Nonlinear Identification of Vehicle's coupled Lateral and Roll Dynamics

Houssem Abdellatif, Bodo Heimann, Juergen Hoffmann

Abstract— **The implementation and design of modern car dynamics controller or driver assistance systems require suitable as well as high accurate dynamics models. The Parameters of such models are generally unknown and have to be identified and used to design the controller systems. This paper presents a vehicle's model, by removing conventional simplification and coupling the lateral and roll car dynamics. The resulting Model is high nonlinear in its parameters, thus the methods of nonlinear optimization are used for its identification. The sensitivity analysis in frequency domain is used to improve the convergence of the algorithms. The application of the developed technique on experimental data demonstrates the accuracy of the considered model, as well as the successful implementation of the identification method.**

Keywords— **Vehicle Dynamics, Vehicle Control, Identification, Nonlinear Optimization, Sensitivity Analysis.**

I. Introduction

In the sector of transportation and highway, several programs have been developed over the last few years by taking advantages of recent technologies in mechatronics and computer science. The aim of these programs, such ESP (Electronic Stability Program) or X-by-Wire Systems, is to increase the passenger safety and to improve the dynamic behaviour of transportation systems. The driver assistance systems are generally real-time and embedded controller, which are designed in subject to the vehicle's dynamics models. It's obvious that the quality and efficiency of the whole program depends on the accuracy of the related models and the precision of their parameter estimation. The two last mentioned requirements are the subject of this paper. The related research occurs within the scope of a cooperation between the Volkswagen AG and the hannover center of mechatronics.

Majority of previous research on vehicle motion control or vehicle model identification were based on either strictly lateral [2], [8], [14] or strictly roll [1], [15], or pure longitudinal [1] dynamics models. It is known, however, that the vehicle dynamics are not independent in those directions. It was shown in [14], that the identification of pure lateral dynamics model yields inconsistent and operating point dependent model parameters. Other very recent works focused on coupling the longitudinal with the lateral motion [3], [11]. The importance of coupling the roll and lateral dynamics for the purpose of motion controller's design were demonstrated in [5] and [9].

In section II we present a vehicle dynamics model, which is based on coupling the lateral and roll DOF's over the tire's slip angels. We remove several conventional simplification on vehicle dynamics, such stationary tire behaviour and the bicycle model assumption.

In respect to the identification, the study of the model's identifiability and sensitivity follows in section III. This study occurs by analyzing the sensitivity functions and the transformation of the jacobi-matrices in the frequency domain. The identification methodology is presented in section IV. Its successful application to measurements of two car types are then illustrated in section V

II. Vehicle Dynamics Model

As mentioned in the introduction, many studies on vehicle's model identification assume wide model simplification [2], [3], [12]. In this chapter we will remove some of those assumptions and present a more complex dynamics model for vehicle's motion.

A. Tire Dynamics

Most common tire model for lateral forces considers a linear stationary relation between the lateral tire force F_y and the slip angle α: $F_y = c_\alpha \alpha$, where c_α is the tire cornering stiffness. It is known, that this assumption is valid only for slow changing slip angles [6]. Thus a dynamic tire model has to be considered, in order to design a suitable controller for critical driving situations, at high steering frequencies. The following figure describes such a model.

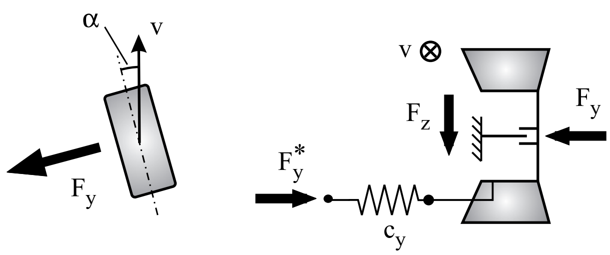

Fig. 1. dynamic tire model

The definition of a tire lateral stiffness c_y yields the following differential equation for the nonstationary lateral force:

$$\dot{F}_y + \frac{c_y}{c_\alpha} v F_y = c_y v \alpha \tag{1}$$

one obtains two tire's parameters, which have lately to

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be identified: the cornering stiffness c_α and the tire delay constant $l_T = \frac{c_\alpha}{c_y}$

