Model updating for Digital Twins using inverse mapping models

Citation for published version (APA):
Kessels, B. M., Fey, R. H. B., & van de Wouw, N. (2021). *Model updating for Digital Twins using inverse mapping models*. Poster session presented at 24th Engineering Mechanics Symposium , Arnhem, Netherlands. https://engineeringmechanics.nl/wp-content/uploads/2021/11/Symposiumbook-2021_WEB.pdf

Document status and date:
Published: 26/10/2021

Document Version:
Author's version before peer-review

Please check the document version of this publication:

Model updating for Digital Twins using inverse mapping models

B.M. Kessels[1], R.H.B. Fey[1], N. van de Wouw[1,2]

[1] Eindhoven University of Technology, Mechanical Engineering,
[2] University of Minnesota, Civil, Environmental, and Geo-Engineering

Introduction

To ensure that a high-tech system digital twin is and remains an accurate representation of the physical system, model updating can be applied. However, methods for model updating, generally, do not enable:

- (near) real-time updating,
- updating of physically interpretable parameters,
- updating nonlinear models.

Therefore, in this research, the Neural Network Updating Method (NNUM) [1] is used as a basis to develop an updating method which does meet these requirements.

Methodology

An inverse model updates a reference model by mapping features of output signals, measured at the physical system, to a set of interpretable parameter values, see Figure 1.

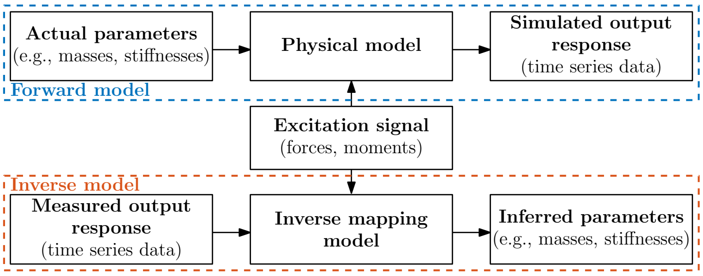

Figure 1: Inverse models for parameter updating.

In the NNUM, this inverse model is given by an Artificial Neural Network (ANN). This ANN is trained using the combination of simulated output features and the associated parameter values of a forward dynamics model, see Figure 1. The values inferred from features extracted from (real-world) measurements are then used to parameterize, i.e., update, the reference model. In this research, in contrast to [1], nonlinear models are updated.

Preliminary Application

The NNUM is employed to update a (nonlinear) multibody demonstrator system, see Figure 2. Here, the degrees of freedom y and θ are available through (simulated) measurements and for F and M sinusoidal excitation signals are used. In this example, the updating parameters are m_2 and m_3. Here, it is assumed that their true values lie in some user-defined ranges. The ANN is trained using 9000 simulations in which the parameters vary randomly in the specified ranges. The features consist of 10 time samples per output signal, as indicated by the red diamonds in Figure 3.

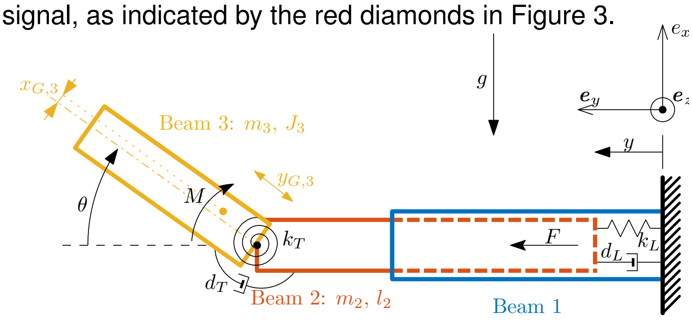

Figure 2: Demonstrator system.

Results

Parameter values are estimated for 2000 simulated experiments. The average error of the estimates is shown in Table 1, where we see that these estimates are relatively accurate. Output signals obtained by simulating the model with the updated values, show high agreement with the reference simulations, see Figure 3.

Future work

The NNUM enables (near) real-time updating of models. However, some yet unexplored research topics are:

- optimal excitation design,
- employing different types of output signal features,
- quantification of uncertainty in parameter estimates,
- hyperparameter tuning of the ANN,
- application to complex systems/updating problems.

References

[1] Levin, R.I. and Lieven, N.A.J. "Dynamic finite element model updating using neural networks". In: *Journal of Sound and Vibration* 210.5 (1998), pp.593-607.

Acknowledgments

This publication is part of the project Digital Twin project 2 with project number P18-03 of the research programme Perspectief which is (mainly) financed by the Dutch Research Council (NWO).

Table 1: Updating parameter errors.

Updating parameter	Mean absolute relative error [%]
m_2	1.83
m_3	3.66

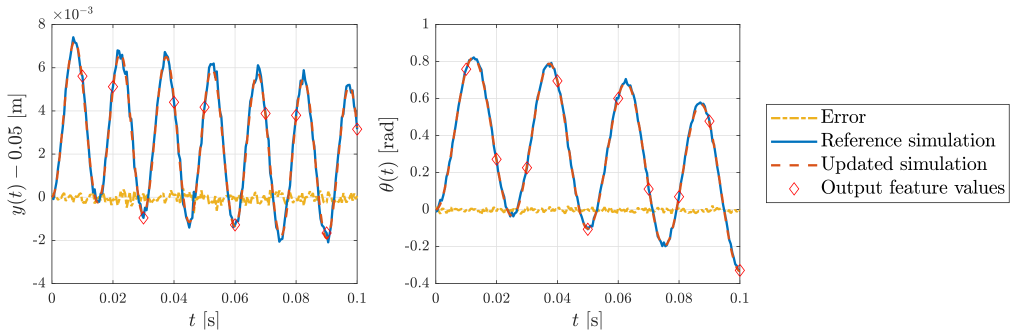

Figure 3: Simulated output signals related to the reference system and the updated system.

PhD progress
1 2 3 4