

Optimization of inverse model identification for multi-axial test rig control

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Abstract. Laboratory testing of multi-axial fatigue situations improves repeatability and allows a time condensing of tests which can be carried out until component failure, compared to field testing. To achieve realistic and convincing durability results, precise load data reconstruction is necessary. Cross-talk and a high number of degrees of freedom negatively affect the control accuracy. Therefore a multiple input/multiple output (MIMO) model of the system, capturing all inherent cross-couplings is identified. In a first step the model order is estimated based on the physical fundamentals of a one channel hydraulic-servo system. Subsequently, the structure of the MIMO model is optimized using correlation of the outputs, to increase control stability and reduce complexity of the parameter optimization. The identification process is successfully applied to the iterative control of a multi-axial suspension rig. The results show accurate control, with increased stability compared to control without structure optimization.

1 Introduction

Reliable durability testing with multi-axial servo-hydraulic systems requires precise load data reconstruction. To obtain realistic load profiles the reference (desired) data is generated in test drives recorded by measuring wheels, accelerometers and strain gauges directly located at the specimen. To attain stability, repeatability and high control accuracy in rig testing, compensation methods adapting the control inputs (Drive) of the test system are applied in an outer control loop [1]. The outer loop feedback (response data of the test system) is given by the equivalent quantities measured in the test drive. For achieving accurate control of the rig, the single hydraulic actuators are controlled by PID controllers in closed loop. This inner loop uses force or displacement feedback measured at the hydraulic cylinders. The central element of the outer control loop is given by the inverse system model, which calculates drive corrections based on the desired data and the current system response, as depicted in Fig. 1.

Frequency domain based formulations are well established and reflect the state of the art for describing inverse system models of multi-axial durability test systems [2-5]. In the end of 1990s, Raath introduced parametric time domain models for simulating test systems with multiple axis [6]. He concluded that frequency domain methods require Fast Fourier Transform (FFT) analysis and identification data measurements with longer data sequences for attaining a model of high quality compared to time domain models, which achieve comparable accuracy with shorter measurements.

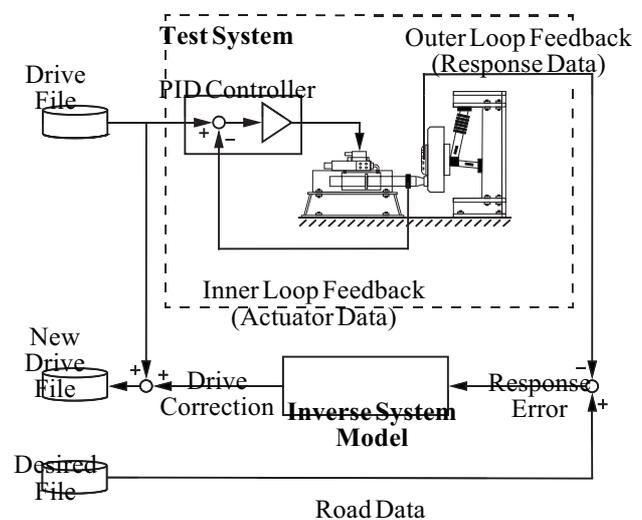


Figure 1. Servo-hydraulic test system.

In multi-axial test systems, disturbances caused by cross-talking reduce the control accuracy of the individual channels [6,7]. An inverse system model capturing all of these mechanical coupling effects is essential for precise load data reconstruction. In automotive applications, especially in axle testing, it is common that the number of response channels exceeds the number of controllable rig (Drive) channels. Despite dependencies between some of these system outputs, an accurate control of all response channels is challenging. Normally, all system outputs are considered for identification of the inverse system model. However, investigations revealed instabilities of the outer control loop, which has been overcome by assessing the

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relevance and subsequently selecting system outputs for calculating the drive corrections of the outer loop.

The following article firstly describes the general process of load data reconstruction. Subsequently, the time domain model is presented with the deviation of the model order and the structure optimization to combat the issue of instability in the outer control loop. Finally, the results of a case study comprising the laboratory load data simulation on an axle durability test rig are presented.

2 Load data reconstruction process

Load data reconstruction is generally an iterative process described in the following six steps:

- 1) First all channels of the rig are independently excited by pseudo random white noise signals. During the excitation, all inputs and system responses are recorded simultaneously.
- 2) The inverse system model is identified using the previously recorded input/output data.
- 3) All actuator drive signals are calculated by simulating the road recorded data (desired data) through the model of the inverse system.
- 4) These drive signals are applied as system inputs to the rig with simultaneous recording of the system responses.
- 5) The drive signals are updated by adding the drive correction. This drive correction is given by the simulated response error, the difference between desired and system response data.
- 6) Depending on the model quality, a number of repetitions of steps 4 and 5 are necessary to achieve accurate load data reconstruction.