B. Roll Dynamics

The roll dynamics of vehicle has been studied in many literature with varying complexity. For the purpose of controller design, models have to be simple and accurate as possible. For lateral dynamics identification and control, it is important to consider also the roll dynamics, since both are coupled in reality [5], [14]. The schematic model is shown in figure 2. One distinguishes the sprung mass m_a from the masses of front and rear axis m_{uf} and m_{ur}.

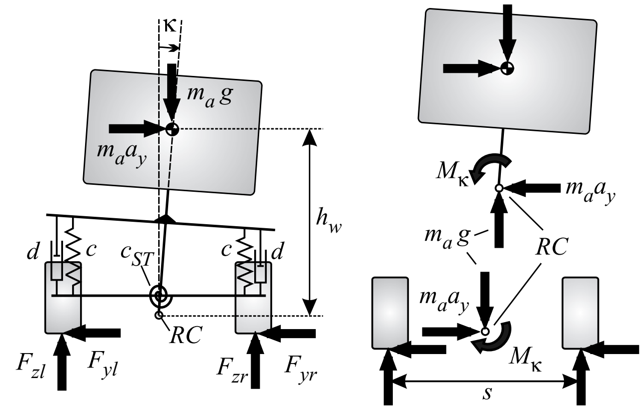

Fig. 2. roll dynamics

m_a is suspended on four damper-, four spring- and two stabilisator- devices. The dynamic equation of the roll motion is then :

$$J_\kappa \ddot{\kappa} + (d_f + d_r)\dot{\kappa} + (c_{STf} + c_{STr} + c_f + c_r)\kappa = m_a h_w a_y \quad (2)$$

with the damping constants:

$$d_f = \frac{s^2}{4}(d_{fl} + d_{fr}), d_r = \frac{s^2}{4}(d_{rl} + d_{rr}), \quad (3)$$

the spring's roll stiffness:

$$c_f = \frac{s^2}{4}(c_{fl} + c_{fr}), c_r = \frac{s^2}{4}(c_{rl} + c_{rr}), \quad (4)$$

Summarizing the terms in the equations yields the following simple differential motion equation of the vehicle's roll dynamics:

$$J_\kappa \ddot{\kappa} + d_\kappa \dot{\kappa} + c_\kappa \kappa = m_a h_w a_y \quad (5)$$

where suffixes f, r, l, r represent respectively front, rear, left and right. Variables and Parameters in these and subsequent equations are defined in Table I.

C. Lateral Dynamics

The dynamics equations of motion in terms of lateral acceleration a_y and yaw velocity $\dot{\psi}$ can be written as

$$m a_y = F_{y,fl} + F_{y,fr} + F_{y,rl} + F_{y,rr} \quad (6)$$

$$J_z \ddot{\psi} = -l_f(F_{y,fl} + F_{y,fr}) + l_r(F_{y,rl} + F_{y,rr}) \quad (7)$$

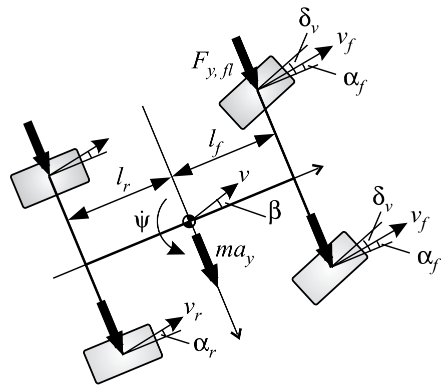

Fig. 3. lateral dynamics

The system input is the steering wheel's angle δ_H. Considering the gear-ratio i_s and with the assumption of small resulting front wheel's angle $\delta_v = \delta_H \cdot i_s^{-1}$ and also small slip angles α_f, α_r and β, the lateral forces can be obtained from the tire dynamics model (equation 1). After building the time derivatives of lateral acceleration and the yaw velocity, the lateral dynamics can be described by the following differential equations:

