Detection of Mechanical Clearances with Data-Driven Approaches

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EXTENDED ABSTRACT

1 Introduction

Joint clearances cause vibration and impacts in mechanical systems, decreasing machine efficiency and causing heat, noise, and additional wear. Clearances can eventually cause damage to components and lead to premature system failure. The monitoring and characterization of this defect are necessary tools in machine maintenance. Often, these tasks need to be performed using data from a reduced set of sensors, which is usually limited because industrial machinery does not include extensive sensor arrays.

This work explores the use of neural networks for estimating the clearance radius using the data gathered through a pair of accelerometers. The mechanism under study is the slider-crank linkage depicted in Figure 1, moving under gravity effects. In order to train the neural network, a multibody model of the slider-crank is developed. This model includes a clearance at joint A, which is modeled following the contact model described in [3], and a pair of accelerometers in the center of the crank, measuring the acceleration in the longitudinal and perpendicular directions of the crank. Varying the radius of the clearance and the initial velocity of the mechanism, 3 different datasets were generated, corresponding to initial velocities of 0 rpm, 250 rpm and 500 rpm. Each dataset is divided into training, validation and testing with proportions of 70%, 15% and 15% respectively.

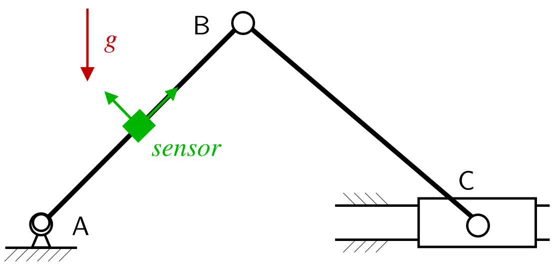

Figure 1: Slider-crank model employed in this work with a pair of accelerometers as sensor.

The architecture of the model is based on a Long Short-Term Memory (LSTM) network [4], selected for its ability to handle sequential data and model long-range dependencies. The input to the network consists of time series sequences with time steps of 100 and 50 features, including generalized coordinates and angular data represented as sine and cosine values. The model includes a single LSTM layer with 64 hidden units, configured to only output the final time step, summarizing the sequence into a compact representation. This is followed by a fully connected layer with a single neuron, which maps the final time step to a regression output that represents the clearance size. To constrain the output within a specific range, the sigmoid activation function is applied. The model is trained using Mean Absolute Error (MAE) [5] as the loss function, a batch size of 64 and a learning rate of 0.001, optimized with the Adam algorithm[6].

Several tests were conducted on three different datasets, each characterized by varying initial velocities. The results demonstrate that the model performed better on datasets with higher initial velocities. As shown in Figure 2, the model's performance is illustrated after training on a dataset with an initial velocity of 500 rpm. The graph clearly highlights the predicted values, represented by a blue line, where each data point corresponds to a sample sequence. This visualization not only shows the close alignment between the actual values (represented by the red line) and the predicted values, but also emphasizes the model's ability to accurately capture the underlying patterns within the data.

Acknowledgments

Authors from Universidade da Coruña acknowledge the support of project PID2022-139832NB-I00 funded by MICIU/AEI/10.13039/501100011033 and ERDF, EU, and grant ED431C 2023/01 from the Government of Galicia.

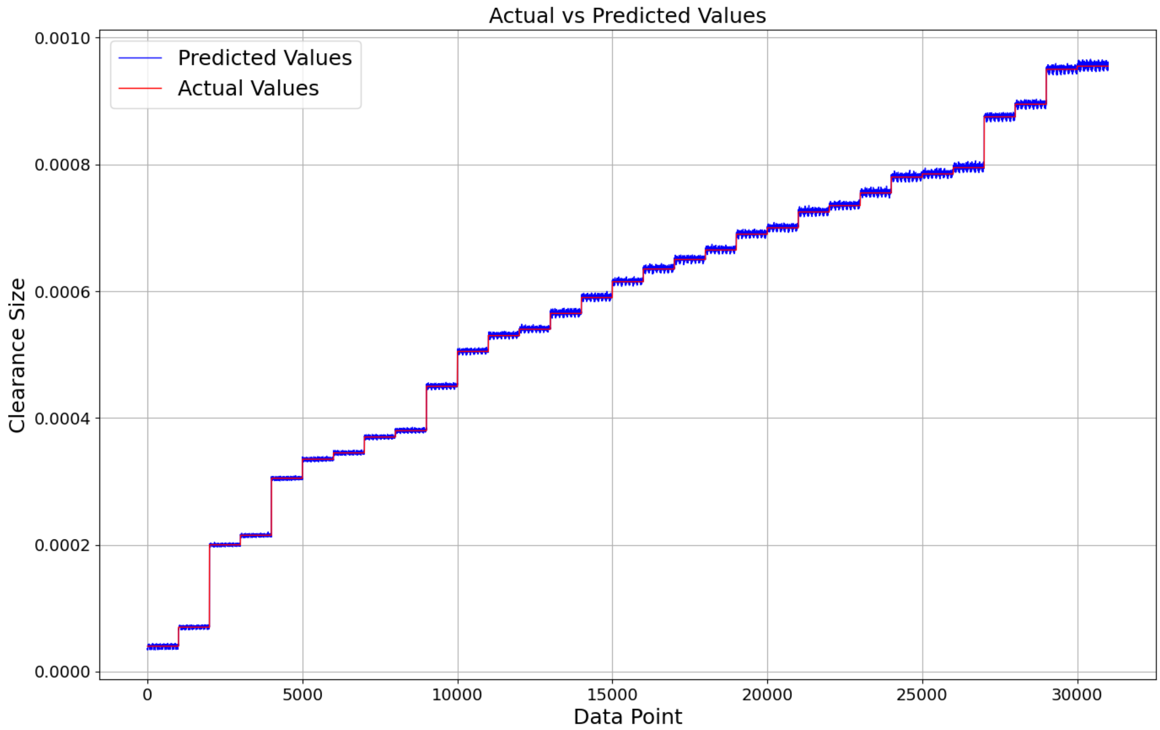

Figure 2: Model predictions on test set with an initial velocity of 500 rpm.

References

[1] M. López-Lombardero, J. Cuadrado, M. Cabello, F. Martinez, D. Dopico and A. López-Varela. A multibody-dynamics based method for the estimation of wear evolution in the revolute joints of mechanisms that considers link flexibility. Mechanism and Machine Theory, 194, art. 105583, 2024.

[2] E. Chaturvedi, C. Sandu, A. Sandu. A nonsmooth dynamics framework for simulating frictionless spatial joints with clearances. Multibody System Dynamics, online, 2024.

[3] H. M. Lankarani, P. E. Nikravesh. A contact force model with hysteresis damping for impact analysis of multibody systems. Journal of Mechanical Design, 112(3):369–376, 1990.

[4] S. Hochreiter, J. Schmidhuber. Long Short-Term Memory. Neural Computation, 9(8):1735–1780, 1997.

[5] Mean Absolute Error. In: C. Sammut, G. I. Webb (eds). Encyclopedia of Machine Learning and Data Mining, Springer, 2010.

[6] D. P. Kingma, J. Ba. Adam: A method for stochastic optimization. 3rd International Conference for Learning Representations (ICLR), San Diego, CA, USA, 2015.