



MODELICA

Proceedings
of the 3rd International Modelica Conference,
Linköping, November 3-4, 2003,
Peter Fritzson (editor)

Angelika Peer, Naim Bajcinca, Christian Schweiger
Institute of Robotics and Mechatronics, DLR:
Physical-based Friction Identification of an Electro-Mechanical
Actuator with Dymola/Modelica and MOPS
pp. 241-248

Paper presented at the 3rd International Modelica Conference, November 3-4, 2003,
Linköpings Universitet, Linköping, Sweden, organized by The Modelica Association
and Institutionen för datavetenskap, Linköpings universitet

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Physical-based Friction Identification of an Electro-Mechanical Actuator with Dymola/Modelica and MOPS

Angelika Peer

Naim Bajcinca

Christian Schweiger

German Aerospace Center (DLR)
Institute of Robotics and Mechatronics
Oberpfaffenhofen, 82234 Weßling, Germany
<http://www.robotic.dlr.de/control/>

Abstract

An identification procedure consisting of iterative parameter optimization and model validation tasks using the optimization tool MOPS and Dymola/Modelica simulation environment is presented. This method is used for modelling of a force-feedback electro-mechanical actuator with Harmonic-Drive gear. A modelling approach for speed and torque dependent gear losses introduced in a prior work is validated.

1 Introduction

Several objectives, such as model-based control, simulation and design of complex systems require accurate system models. Especially, mechanical systems exhibit complex nonlinear phenomena, e.g. stick-slip effects, whose modelling may play an essential role in the dynamics of the whole system. Such complex modelling tasks require tools, which should provide a clear hierarchical model structure, efficient equation solvers and fast component parametrization. These requirements are e.g. fulfilled by Dymola/Modelica simulation environment. Modelica is a physical object-oriented modelling language suitable for modelling and simulation of heterogeneous multi-physical systems. It is designed in such a way, that the user can build a physical model in a natural way, as he would build it in real-world. Additionally, due to symbolical code preprocessing, Dymola/Modelica enables real-time simulation of complex physical systems, [OE00]. While the structure of a model is physically defined by Modelica, yet for modelling completion, its parameters need to be computed or identified via measurements. A convenient environment for parameter

identification is the optimization tool MOPS (Multi-Objective Parameter Synthesis), [JBL⁺02]. Multi-objective optimization is enhanced by providing robust gradient-free direct-search solvers and an intuitive user interface. Parameter optimization with MOPS is especially convenient since different measurement data can be handled simultaneously in the context of a multi-objective optimization task with respect to different criteria types (typically least-squares).

The main aim of this paper is to present an identification procedure for accurate modelling in the example of an electro-mechanical actuator. Therefore an identification feedback-loop consisting of iterative parameter optimization and model validation tasks. While the latter is performed in a Dymola/Modelica simulation environment, the parameter optimization is done in MOPS.

A natural way of a parameter identification task is to split it in subtasks by discriminating between different physical conditions, which primarily excite a certain parameter subset. This paper uses this strategy for separate identification of linear stiffness, damping and inertia, as well as, non-linear bearing- and mesh-friction parameters. Thereby, a modelling formalism for gear friction as proposed in [PSO02] has been used. The latter work introduces a tabular description of friction (loss table), which includes speed- and torque-dependent gear losses terms, i.e. bearing- and mesh-friction parameters for braking and driving gear conditions. While carrying out of physical conditions needed to measure the loss table sets great demands on technical equipment, in this paper it is shown that identification is an effective alternative.

The paper is organized as follows. In the next section the electromechanical force-feedback actuator is

introduced. Section 3 describes the identification loop with MOPS and Dymola/Modelica. Section 4 provides the identification of a linear actuator model, including the Dymola/Modelica actuator scheme and linear parameter identification with MOPS. Section 5 recalls the modelling approach of gear losses as proposed in [PSO02], which has been further used to extend the linear model by inclusion of nonlinear gear losses. Finally, concluding remarks and future related work complete the paper.

2 Actuator physical description

This chapter provides the physical description of an electro-mechanical actuator, see Fig. 1 and Fig. 2, which has been used in a steer-by-wire control structure for force-feedback. In order to avoid rotating wiring a strain-gauge torque sensor is placed between the motor housing and a fixed console, as shown in the figure. Thus, in addition to the torque at the output shaft, a dynamical component resulting from housing rotation is measured, as well.