$$\begin{aligned} m\dot{a}_y &= -\tfrac{v}{l_{T,f}}(F_{y,fl} + F_{y,fr}) - \tfrac{v}{l_{T,r}}(F_{y,rl} + F_{y,rr}) \\ &\quad + c_{\alpha f}\tfrac{v}{l_{T,f}}\alpha_f + c_{\alpha r}\tfrac{v}{l_{T,r}}\alpha_r \end{aligned} \quad (8)$$

$$\begin{aligned} J_z \tfrac{d^3}{dt^3}\psi &= \tfrac{v l_f}{l_{T,f}}(F_{y,fl} + F_{y,fr}) - \tfrac{v l_r}{l_{T,r}}(F_{y,rl} + F_{y,rr}) \\ &\quad - c_{\alpha f}\tfrac{v l_f}{l_{T,f}}\alpha_f + c_{\alpha r}\tfrac{v l_r}{l_{T,r}}\alpha_r \end{aligned} \quad (9)$$

D. coupled models

The coupling of lateral and roll dynamics can be achieved by considering the vertical tire forces and their relation to the lateral ones. This yields however an escalation of the model complexity, which is desired neither in terms of identification nor in respect to control design. Another physical effect can hence be used for this purpose. In fact the roll motion contributes to the scaling down of the tire slip angles:

$$\begin{aligned} \alpha_f &= \delta_v - \tfrac{l_f}{v}\dot{\psi} - \beta - \tfrac{h_w}{v}\dot{\kappa} \\ \alpha_r &= \tfrac{l_r}{v}\dot{\psi} - \beta - \tfrac{h_w}{v}\dot{\kappa} \end{aligned} \quad (10)$$

The substitution of eq. 10 in eq. 8 and eq. 9 yields a high coupled differential equation system. Here is the example for eq. 9:

$$\begin{gathered} J_z \tfrac{d^3}{dt^3}\psi - (c_{\alpha f}\tfrac{l_f^2}{l_{Tf}} + c_{\alpha r}\tfrac{l_r^2}{l_{Tr}})\dot{\psi} - \\ (c_{\alpha f}\tfrac{l_f}{l_{Tf}} + c_{\alpha r}\tfrac{l_r}{l_{Tr}})(v_y + h_w\dot{\kappa}) = -c_{\alpha f} v \tfrac{l_f}{l_{Tf} i_s}\delta_H \\ v\tfrac{l_f}{l_{T,f}}(F_{y,fl} + F_{y,fr}) - v\tfrac{l_r}{l_{T,r}}(F_{y,rl} + F_{y,rr}) \end{gathered} \quad (11)$$

TABLE I

PARAMETERS AND VARIABLES

J_z	yaw inertia	J_κ	roll Inertia
l_{Tf}	front delay	$c_{\alpha f}$	front stiffness
l_{Tr}	rear delay	$c_{\alpha r}$	rear stiffness
c_κ	roll stiffness	d_κ	roll damping
ψ	yaw angle	a_y	lat. accel.
κ	roll angle	β	vehicle slip

III. Model Identifiability and Sensitivity

The study of the identifiability and sensitivity is the first step of the identification procedure. It informs, whether the planned measurements will contain enough information for the estimation of the parameter vector $\mathbf{p}$. In the view of the model complexity, the vehicle dynamics are subsequently considered in frequency domain. In this chapter, an identifiability study is briefly presented. The following sensitivity analysis allows to determine the effects of parameter, and parameter changes on the model's response in frequency domain.

