The 8th International Conference on Multibody System Dynamics
June 16-19, 2026, Seville, Spain

# A Test Bench for Data-Driven Input Prediction in Physical-Virtual Co-Simulation

**Antonio J. Rodríguez***, **Maciej Pikuliński**#, **Paweł Malczyk**#, **Francisco González***

* Laboratorio de Ingeniería Mecánica
Campus Industrial Ferrol - CITENI
Universidade da Coruña
Campus de Esteiro, 15403, Ferrol, Spain
{antonio.rodriguez.gonzalez, f.gonzalez}@udc.es

# Division of Theory of Machines and Robots
Institute of Aeronautics and Applied Mechanics
Faculty of Power and Aeronautical Engineering
Warsaw University of Technology
Nowowiejska 24, 00-665 Warsaw, Poland
{maciej.pikulinski.dokt, pawel.malczyk}@pw.edu.pl

**Abstract**
Co-simulation consists in the coupling of two or more dynamic solvers by means of the exchange of a set of variables (*coupling variables*) through a discrete-time interface. Each solver performs the integration of its subsystem dynamics between two *communication points*, i.e., during a *macro-step*, without additional input from the rest of the co-simulation setup. This makes co-simulation a modular solution to describe complex mechanical and multiphysics systems but, at the same time, it requires a careful coordination of the overall numerical integration process.

Cyber-physical systems (CPS), in which physical devices interact with numerical simulations of their environment, can be considered a particular case of co-simulation. In these setups, it is often impractical to repeat the integration of subsystem dynamics between communication points and noniterative *explicit* co-simulation schemes are frequently used. Explicit co-simulation is computationally efficient, but suffers from accuracy and stability issues caused by the nature of the discrete-time coupling interface. If left uncorrected, these lead to unreliable results and, in extreme cases, unstable system behaviour [3]. Besides the issues at the explicit co-simulation interface, CPS contain additional sources of error, derived from sensor and actuator limitations, variability and uncertainty in physical components, delays and loss of data in information transfer, and imperfect computational models [1].

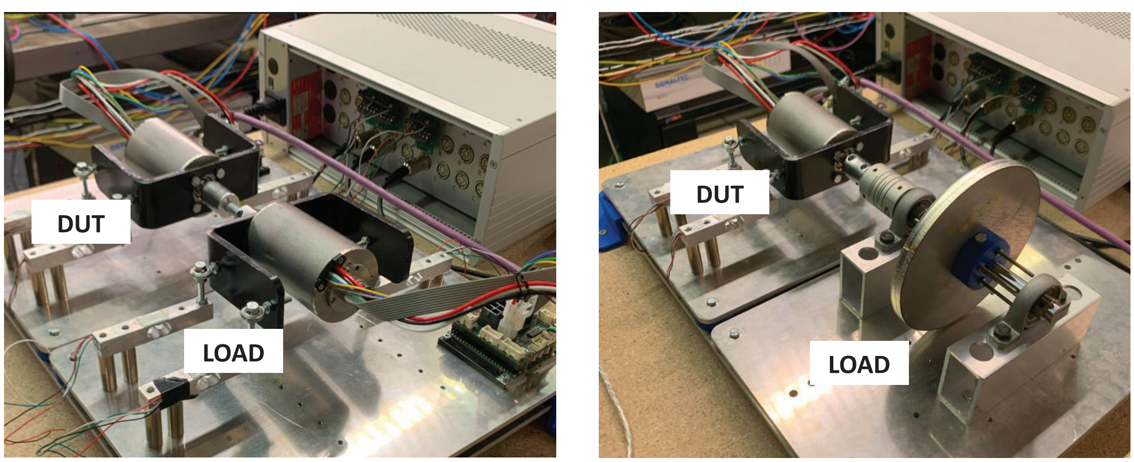


Figure 1: The test bench for electric motors used in this research, shown in a back-to-back cyber-physical configuration (left) and mounting a physical load (right).

Different solutions have been put forward in the literature to mitigate interface errors in explicit co-simulation using only the information contained in the coupling variables. These include, among others, energy-based stabilization approaches [3] as well as data-driven techniques, such as Dynamic Mode Decomposition (DMD) [2]. In this paper, we consider a data-driven framework for inferring local linear representations of subsystem dynamics in explicit co-simulation environments, with the objective of reducing the sensitivity to interface-induced numerical errors. The central idea is to extract an approximate input–output model of one subsystem based solely on state and actuation measurements exchanged with the coupled subsystem during co-simulation.