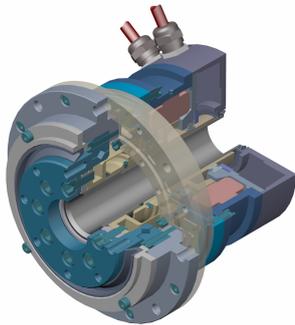


Figure 1: The force-feedback actuator

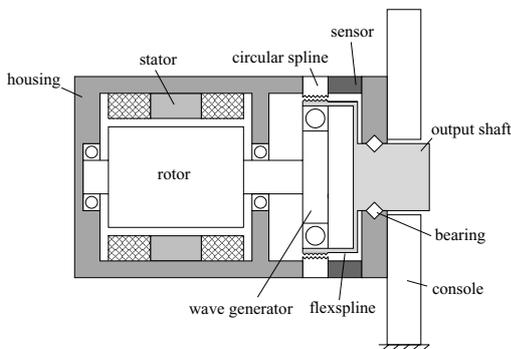


Figure 2: Force-feedback actuator components

Besides the torque sensor, the main component in the force feedback actuator is a Harmonic Drive series hollow-shaft gear. In Fig. 3 its main components, Wave Generator, Flexspline and Circular Spline are shown. The teeth on the nonrigid Flexspline and the rigid Circular Spline are in continuous engagement. Since the Flexspline has two teeth fewer than the Circular Spline, one revolution of the input causes relative motion between the Flexspline and the Circular Spline equal to two teeth. With the Circular Spline rotationally fixed, the Flexspline rotates in the opposite direction to the input at a reduction ratio equal to one-half the number of teeth on the Flexspline. Typical characteristics of a Harmonic-Drive gear are high positioning accuracy, virtually no backlash, periodic torque ripples and a high gear ratio. One of the main topics of this paper is modelling of friction losses of this gear using Modelica.

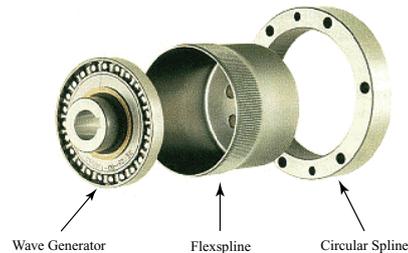


Figure 3: Harmonic Drive gear components

3 Parameter identification with Dymola/Modelica and MOPS

Modelica is an object-oriented language for modelling of large, complex and heterogeneous multi-physical systems involving mechanical, electrical and hydraulic subsystems. The engineer can build its model in a fraction-by-fraction manner, as he would build it in real-world, that is link components like motors, pumps and valves using their physical interfaces. Such a simulation framework is very convenient to use in an identification feedback-loop consisting of parameter optimization and simulation tasks, as shown in Fig. 4. Thereby, one can perform parameter identification of specific components or/and of specific physical conditions independently and integrate them easily in the next identification setup. The insight into physical system is important for decoupling of different physical conditions which primarily excite a known set of parameters. Note that using Modelica for physical sim-

ulation may be indispensable for complex systems, since a signal-flow simulation model may be essentially influenced by additional physical fractions.

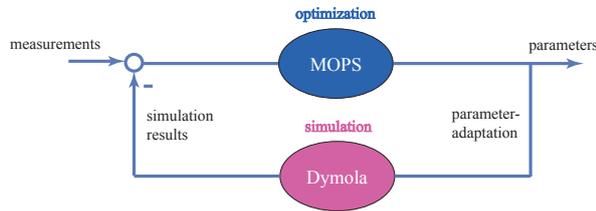


Figure 4: Identification loop

The parameter optimization in the fraction-by-fraction identification procedure is done using the optimization tool MOPS (Multi-Objective Parameter Synthesis), [JBL⁺02]. Basically, MOPS provides a multi-objective optimization environment for the design of systems with a large amount of parameters and criteria, but it may be used equally well for parameter estimation in identification problems. The multi-criteria optimization problem in MOPS is handled by reformulating it as a standard Nonlinear Programming Problem (NLP) with equality, inequality and bound constraints. MOPS uses several available gradient-free direct-search solvers, which are more robust compared to though more efficient gradient-based solvers. These include algorithms such as sequel quadratic programming (SQP), Quasi-Newton, pattern search, simplex method and genetic algorithms. To overcome the problem of local minima to some extent, solvers based on statistical methods or genetic algorithms can be alternatively used. An identification problem may be formulated as a multi-objective optimization problem, whereby measured data corresponding to different physical conditions or/and inputs define a set of optimization objectives. Different scalar or/and vector criteria may be defined, e.g least-square-error, error-vector, etc.