A. *model identifiability*

Identifiability is a property of parametrization assuming that there is a unique *a priori* system representation independently of the experimental data [3], [4]. There are several methods for such a study. In [3] the identifiability of the lateral dynamics sub-model was proved by using the Taylor series approach [4]. Subsequently the Laplace transform approach is used to prove the identifiability of the roll dynamics sub-model. The transfer function $\frac{\kappa(s)}{a_y(s)}$ in its canonial form is:

$$\frac{\kappa(s)}{a_y(s)} = H_r(s, \mathbf{p}) = m_a h_w \frac{J_\kappa^{-1}}{s^2 + \frac{d_\kappa}{J_\kappa}s + \frac{c_\kappa}{J_\kappa}} \tag{12}$$

With the known roll height h_w and sprung mass m_a, it is easily to prove, that the set of equations binding the canonial form of the transfer function with the unknown model parameter has a unique solution. Thus the model is structurally globally identifiable. The identifiability (at least local) of the whole coupled dynamics model can be also easily proved by a numerical local approach proposed in [4]. It consists into, producing fictitious data by simulating the model with a nominal value of the parameter vector. If the Estimation of the parameters by using a second-order optimization method leads to stable results, then the model is at least structurally locally identifiable.

B. *sensitivity study*

The effects of parameter and parameter changes on the response of the model can be determined by investigating the sensitivity matrix (or functions). Due to the complexity of the differential equations and the dependency of the system's response on different steering frequencies, it's reasonable to consider the system sensitivity in frequency domain. One consider the state vector:

$$\mathbf{x} = \left[\begin{array}{ccc} a_y & \dot{\psi} & \kappa \end{array}\right]^{\mathrm{T}} \tag{13}$$

and the parameter vector

$$\mathbf{p} = \left[\begin{array}{cccccccc} J_z & l_{Tf} & l_{Tr} & c_{\alpha f} & c_{\alpha r} & J_\kappa & d_\kappa & c_\kappa \end{array}\right]^{\mathrm{T}} \tag{14}$$

The sensitivity matrix is defined as:

$$\mathbf{S} = \frac{\partial \mathbf{x}}{\partial \mathbf{p}} \quad , \quad S_{ij} = \frac{\partial x_i}{\partial p_j} \tag{15}$$

By considering the relation

$$\dot{s}_{ij} = \frac{d}{dt}\left(\frac{\partial_{x_i}}{\partial_{p_j}}\right) = \frac{\partial}{\partial_{p_j}}\left(\frac{d}{dt}x_i\right) \tag{16}$$

one can deduce the differential equations of the sensitivity s_{ij} by differentiating the state differential equations and initial conditions with respect to the parameters (witch are set to zero) and changing the order of differentiation [4]. The laplacian transformation leads then to the transfer function in respect to the model input δ_H:

$$(H)_{s,ij} = \frac{\mathcal{L}(s_{ij})}{\mathcal{L}(\delta_H)} \tag{17}$$

since the system input is supposed to be independent on model parameters. This procedure is shown for the example of the sensitivity functions s_{36}, s_{37} and s_{38} of the roll angle κ in respect to the parameters J_κ, d_κ and c_κ. The differential equations are:

$$\begin{aligned} J_\kappa \ddot{s}_{36} + d_\kappa \dot{s}_{36} + c_\kappa s_{36} &= -\ddot{\kappa} \\ J_\kappa \ddot{s}_{37} + d_\kappa \dot{s}_{37} + c_\kappa s_{37} &= -\dot{\kappa} \\ J_\kappa \ddot{s}_{38} + d_\kappa \dot{s}_{38} + c_\kappa s_{38} &= -\kappa \end{aligned} \tag{18}$$