3 The time domain model

The presented system description is a parametric time domain model. When applying parametric models, successful dynamical system identification is directly related to a convenient model structure. It is therefore appropriate to define model orders and structures depending on the properties of the system under consideration. In a first step, the test system will be presented for which the order and structure of the model is derived subsequently.

3.1. Laboratory test system

The considered system is a half-axle durability test rig with four servo-hydraulic actuators. The system outputs are measuring wheel forces in longitudinal y_{FX} , lateral y_{FY} and vertical y_{FZ} direction. Additional outputs are the braking moment y_{MY} and local component loads at the specimen given by the upper link y_{UL} and the track rod y_{TR} . All acting forces are applied in direction of motion using reversing levers and struts. The actuators of the longitudinal u_{FX} , lateral u_{FY} and brake moment u_{MY} channels are in force, the vertical u_{SZ} in displacement command mode. Consequently the system is of type MIMO with four controllable inputs and six outputs. All

rig channels are real-time controlled by digital servo controllers.

3.2. MIMO model decomposition

An efficient way to handle multiple input/multiple output systems is to build up separated sub-models with single output (MISO), depicted in Fig. 2.

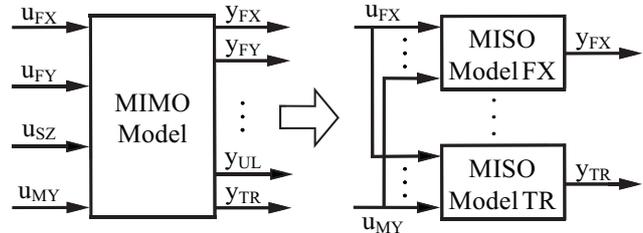


Figure 2. MIMO model decomposition.

Thus the optimization is broken down into simpler sub-problems [8], whereby effects through cross-coupling are still preserved. For each input u of the model the numerator and denominator polynomials B and F with delay operator q are learned [9]. All parameters are optimized simultaneously based on the corresponding discrete time domain models using the *prediction error method* [9]. B and F can be represented by the transfer function $G(s)$ in the Laplace domain, see Fig. 3 and Eq. 1.

$$y(t) = \frac{B(q)}{F(q)} \cdot u(t) \Leftrightarrow Y(s) = G(s) \cdot U(s) \quad (1)$$

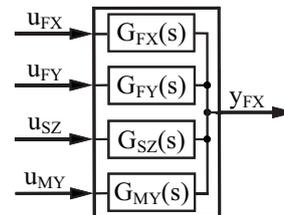


Figure 3. MISO model.

3.3. MIMO order estimation

A common way of determining model orders is to identify Autoregressive Models with Exogenous Inputs (ARX) [9] structures of different orders and choosing the most convenient one. Here the model order is estimated based on a physical model of a one degree of freedom test system, as depicted in Fig. 4. The force controlled

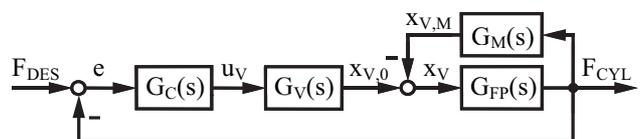


Figure 4. Signal flow diagram of a one degree of freedom system.

system consists of the PID controller $G_C(s)$ [10], a two stage servo-valve $G_V(s)$ [11], the linearized flow pressure dynamics $G_{FP}(s)$ [12] and a damped mass oscillator as a rough description of the specimen $G_M(s)$ [10]. The transfer function $G(s)$ of the one channel system with desired force input F_{DES} and actuator force F_{CYL} is given in Eq. 2.

$$G(s) = \frac{F_{CYL}(s)}{F_{DES}(s)} = \frac{G_C(s) \cdot G_V(s) \cdot G_{FP}(s)}{1 + G_C(s) \cdot G_V(s) \cdot G_{FP}(s) + G_M(s) \cdot G_{FP}(s)} \quad (2)$$

The so obtained transfer function $G(s)$ has four zeros and seven poles and gives the model order of the numerator and denominator polynomials B and F .