4 Linear model

4.1 Actuator Modelica Model

Fig. 5 represents a Modelica modelling setup of the electro-mechanical actuator. Since a Harmonic-Drive gear can be classified as a typical sun-carrier-ring planetary gear (Wave Generator corresponding to the sun, Circular Spline to the carrier and Flexspline to the ring), a planetary gear component from the Modelica

rotational mechanics library has been used for its modelling. The torque balance and angular equations of Harmonic-Drive are modelled as follows,

$$\begin{aligned}\tau_C &= (n-1)\tau_W \\ \tau_F &= -n\tau_W \\ \Phi_W &= (1-n)\Phi_C + n\Phi_F,\end{aligned}\quad (1)$$

with

τ_C : torque at the Circular Spline

τ_F : torque at the Flexspline

n : gear ratio

Φ_C : Circular Spline angle

Φ_F : Flexspline angle.

Note that in the linear model the losses of this component are neglected.

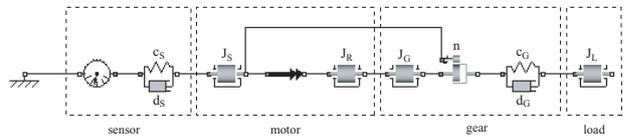


Figure 5: Linear physical model of the actuator

The following listing introduces the physical description of the setup parameters.

n : gear transmission ratio

J_L : gear output inertia

d_s : sensor damping

c_s : sensor stiffness

d_g : gear damping

c_g : gear stiffness

J_R : rotor inertia

J_S : stator (housing) inertia.

4.2 Parameter identification

Two different physical conditions are respectively discriminated for parameter identification of the linear and nonlinear actuator model. In the linear model the friction losses in Harmonic-Drive gear are neglected. In order to match the physical model as close as possible to such a linear one, the non-linear effects excited on Harmonic-Drive gear are minimized by fixing the output shaft.

With the output shaft keeping fixed, load inertia, J_L in Dymola/Modelica model in Fig. 5 has no dynamical effect. While several parameters, such as Harmonic-Drive gear ratio ($n = 50$), the *emf* motor constant ($K_m = 0.7 \text{ Nm/rad}$), torque sensor stiffness ($c_s = 130000 \text{ Nm/rad}$) and Flexspline stiffness ($c_g = 25500 \text{ Nm/rad}$) are given by the manufacturer, the rest

of parameters, i.e. sensor damping (d_S), motor housing inertia (J_S) and Flexspline damping (d_G) need to be identified. Their initial values for optimization are set to reasonable values estimated by some simple experiments,

$$\begin{aligned} d_S &= 0.6 \text{ Nm s/rad}, \\ J_S &= 0.003 \text{ kgm}^2, \\ d_G &= 50 \text{ Nm s/rad}. \end{aligned}$$

Thereby, as input data in Fig. 4 are used measurements corresponding to a set of current inputs (step, sinusoidal and PRBS) of different amplitudes and frequencies and torque response is measured by the sensor. After 18 successive iterations of the identification feedback-loop in Fig. 4, the parameter values listed below result,

$$\begin{aligned} d_S &= 2.66 \text{ Nm s/rad}, \\ J_S &= 0.003039 \text{ kgm}^2, \\ d_G &= 70.625 \text{ Nm s/rad}. \end{aligned}$$

The respective optimization history is shown in Fig. 6. Further in Fig. 7 several validation results for different input and measurement data are collected.