The transfer function of the roll angle in respect to the steering angle $H_\kappa(s) = \frac{\kappa(s)}{\delta_H(s)}$ is already known form the motion equations. The transfer functions of the sensitivity functions of equation (18) can be formulated as:

$$\begin{aligned} s_{36}(s) &= -\frac{s^2}{J_\kappa s^2 + d_\kappa s + c_\kappa} H_\kappa(s) \cdot \delta_H(s) \\ s_{37}(s) &= -\frac{s}{J_\kappa s^2 + d_\kappa s + c_\kappa} H_\kappa(s) \cdot \delta_H(s) \\ s_{38}(s) &= -\frac{1}{J_\kappa s^2 + d_\kappa s + c_\kappa} H_\kappa(s) \cdot \delta_H(s) \end{aligned} \tag{19}$$

The computation of the sensitivity functions seems to require higher model order. All the algebraic equations (e.g. equation 18) have the same homogeneous form, so that actually the computation can be considerably simplified [4]. The Figures 4, 5 and 6 show the resulting 24 sensitivity functions in frequency domain. The pictured functions are normalized with respect to the maximum of each amplitude.

The computed "Gain Response" of the sensitivity functions informs about the effects of parameter uncertainty on the system output at a given steering frequency. Changes of the moment of inertia J_κ, for e.g. would have more influence in the range of fast steering maneuvers. Besides the analysis could help to inform about the optimal frequency range, where the identification of the parameters can be performed.

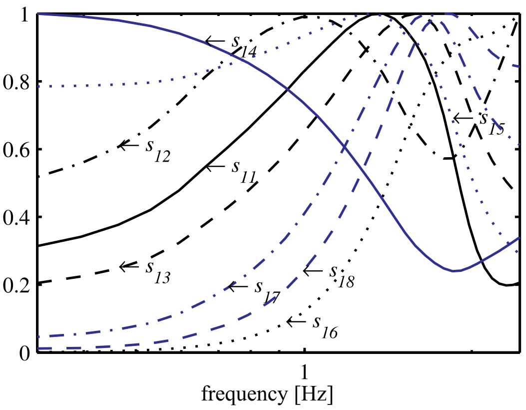

Fig. 4. The sensitivity functions $\frac{\partial a_y}{\partial p_j}$ in frequency domain

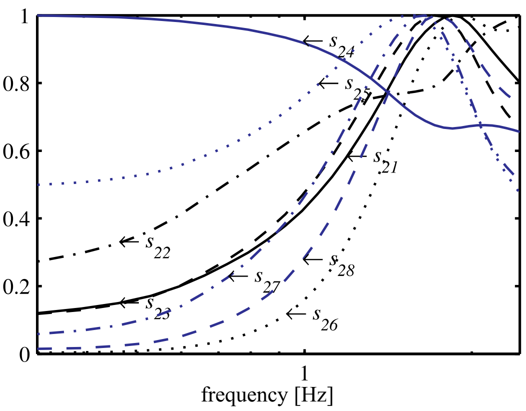

Fig. 5. The sensitivity functions $\frac{\partial \dot{\psi}}{\partial p_j}$ in frequency domain

IV. The Identification Technique

Since the considered dynamics model is nonlinear in its parameter,a nonlinear least square problem is formulated for its identification. The following loss function is considered:

$$\mathbf{I}(\mathbf{p}) = f^{\mathrm{T}} \mathbf{Q} f \tag{20}$$

where f is a vector of the three nonlinear functions $f(l, \mathbf{p})$, which describe the errors between measured and estimated data (obtained from the dynamics model). The data consists respectively in the lateral acceleration a_y, the yaw velocity $\dot{\psi}$ and the roll angle κ. $\mathbf{Q}$ is a diagonal weight matrix, whose coefficients are determined with regard to the sensitivity functions. The minimization of the loss function yields the estimated parameter vector $\hat{\mathbf{p}}$. The principle of the identification procedure is depicted in figure 7.

