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Estimating Unknown Parameters in Mechatronic Systems Using Data-Driven Surrogates

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1 INTRODUCTION

Complex mechatronic systems, such as non-road mobile machinery and heavy equipment, can present challenges in model-based control operation due to the presence of unknown states [1] and parameters [2] within the system. Accurate control of these systems requires real-time information on parameters, such as lifting mass, which are often unknown. Recent developments in the parameter estimation, online and offline estimation methods [2, 3], combined nonlinear multibody dynamic models and Extended Kalman filters (EKF). However, the proposed methods in [2, 3] require the computation of system Jacobean matrices and variances of unknown parameters, adding complexity to the parameter estimation process. To end this, this study proposes a artificial intelligence (AI) based data-driven surrogate approach to estimate parameters in a mechatronic system. As an example, the unknown mass m at the end of the hydraulically actuated flexible boom is estimated using feedforward neural network (FFN) [4].

2 PREPARING DATA-DRIVEN SURROGATE

For a data-driven surrogate, this study uses the following regression-based neural network model,

$$\boldsymbol{\mathcal{Y}}_j = \boldsymbol{\mathcal{N}}(\boldsymbol{\mathcal{X}}_i; \boldsymbol{\Psi}), \quad i = 1, 2, \ldots, N_i, \quad j = 1, 2, \ldots, N_o, \tag{1}$$

where $\boldsymbol{\mathcal{Y}}_j$ is the vector of output parameter, $\boldsymbol{\mathcal{N}}$ is the FFN, $\boldsymbol{\mathcal{X}}_i$ is the vector of input parameter, $\boldsymbol{\Psi}$ is the vector of trainable parameters, N_i and N_o are the numbers of input and output parameters. Eq. (1) is used to train the mechatronic system shown in Figure 1. It illustrates an unknown mass m at the end

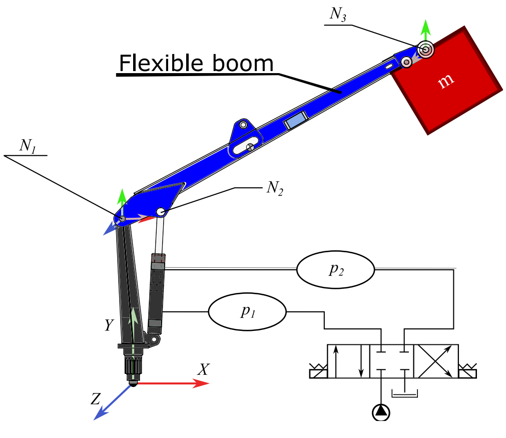

Figure 1. A hydraulically actuated flexible multibody system.

of a hydraulically actuated flexible multibody system (boom). The finite element mesh of this boom is created in the commercial software with 4 bending modes in Y direction, ANSYS. Master nodes N_1, N_2 and N_3, as can be seen in Figure 1, on the flexible boom define the joints and force locations. The mass m is attached to the flexible boom as a rigid body through a fixed joint. This system is modeled using the well-established coupled floating frame of reference formulation (FFRF) [5] and lumped fluid theory in a monolithic approach [1]. From the simulation model, the input vector for FFN is obtained as $\boldsymbol{\mathcal{X}} = \begin{bmatrix} s & \dot{s} & p_1 & p_2 & U \end{bmatrix}^{\mathrm{T}}$. Here, s, $\dot{s}$, p_1,p_2 and U represent the actuator position, actuator velocity, cylinder pressures and control signal, respectively.

3 RESULTS AND CONCLUSIONS

Simulation data was obtained from the commercial multibody software, Mevea. This data contains $\mathcal{X}$ from 0 kg, 10 kg, 20 kg, 30 kg, 35 kg and 50 kg lifting load simulations. The data set comprises 33000 samples. This data set is divided into 80 % training samples and 20 % validation samples. FFN model is built in the standard Keras Python environment. The FFN is trained with the three layers having ReLU activation function and 64 units in each layer, 256 batch size, and a learning rate of 0.0002. FFN model took 1000 epochs during the training process and approximately 480 s.The training performance of FFN is described in Figure 2. The trained FFN model can predict unknown mass for the training data with 98.5 % accuracy.

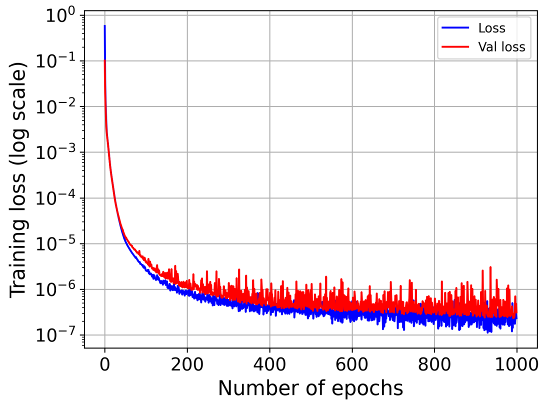

Figure 2. Training performance of FNN.

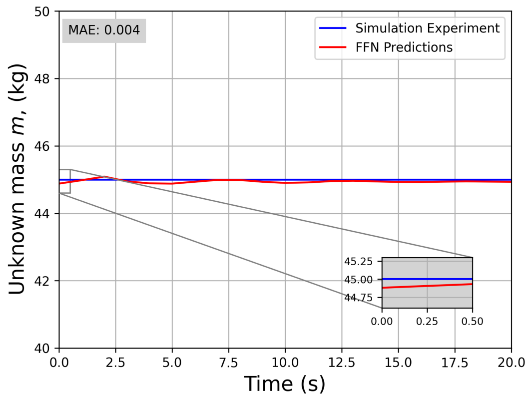

Figure 3. Predicting unknown mass m.

Figure 3 depicts the trained FFN model verified to predict the unknown mass of 45 kg. Note that this data was not provided in the training phase. It can be seen that FFN predicts unseen mass with a relative mean absolute error (MAE) of 0.006. Note this load data was not provided during the training process. In this study, a constant mass is estimated. In the future, the variable mass should be estimated to justify the performance of FFN in solving this problem. Furthermore, an automated approach for hyperparameter tuning can be explored, as manual tuning is challenging. The results of this approach can then be compared with those obtained from EKF. This study is expected to improve the AI based control and digital maintenance of complex mechatronic systems. However, more investigations are needed to make a fair comparison between the model-based controller and AI based controller for this application.

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