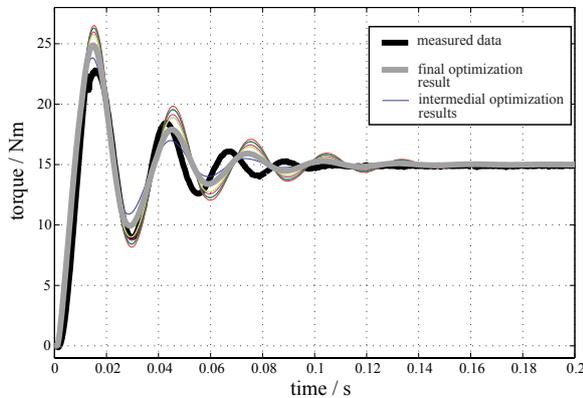


Figure 6: Optimization step response history of linear model

5 Nonlinear model

5.1 Gear losses

The nonlinear model of Harmonic-Drive Gear used in this paper is based on the friction modelling approach proposed in [PSO02]. Therefore, the gear model implemented in component `Lossy Planetary` of

the Modelica Power Train library includes a torque-dependent (due to mesh friction in the gear teeth contact) and speed-dependent friction (due to bearing friction). Similar to the standard Modelica friction model, the three modes *forward sliding*, *stuck* and *backward sliding* are available. The friction torque $\Delta\tau$ for the sliding modes is given by Table 1, whereby τ_W denotes the driving torque, τ_{bf} the bearing friction and η_{mf} the mesh friction coefficient.

ω_W	τ_W	$\Delta\tau =$
> 0	≥ 0	$(1 - \eta_{mf1}) \tau_W + \tau_{bf1} \quad (= \Delta\tau_{\max 1} \geq 0)$
> 0	< 0	$(1 - 1/\eta_{mf2}) \tau_W + \tau_{bf2} \quad (= \Delta\tau_{\max 2} \geq 0)$
< 0	≥ 0	$(1 - 1/\eta_{mf2}) \tau_W - \tau_{bf2} \quad (= \Delta\tau_{\min 1} \leq 0)$
< 0	< 0	$(1 - \eta_{mf1}) \tau_W - \tau_{bf1} \quad (= \Delta\tau_{\min 2} \leq 0)$

Table 1: $\Delta\tau = \Delta\tau(\omega_W, \tau_W)$ in sliding mode

It can be shown, that the linear torque equations in (1) are extended by the friction component, $\Delta\tau$ as follows,

$$\begin{aligned} \tau_F &= -n(\tau_W - \Delta\tau) \\ \tau_C &= (n - 1)\tau_W - n\Delta\tau. \end{aligned} \quad (2)$$

The typical relationship between τ_W and $\Delta\tau$ is illustrated in Fig. 8 for both the sliding and the stuck mode and in combination in Fig. 9.

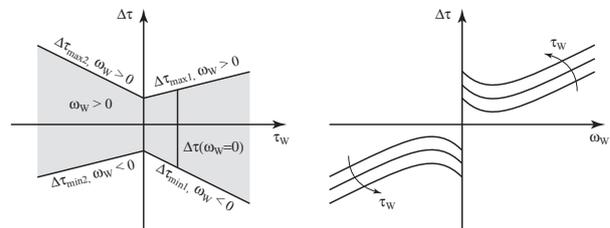


Figure 8: friction torque in sliding and stuck mode

The parameters to be provided are the stationary gear ratio n and table `lossTable` to define the gear losses, see Table 2.

Whenever η_{mf1} , η_{mf2} , τ_{bf1} or τ_{bf2} are needed, they are determined by interpolation in `lossTable`. The interface of this Modelica model is therefore defined as

```
parameter Real i = 1;
parameter Real lossTable[:,5]
    = [0, 1, 1, 0, 0];
```

using the unit gear ratio and no losses as a default.