3.4. Inverse system modelling

The quality of the load data reconstruction is significantly depending on the quality of the inverse system model. When the system model is learned and inverted, the inverse model can become instable. To overcome this problem, the inverse system model is directly identified in this study. Therefore, system inputs become model outputs whereas system outputs become model inputs. The previously estimated model order had four zeros and seven poles. The inverse model order consequently has seven zeros and seven poles. Additionally the time-history of the recorded data has to be reversed.

3.5. Model structure optimization

Investigations revealed instabilities in the outer control loop when using all system outputs as model inputs. Fig. 7 shows the simulated system outputs for a model obtained by using all inputs compared to one using a defined subset of all inputs. The system with all inputs already diverges after one second. This is caused by destabilizing effects of model inputs that are weakly correlated with the output of the corresponding sub-model. A cross-correlation analysis determines similarities between the different system outputs y . According to Eq. 3 the cross-correlation for signals y_a and y_b with sequence length K is calculated [13]. Afterwards the correlation Φ is scaled by the product of the *root-mean square* values of y_a and y_b . The output channel relevance is rated by the maximal absolute values of the scaled correlations.

$$\Phi_{y_a, y_b}[\tau] = \frac{1}{K} \cdot \sum_{k=0}^{K-1} y_a[k] \cdot y_b[k-\tau] \quad (3)$$

The maximal absolute values of the scaled correlation with output y_{FX} (Fig. 5) reveal a high consistency between output y_{FX} and y_{TR} . According to the previous laboratory test system description, the rig design allows an interpretation between system inputs and significantly influenced outputs. For instance, the hydraulic actuator

with input u_{FX} introduces a force in the same direction as the output y_{FX} is recorded. According to Fig. 5 the determined inputs of the inverse model for calculating the drive correction of u_{FX} are given by the outputs y_{FX} and y_{TR} respectively, as used for the system identification in Fig. 7 (solid line). This process is executed in every particular iteration step for each inverse MISO model.

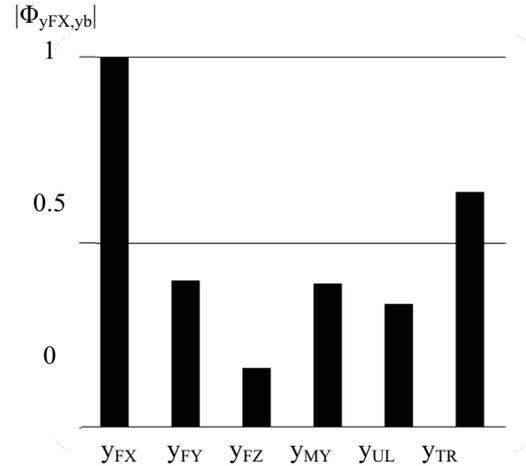


Figure 5. Correlation with output y_{FX} .

4 Case study: Load data simulation with axle test rig

4.1. Steering maneuver properties

The considered driving maneuver is characterized by a certain number of drive direction reversals without braking action. Depending on the steering angle, high load amplitudes in lateral y_{FY} and vertical y_{FZ} direction can occur while forces in longitudinal direction y_{FX} are comparable small because of the lack of braking action. Caused by mechanical couplings, an accurate rig control of the small longitudinal amplitudes is challenging.

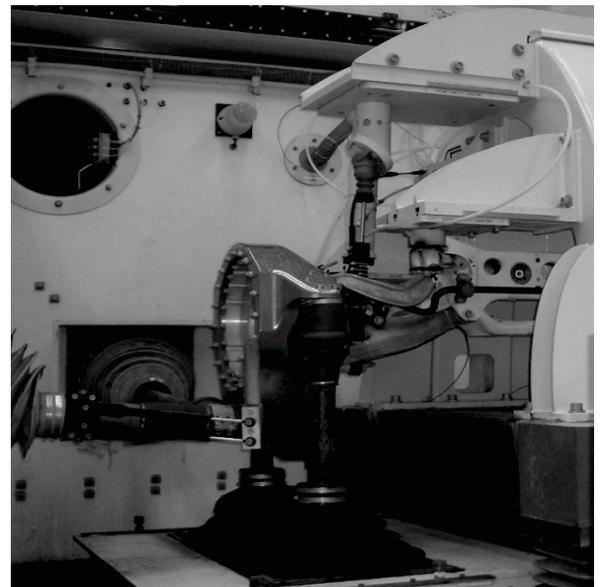


Figure 6. Axle test rig.

