Neural network hyperparameter tuning for online model parameter updating using inverse mapping models

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Abstract. To decrease the mismatch between a model and a physical system, physically interpretable model parameter values of nonlinear systems can be updated in real-time by using the Inverse Mapping Parameter Updating (IMPU) method. In this method, an Inverse Mapping Model (IMM), constituted by an Artificial Neural Network (ANN), is trained, offline, using simulated data that consists of features of output responses (ANN inputs) and corresponding parameter values (ANN outputs). In an online phase, the trained ANN can then be used to infer parameter values with high computational efficiency. The (non-trivial) choice of ANN-hyperparameters, e.g., ANN structure and training settings, may significantly influence the accuracy of the trained ANN. Therefore, this work discusses multiple ANN-hyperparameter tuning techniques to increase the accuracy of the IMPU method, of which the Bayesian search technique is the most promising considering accuracy and efficiency as it learns from previously evaluated hyperparameter values.

Introduction

In a digital twin context, model updating is required to ensure that a model accurately represents a physical systems throughout its operational life. In this research, an IMM is employed that enables (near) real-time inference of interpretable parameter values of nonlinear dynamics systems on the basis of a set of features representing measured output response data. This is achieved by training the IMM, which is constituted by an ANN, offline, using simulated training data (pairs of output response functions and corresponding parameter values) should be chosen appropriately. Afterwards, in an online phase, the trained ANN is used to infer parameter values from measured features with little computational cost. For a detailed explanation of this IMPU method, see [1]. To ensure that the ANN accurately estimates parameter values, careful design of the ANN is essential, i.e., its activation functions, its number of layers and neurons, and its training settings (learning rate, number of epochs, and batch size). These hyperparameters should be tuned to minimize the validation loss, i.e., the mean squared error of the inferred parameter values (normalized between 0 and 1), as evaluated on a validation set. In this paper, different tuning strategies are compared: grid, random, and Bayesian searches [2].

Results and discussion

ANN hyperparameter tuning is applied to a closed-loop nonlinear multibody dynamics system consisting of four connected rigid bodies with, in total, 10 Degrees of Freedom (DoFs) of which 3 DoFs are excited and ‘measured’. Using the ‘measured’ output responses, we tune the above-mentioned ANN-hyperparameters such that the values of eight parameters (among which stiffness constants and damping factors) are inferred with high accuracy. In Figure 1, the validation losses obtained using different ANN-hyperparameter searches, as well as one manually tuned ANN (using engineering insight and experience), are ranked in ascending order. Note that, for all search types, the hyperparameter values lie within the same bounded space and the same training and validation data is used. Performing these grid, random, and Bayesian searches takes roughly 78, 15, and 20 hours, respectively and especially the grid search is thus a time consuming (offline) task. In contrast, online inferring of one set of parameter values using the trained ANN only takes approximately 6 ms. From Figure 1, we observe that the Bayesian search finds relatively many ANNs that outperform the manually tuned ANN, while requiring much less computation time than the grid search. The mean relative (non-normalized) parameter value error (averaged over the eight parameters) for a test data set as obtained using the IMPU method equals 0.26% for the manually tuned ANN and only 0.14% for the best performing ANN of the Bayesian search.

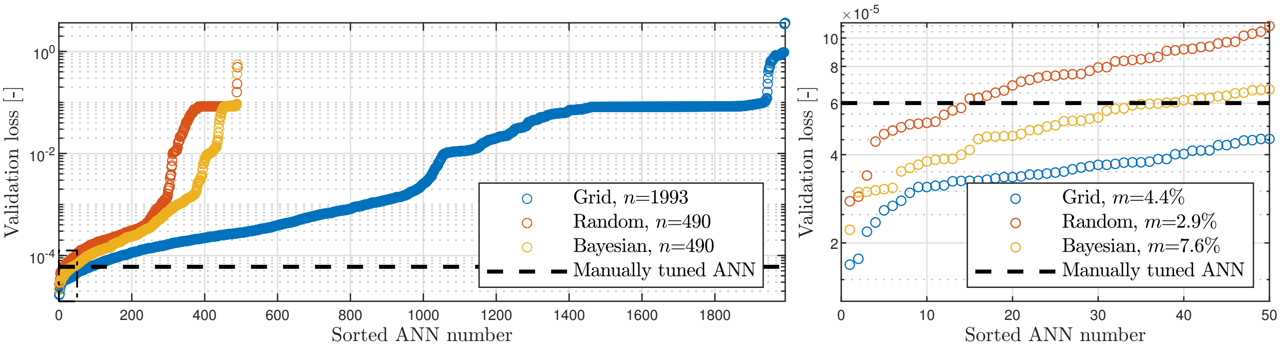

Figure 1: Validation losses as obtained by grid, random, and Bayesian searches. The validation loss of the manually tuned ANN is indicated by the dashed line. The right figure presents a detail of the 50 best performing ANNs per search. The total number of trained ANNs and the relative percentage of ANNs that outperform the manually tuned ANN per search are indicated by n and m, respectively.

References

[1] Kessels, B.M., Fey, R.H.B, van de Wouw, N. (2022) Real-time parameter updating for nonlinear digital twins using inverse mapping models and transient-based features. *Nonlinear Dynamics (submitted, preprint available at researchsquare.com).*

[2] Zulfiqar, M., Gamage, K.A.A., Kamran, M., Rasheed, M. B. (2022) *Sensors **22(12)**:4446.*