5.2 Parameter Identification

This section deals with identification of the `lossTable` in Table 1. For mesh friction, it is

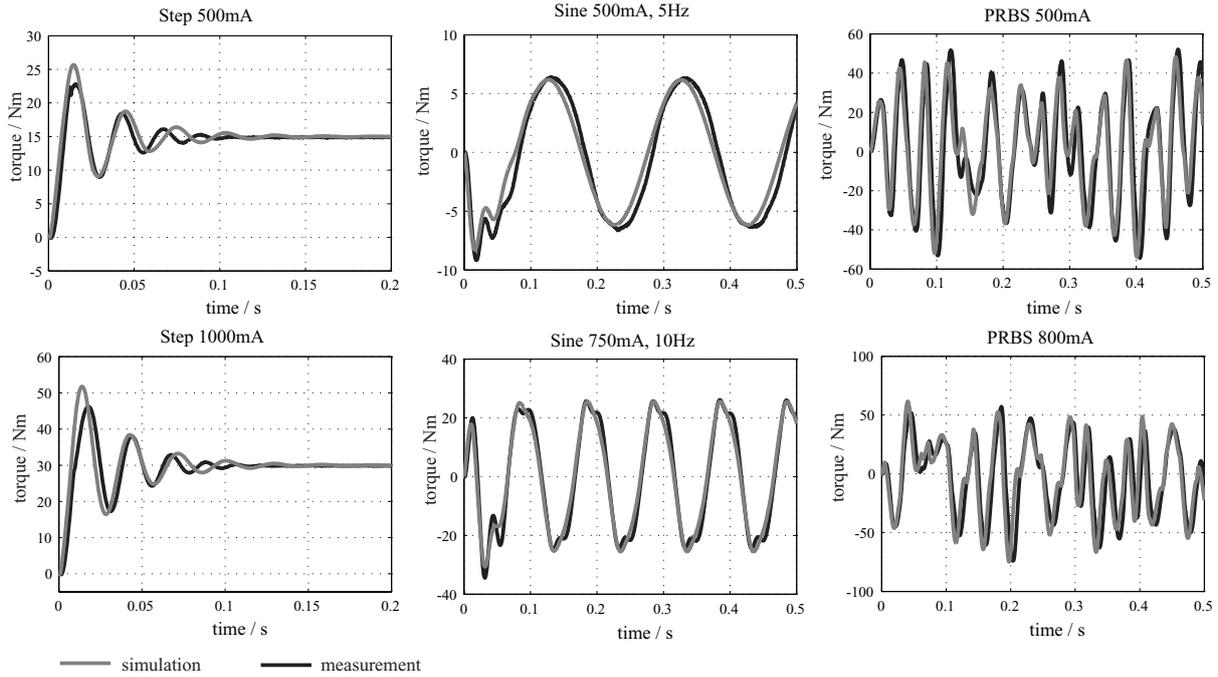


Figure 7: Validation results linear model

$ \omega_W $	η_{mf1}	η_{mf2}	$ \tau_{bf1} $	$ \tau_{bf2} $
\vdots	\vdots	\vdots	\vdots	\vdots

Table 2: Format of table `lossTable`

natural to assume no-loss (ideal gear) conditions as initial values. Besides, it is relatively difficult to set an experimental setup for its measurement, since additional drives have to be installed on the output shaft for covering the whole set of conditions as described in Table 2. While measurement of bearing friction is not essentially simpler, it may be roughly assumed that,

$$\tau_{bf1} \approx \tau_{bf2}.$$

However, assuming ideal conditions as initial ones may cause difficulties in optimization of bearing-friction, since the solvers are required to change the initial structure by including additional damping into the model. Fortunately, using the above assumption initial values are relatively easily estimated in a setup with free rotation of the output shaft (no external load) at different constant velocities. Given that torque sensor sits between the input and output bearing friction, it can see just the output bearing friction. Thus, assuming that the torque generated on the motor shaft balances the net (both input and output) bearing friction

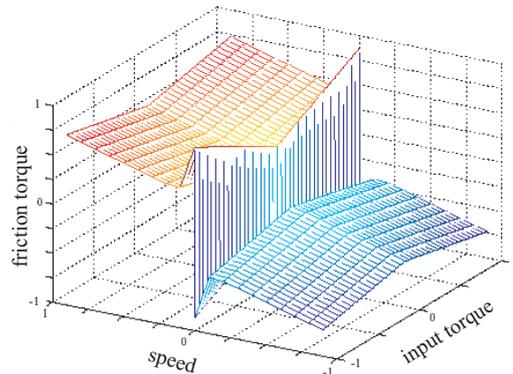


Figure 9: Friction model

(output load effects due to the Flexspline inertia are neglected), motor current can be used for its estimation. Fig. 10 presents the estimation results corresponding to rotation in both directions. From this curve the τ_{bf1} , i.e. τ_{bf2} are read as initial values for the optimization. Note that the above figure indicates clearly the appearance of the Stribeck effect when switching from stuck to sliding mode.