Dynamic Mode Decomposition with control is employed to identify local linear dynamics from snapshot data. For state measurements $\mathbf{x}$ and input (actuation) signals $\mathbf{u}$, the discrete-time linear subsystem dynamics are assumed to be in the form:

$$
\begin{aligned}
&\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \quad \rightarrow \quad \mathbf{X}' = \mathbf{A}\mathbf{X} + \mathbf{B}\mathbf{U}, \quad \text{where} \\
&\mathbf{X} = \begin{bmatrix} | & | & & | \\ \mathbf{x}_1 & \mathbf{x}_2 & \dots & \mathbf{x}_{m-1} \\ | & | & & | \end{bmatrix}, \mathbf{X}' = \begin{bmatrix} | & | & & | \\ \mathbf{x}_2 & \mathbf{x}_3 & \dots & \mathbf{x}_m \\ | & | & & | \end{bmatrix}, \mathbf{U} = \begin{bmatrix} | & | & & | \\ \mathbf{u}_1 & \mathbf{u}_2 & \dots & \mathbf{u}_{m-1} \\ | & | & & | \end{bmatrix},
\end{aligned} \tag{1}
$$

Here, $m$ denotes the total number of data snapshots, and $\mathbf{X}$, $\mathbf{X}'$, and $\mathbf{U}$ collect state and input measurements obtained during the co-simulation. The DMD procedure seeks best-fit approximations of the unknown subsystem matrices $\mathbf{A}$ and $\mathbf{B}$ by solving a least-squares problem that minimizes the Frobenius norm $\left\| \mathbf{X}' - \begin{bmatrix} \mathbf{A} & \mathbf{B} \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{U} \end{bmatrix} \right\|_F$, leading to the closed-form solution $\begin{bmatrix} \mathbf{A} & \mathbf{B} \end{bmatrix} = \mathbf{X}' \begin{bmatrix} \mathbf{X} \\ \mathbf{U} \end{bmatrix}^{\dagger}$. The algorithm for inferring subsystem dynamics within the co-simulation framework can be reformulated in a sliding-window manner, which exploits a recursive least-squares approach to reduce memory requirements during the solution process.

A configurable cyber-physical test bench for electric motors, shown in Fig. 1, is used as experimental platform. In its cyber-physical configuration, two identical motors are mounted opposite to each other, connected at their axles, as shown in the left picture in Fig. 1. One of the motors is the Device Under Test (DUT), while the other represents the load applied to the DUT, predicted by a numerical simulation. In order to enable the comparison of cyber-physical tests to real experiments, the load motor can be replaced by a physical load, coupled to the axle of the DUT by means of a torsional spring-damper system.

In this research, the performance of data-driven strategies for correcting explicit co-simulation errors is evaluated on an electric motor test bench, shown in Fig. 1. The relative contribution of different error sources to the overall CPS behaviour is investigated by systematically varying operating conditions, including changes in the macro step-size and the injection of communication errors in the exchanged coupling variables. In addition, the real-time feasibility of the proposed correction methods is examined under realistic operating conditions.

These experimental investigations are enabled by a data-driven identification framework that relies exclusively on snapshot data available during explicit co-simulation and does not require prior knowledge of internal subsystem models. This makes the approach particularly well suited for physical–virtual and cyber–physical system scenarios with limited subsystem transparency. The overarching objective is to assess the extent to which locally identified linear models can mitigate numerical errors in explicit co-simulation and to establish a foundation for systematic experimental validation on physical testbeds.

**References**


[1] Glumac, S.; Varga, N.; Raos, F.; Kovačić, Z.: Co-simulation Perspective on Evaluating the Simulation with the Engine Test Bench in the Loop. Automatika, Vol. 63, No. 2, pp. 275–287, 2022.

[2] Pikuliński, M.; Malczyk, P.; Rodríguez, A.J.; González, F.: Data-Driven Prediction of Subsystem Dynamics in the Explicit Co-Simulation of Multibody Systems. Mechanics Based Design of Structures and Machines, online, 2025.

[3] Rodríguez, B.; Rodríguez, A.J.; Sputh, B.; Pastorino, R.; Naya, M.Á.; González, F.: Energy-Based Monitoring and Correction to Enhance the Accuracy and Stability of Explicit Co-Simulation. Multibody System Dynamics, Vol. 55, No. 1–2, pp. 103–136, 2022.