The used technique is a trust region method for nonlinear optimization [12], [4], since the functions $f(l)$ are not available analytically. For this purpose, the formulation of the hessian matrix $\mathbf{H}$ of the loss function is needed. The entries of this matrix with respect to parameter i are:

$$H_{ij} = \frac{\partial^2 \mathbf{I}(\mathbf{p})}{\partial p_i \partial p_j} = 2 \sum \left(\frac{\partial f(l)}{\partial p_i} \frac{\partial f(l)}{\partial p_j} + f(l) \frac{\partial^2 f(l)}{\partial p_i \partial p_j}\right) \tag{21}$$

By taking the jacobian $\mathbf{J}$ of the nonlinear function vector

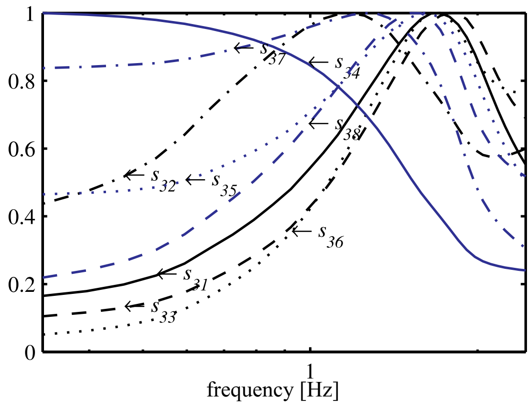

Fig. 6. The sensitivity functions $\frac{\partial \kappa}{\partial p_j}$ in frequency domain

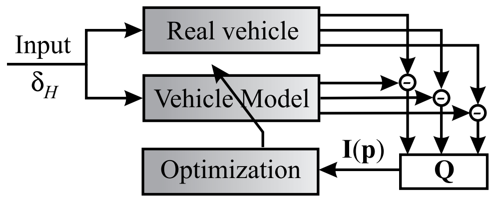

Fig. 7. Model's identification with optimization

f, the Hessian of the loss function becomes:

$$\mathbf{H} = 2\mathbf{J}^{\mathrm{T}}\mathbf{J} + 2 \sum \left(f(l) \frac{\partial^2 f(l)}{\partial p_i \partial p_j}\right) = 2\mathbf{J}^{\mathrm{T}}\mathbf{J} + 2\mathbf{S}^{2nd} \tag{22}$$

where $\mathbf{S}^{2nd}$ is a second order sensitivity matrix. Since no statement can be met about $\mathbf{S}^{2nd}$, its computation becomes necessary. This can be reached by implementing appropriate approximation or using a universal Newton method [12]. The optimization algorithm is then derived from the formulation of the general Newton method by:

$$\mathbf{p}_k = \mathbf{p}_{k-1} - (\mathbf{J}_{k-1}^{\mathrm{T}} \mathbf{J}_{k-1} + 2\mathbf{S}_{k-1}^{2nd})^{-1} \mathbf{J}_{k-1}^{\mathrm{T}} f_{k-1} \tag{23}$$

It exists several numerical methods for the computation of the inverse of the hessian matrix, such the Cholesky factorization or the formulation of a linear least squares problem [12], [4].

V. Experimental Results

In this section, the application of the proposed nonlinear identification technique on experimental data is presented and illustrated. The measurements are taken up to two vehicle types. Vehicle No. 1 is a middle class car, while vehicle No. 2 is a transporter.

A. The Data Measurement

According to the sensitivity study in section III the steering angle as system input, should cover a frequency interval up to at least 2.0 Hz. Such input is able to ensure optimal excitation of all considered model parameters, and therefore a well conditioned identification. For that reason, a frequency sweep with a target frequency of about 2.2 Hz.

is chosen as a system input. The measurements were accomplished at different constant vehicle forward velocities. This helps avoiding the influence of the longitudinal dynamics, which were not taken into account in the model.

B. Dynamics estimation

The method of nonlinear optimization was applied on the measurements. This yields the parameter vector $\mathbf{p}$ in respect to the measured vehicle. The identified parameter are presented in the following section. The comparison between the measured data of vehicle no.1 and the identified model's output at a speed of 100 km/h is illustrated in figure 8.