For completion of the `lossTable` the identification procedure is repeated for different constant velocities. Each identification step corresponds to a row in the `lossTable`.

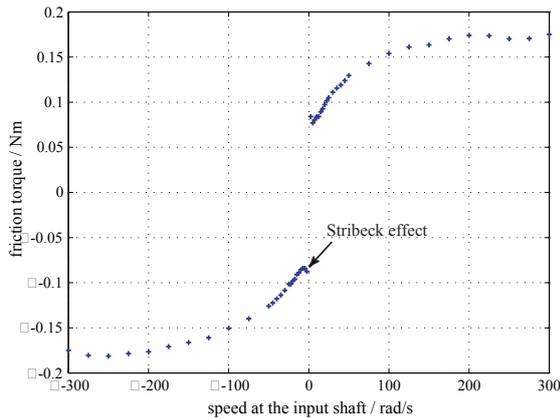


Figure 10: Bearing friction measurement

5.3 Model validation

For illustration purposes the row corresponding to the rotor speed of 10 rad/s will be discussed. Based on the previous discussion the initial values are chosen to be,

$$\begin{aligned} \eta_{mf1} &= 1, \\ \eta_{mf2} &= 1 \\ \tau_{bf1} &= 0.09 \\ \tau_{bf2} &= 0.09. \end{aligned}$$

After 103 optimization/simulation iterations in Fig. 4 these parameters converge to the values,

$$\begin{aligned} \eta_{mf1} &= 0.923, \\ \eta_{mf2} &= 0.864 \\ \tau_{bf1} &= 0.058 \\ \tau_{bf2} &= 0.058. \end{aligned}$$

For model validation the authors have set the setup shown in Fig. 12, whereby a defined torque at the output shaft has been applied by an excentric load. Different load conditions may be realized by varying the load radius. The Dymola/Modelica actuator model corre-

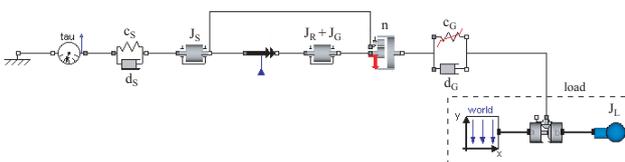


Figure 11: Modelica model with excentric load

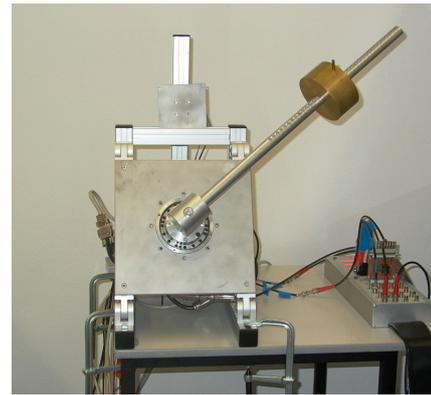


Figure 12: Excentric load experiment

$ \omega_W $	η_{mf1}	η_{mf2}	$ \tau_{bf1} $	$ \tau_{bf2} $
10	0.979	0.945	0.086781	0.086781
15	0.9625	0.92125	0.090313	0.088438
20	0.854	0.847	0.0565	0.049

Table 3: Format of table lossTable

sponding to the physical situation in Fig. 11 is augmented as shown in the above figure, by making use of the new Multi-body Modelica Library, [OEM03].

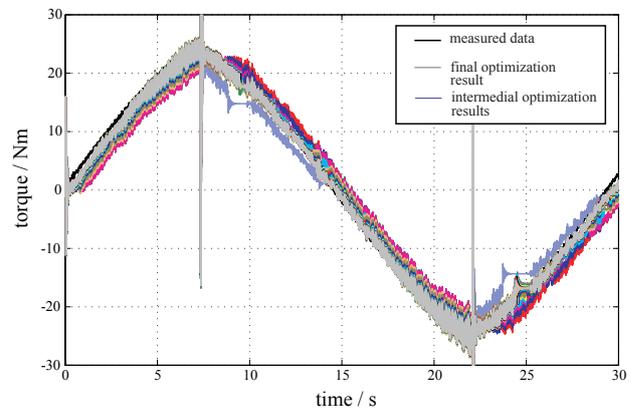


Figure 13: Optimization history of nonlinear model

The identification history of the loop in Fig. 4 for the row 10 rad/s assuming $\tau_{bf1} = \tau_{bf2}$ is shown in Fig. 13.