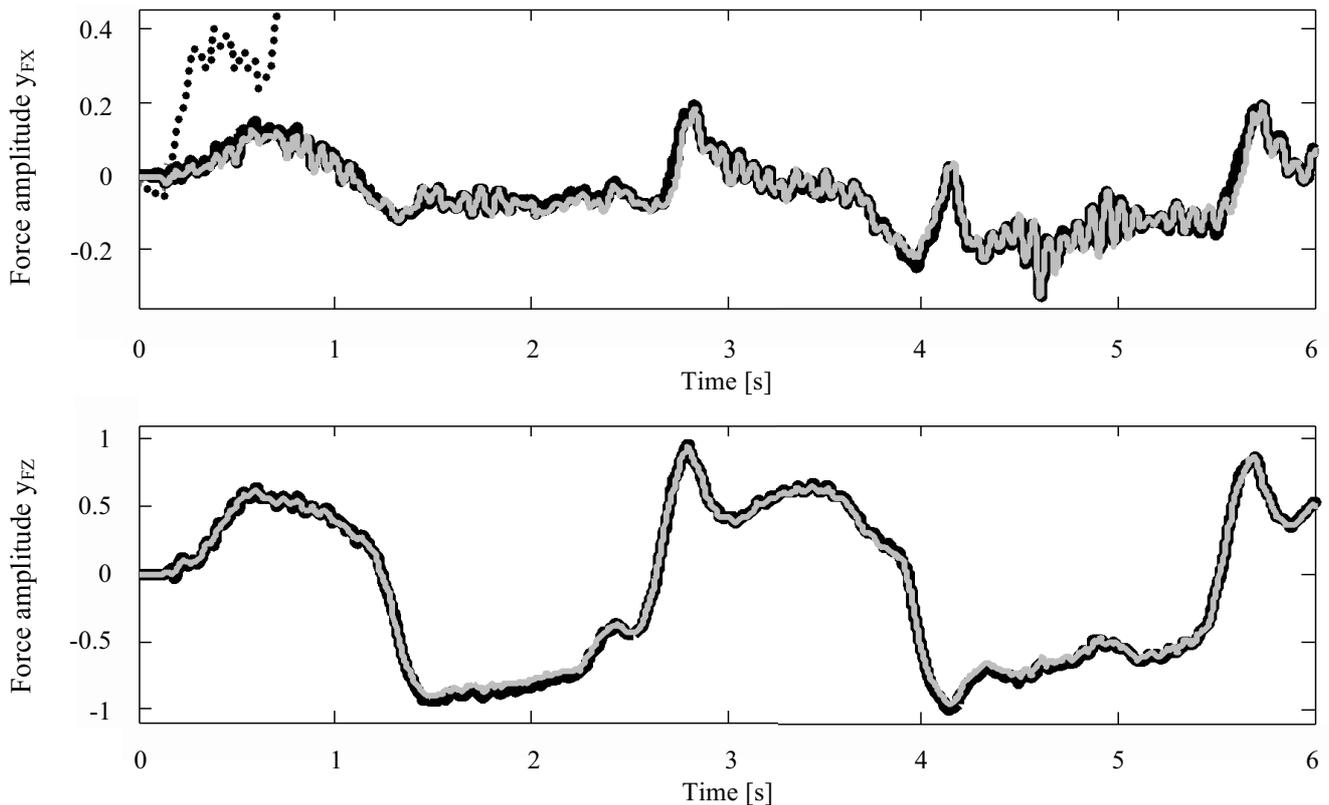


Figure 7. Comparison of road measured forces (black, solid) and laboratory simulated forces with structure optimization (gray solid) and without structure optimization (gray dotted) for system outputs y_{FX} and y_{FZ} (values scaled by the maximum of y_{FZ}).

4.2. Results

The results of the load data reconstruction for output y_{FX} and y_{FZ} are shown in Fig. 7. The signal consistency between the controlled output y_{FZ} and the measured road data is rated with a signal fit of 95.58%. Output y_{FX} is controlled with a fit value of 85.56% when performing structure optimization. In terms of taking all system outputs as model inputs to generate the drive signal u_{FX} , the outer control loop becomes instable (dotted line). All signal fits are calculated using the *normalized root mean square criterion*.

4.3. Conclusion

A multiple input/multiple output system has been identified using a parametric dynamical time domain model. The model was separated into sub-models with multiple inputs and single output. Special attention was paid to the model order estimation and the selection of relevant sub-model inputs leading to more control stability. The method was successfully applied to an axle rig case study. It revealed that structure optimization can improve model stability especially for system outputs with small amplitudes, where outputs with higher amplitude can cause high cross-talk

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