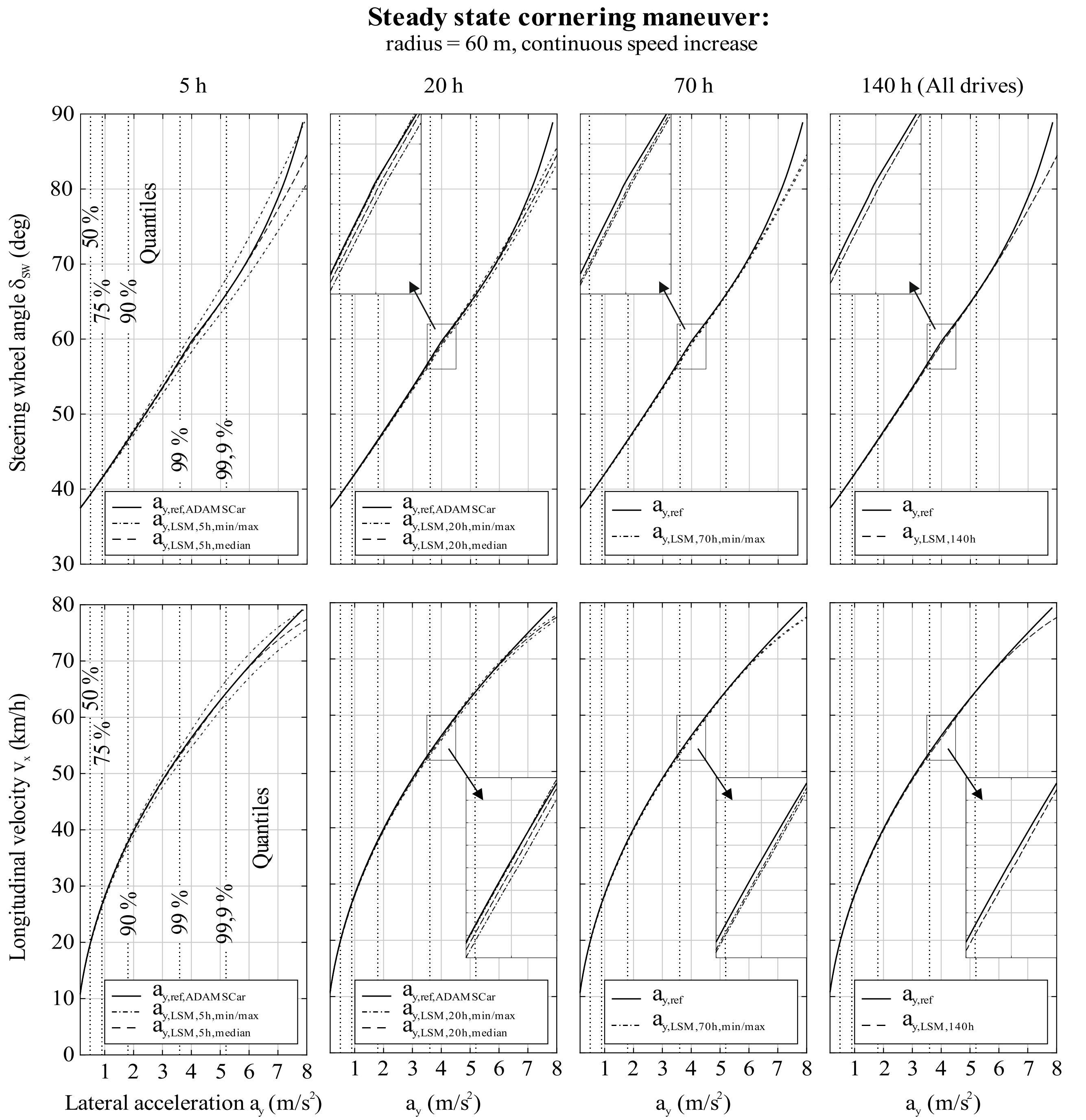


**FIGURE 8.** Validation of the lateral dynamic behavior of the identified models. Comparison of a complex multi-body model with the identified model from naturalistic driving for a steady circle cornering maneuver. The quantiles from the Fig. 2 are plotted and delimit the range for which values were measured. Consequently, valid models can only be expected for this range.

paper, the model quality can be limited by both the chosen model and the database.

70h measurement sets decrease the variation even further. The accuracy, however, compared to the reference model is only improved slightly. In summary:

- An adequate amount of data is reached after 20h to 70h measurement period.
- These data are also sufficient to model the lateral dynamics of a vehicle up to 4m/s$^2$. Beyond that limit, the data do not add much information.
- The pure driver inputs and the simulated acceleration cannot fully match measurements. There are many uncontrollable and also unmeasured influences. A more detailed analysis would be needed.

- Despite very little data processing and filtering, the identification process using large data shows robustness even with the given measurement uncertainties/noise.

## VII. CONCLUSION

This paper's proposed method is proven to work based on NDS data. Researchers can leverage this type of measurement to gain good system knowledge to build and sufficiently characterize models. The method does not demand expensive test facilities nor specific maneuvers. It will not replace existing methods or vehicle testing but can be used as an additional pattern to gain information during regular operation. OEMs can use this method to continually identify vehicles' behavior and use it for condition monitoring or to identify vehicle-specific models.

This paper demonstrates that the information needed for the identification of a vehicle dynamics model is included in everyday drives. For parameter identification purposes, the vehicle's regular sensors and everyday-drives can be used, and no additional specific test maneuvers are required. Parameters from everyday-drives therefore are an alternative option to gain dynamics information. The use of explorative studies (NDS) shifts the focus from planning and executing a study towards data analysis. This leads to new challenges during the identification process.

In extension to previous work, the analysis of captured information related to the identification task was investigated in particular. It could be shown that captured data, collected over a few hours of daily driving, is enough to reach an adequate database for further identification. Further measurements add very little new information. Dynamics boundaries (such as Kamm's circle) can be used when looking at the adequacy of data. The hypothesis of decreasing information growth in the database over time can additionally be confirmed using the derived model and modeled quantities such as the identified *EGs*. The values increasingly converge and only with great effort minimal change can be obtained. The user must be aware that in everyday driving, highly dynamic vehicle behavior is very rare. This is a limitation of the study design and thus, for the identification task.

Additionally, this paper shows what the sufficiency of the data means with respect to a vehicle dynamics model. For any of these considerations, an understanding of what measurements are possible is key to further steps. Using a vehicle for regular everyday drives will most certainly not enable lateral acceleration measurements beyond a certain point. At the same time the proposed method has proven to be robust. Even with many uncertainties and noise during the measurement, a high-quality model for vehicle dynamics can be reached. Regardless of which data set is used, very similar results were reached. Additionally, the identified model is valid within defined limits. The data are therefore sufficient for this purpose.

The method proved to have great potential using data from everyday drives for dynamics model identification. It is not limited for parameter identification of physical models but can also be used for modeling of data-driven approaches. The presented method shows which vehicle dynamic information are contained in the data and which model quality can be expected with data-driven models.

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