In a next identification step the assumption $\tau_{bf1} = \tau_{bf2}$ is removed. Table 3 shows three rows of lossTable corresponding to the rotor speeds of 10, 15 and 20 rad/s. Notice that $\tau_{bf1} \approx \tau_{bf2}$.

Finally, Fig. 14 collects the validation results for different input current signals.

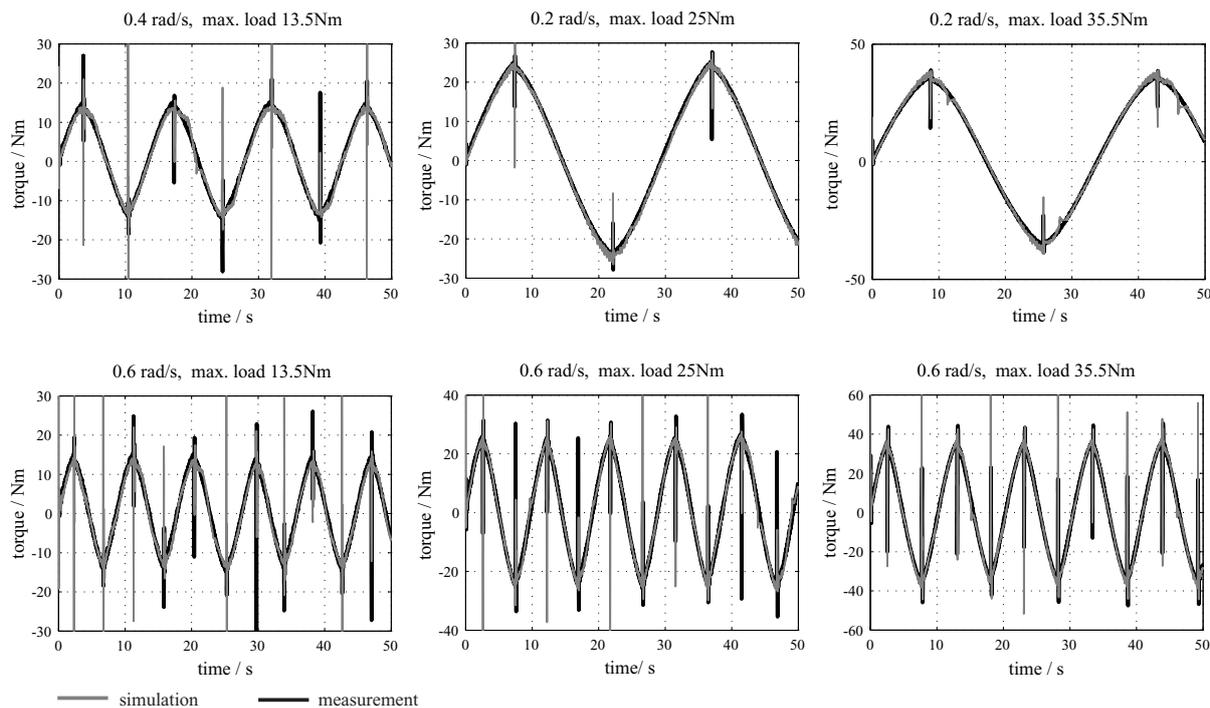


Figure 14: Validation results for nonlinear model

6 Conclusions

It is shown that iterative parameter optimization with MOPS and model validation using Dymola/Modelica is a powerful identification environment. This method is used for modelling of a force-feedback electro-mechanical actuator with Harmonic-Drive gear. A modelling approach for speed and torque dependent gear losses introduced in a prior work is validated. Future work might include identification of dynamical friction models. The procedure presented in this paper may be applied for dynamics identification of other gear technologies.

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