

## Neural Network-Based Surrogate Models Applied to Fluid-Structure Interaction Problems

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Traditional computational methods face significant challenges with ever-increasing complexity in the problems of engineering interest. One set of problems that suffer from this phenomenon is those where Fluid-Structure Interaction (FSI) is present. FSI simulations are traditionally time-consuming and computationally extremely expensive. Potential alternatives rely on using a surrogate model to substitute one or more systems involved. A promising approach employs artificial neural networks as the basis for such a surrogate model combined with strong physics simulations based on finite element methods (FEM).

This approach requires the seamless integration of AI algorithms and packages into the simulation workflow. Such an example is the NeuralNetworkApplication developed in Kratos [1]. This application allows the integration of every step needed to implement and integrate the aforementioned surrogate models in the simulation workflow; namely data generation, model set-up, training, testing, and coupling. The routines related to the neural networks are executed through an interface with the API Keras [3].

Mok's [2] benchmark is chosen as the study case to test the capacity of the previous method applied to FSI problems. In a first instance, the structural model in the example is substituted by a neural network-based surrogate model trained on known data while retaining the original fluid model. Additionally, a second case where a surrogate substitutes the fluid model, keeping the structural one untouched, is evaluated. In both cases, the neural network predicts the total response of the system it substitutes. Strong and weak coupling scenarios are considered. The results present improvements in simulation time without sacrificing accuracy, especially when compared with the original benchmark. This contribution discusses the influence of the original data and network architecture in the outcome of the simulation and different considerations for generating surrogate models for FSI.

### REFERENCES

- [1] Dadvand, Pooyan, Riccardo Rossi, and Eugenio Oñate. "An object-oriented environment for developing finite element codes for multi-disciplinary applications." *Archives of computational methods in engineering* 17.3 (2010): 253-297.
- [2] Mok, Daniel Pinyen. *Partitionierte Lösungsansätze in der Strukturodynamik und der Fluid-Struktur-Interaktion*. 2001.
- [3] Chollet, François and others. <https://keras.io>. 2015.