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Intelligent Model for Endpoint Accelerations of Two link Flexible Manipulator Using a Deep Learning Neural Network

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Abstract*—This article investigates a two-link flexible manipulator (TLFM) that can be modelled utilizing a deep learning neural network. The system was classified under a multiple-input multiple-output (MIMO) system. In the modelling stage of this study, the TLFM dynamic models were divided into single-input single-output (SISO) models. Since coupling impact was assumed to be minimised, the characterizations of TLFM were defined independently in each model. Two discrete SISO models of a flexible two link manipulator were developed using the torque input and the endpoint accelerations of each link. The input-output data pairs were collected from experimental work and utilised to establish the system model. The Long Short-Term Memory (LSTM) algorithm optimised using Particle Swarm Optimization (PSO) was selected as the model structure due to the system's high degree of nonlinearity. The identification of the TLFM system utilizing LSTM optimised by PSO was successful, according to the high-performance result of PSO. Using LSTM-PSO, it is demonstrated that both link 1 and 2 models are accurately identified and that their performance in terms of MSE for links endpoint acceleration 1 and 2 is within a 95% confidence interval.

***Keywords*—Tow link flexible manipulator, Deep learning, Flexible manipulator, LSTM-PSO, Non-parametric modeling**

I. Introduction

Flexible manipulators introduce unwanted vibrations, which are not simple to control because of its high non-linearity. Current research concentrates on enhancing the control schemes to suppress these vibrations. A reliable controller must be developed to keep the advantages linked with the flexibility and lightness of the manipulators, the modeling system's accuracy, and efficiency[1]. Suppressing the vibration on flexible structures is very important. The structure vibration will affect the performance, such as reduced efficiency and accuracy, tracking errors, and lags between tasks. Furthermore, extreme and continuous vibrations will cause the system's early failure and possible deformation [2].

Since the initial emerging of the Long Short-Term Memory (LSTM) network structure in 1997, many theoretical and experimental publications concerning this type of Recurrent Neural Networks (RNN) have been published, describing the great results obtained along a wide range of application fields which mostly sequences data. The fields of language modelling, machine translation, speech to text transcription, and many applications have seen significant advances due to the LSTM network. Researchers have been evaluating the LSTM network's suitability for their research or practical use-cases. The remarkable benchmarks mentioned in the literature served as the motivation behind the decision. The majority of RNN and LSTM network configurations are productively implemented and ready for production in all significant open source machine learning frameworks [3].

LSTM is a RNN architecture created to solve the exploding and vanishing gradient issues in traditional RNN. RNN are effective for simulating sequences because they have cyclic connections, unlike feedforward neural networks [4]. In addition, LSTM is used to create the inverse dynamic of the manipulator F[5]. According to the simulation results, it is essential to prioritise the impacts of the highest number of epochs on model performing for the proposed deep learning architecture. Expectation accuracy will decrease as the number of hidden layers rises, whereas the impacts of hidden nodes on model performing are constrained.

Rueckert and Nakatenus created model of inverse dynamic based on a LSTM with time difficulty. The approach was tested on a KUKA robot arm utilised for object manipulation tasks with varying loads. It was demonstrated that these variation of estimates might be employed to enhance a modify the stiffness or movement representation of the controller[6].

A prediction of LSTM and seq-2-seq structure was applied by Xiang and Yan to estimate hourly rainfall-runoff. The models were calculated using the normalised mean square error, statistical bias, correlation coefficient, and Nash-Sutcliffe Efficiency coefficient [7]. The prediction accuracy could be increased by using the LSTM-seq2seq model, which has a respectable predictive performance. Shen and Njock have suggested a system that incorporates data sequencing and Bi-LSTM in order to expect the jet grouted columns diameter. The findings demonstrate the precision with which the proposed methodologies can calculate the variant in the diameter of column with depth [8].

Gonzalez and Yu made use of the benefits of LSTM and NN in combination. One multilayer perceptron, one hierarchical recurrent network, and a newly used backpropagation through time and backpropagation methods are all components of the innovative neural model[9]. The results showed that the modified LSTM model offered for the simulation model performed noticeably more improved to the other existing neural models. In order to process information in sequences, LSTM additionally makes use of recurrent processes and gate approaches. In comparison to other