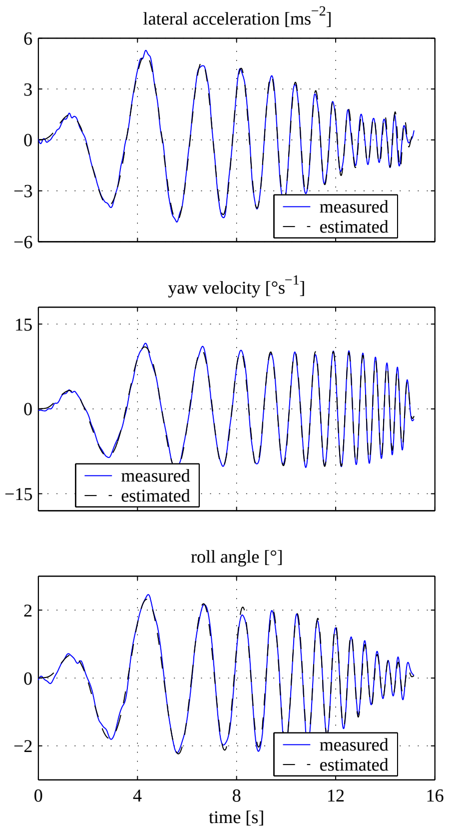

Fig. 8. comparison between measured and estimated vehicle's dynamics

As it can be seen, the identified model is capable to reproduce the measured data with high accuracy. This was approved for all considered system output and is affirmed by the comparison in frequency domain, which is shown in figure 9. In contrast to classic approaches of dynamics modeling the proposed coupled model is able to reconstruct the real vehicle's behaviour for a wide frequency range. The representation of car lateral dynamics by means of the bicycle model for e.g. is only available under strict assumptions, such as low steering frequencies and middle-ranged car speed. This is a disadvantage for designing accurate dynamics controller. The obtained good results in respect to the presented coupled model is due to focusing on accurate tire modeling. Taking account of the non stationary behaviour (equation 1) yields better reconstruction of measured data for high steering frequencies. On the other hand, the influence of the roll motion on the tire slip angles (equation 10) have augmented the model's accuracy for low driving speed.

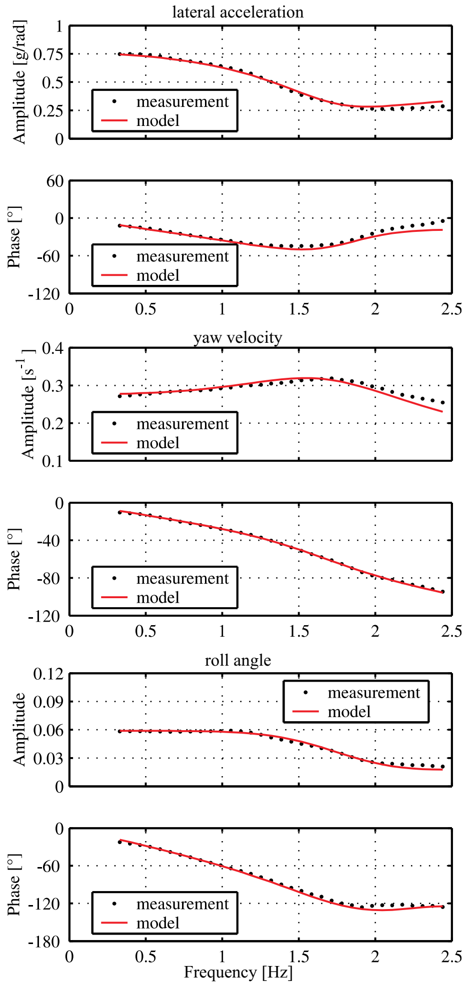

Fig. 9. comparison between the frequency response of real vehicle and the respective identified model

C. Parameter Identification

The results of the successful parameter identification for the two considered vehicles is listed in table 1. To validate the availability of the presented approaches for both dynamics modeling and identification technique, it is interesting to observe the model parameter, determined at different vehicle speed. By means of the experimental results accomplished with Vehicle No.2, we focus on the importance of considering coupled car dynamics. For this purpose, the identification procedure is executed for a coupled and a non-coupled dynamics models. The results are exemplarily depicted in figure 10 and figure 11, respectively for the yaw Inertia and rear cornering stiffness. These parameter are chosen, since they represent an important criteria for evaluating the lateral dynamics behaviour and drive stability and therefore influence the design of controller.

The results show, that ignoring the interaction between the vehicle's roll and lateral dynamics yields nonconstant

TABLE II

IDENTIFIED PARAMETERS FOR TWO VEHICLES

p_i	*unit*	vehicle no.1	vehicle no.2
J_z	[kgm^2]	2760	4820
l_{Tf}	[m]	1.01	0.48
l_{Tr}	[m]	0.56	0.81
$c_{\alpha f}$	[kN]	105.1	118.3
$c_{\alpha r}$	[kN]	174.9	205.6
J_κ	[kgm^2]	447	645
d_κ	[Ns]	590	400
c_κ	[kN]	210	822

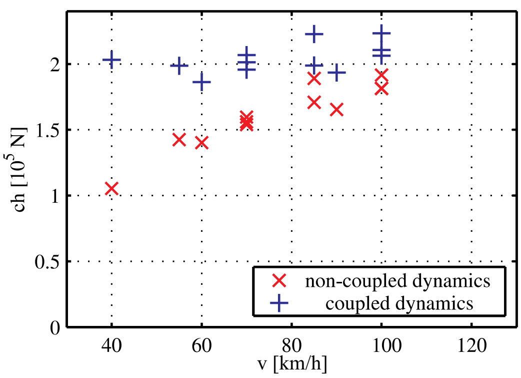

Fig. 10. identified rear cornering stiffness for coupled and non-coupled dynamics at different car speed

parameters for different operating points. This effect was observed in [14], for the identification of truck's lateral dynamics. This case occurs, for all vehicles with high center of gravity, since the roll motion contributes widely to the vehicle's behaviour and can not be therefore neglected. Non-stationary tire characteristics leads merely to better reconstruction of measured data, but not to detect roll dynamics effects. At the other hand, positive roll motion decreases tire slip angles (equation 10). The considered vehicle can then be represented by a coherent dynamics model, which is available for a wide range of speed and steering frequencies.

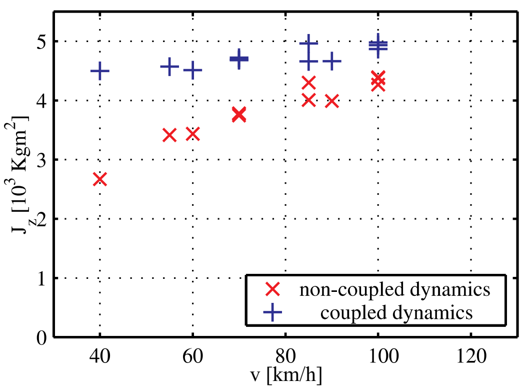

Fig. 11. identified yaw Inertia for coupled and non-coupled dynamics at different car speed

VI. Conclusions

For the purpose of controller design for car dynamics, complex dynamics have been took into account in order to reproduce accurately real vehicle's behaviour. The obtained model is high nonlinear in its parameter, thus a suitable technique for its identification has been proposed. Nonlinear optimization with nonlinear least square approach and based on the trust region methods has been successfully implemented. This procedure was adjusted according to the sensitivity study of the model. The performance of the identified model was shown by means of experimental data. The real car dynamics could been reconstructed with high accuracy, for a wide range of steering frequencies and vehicle's speed.

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