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IMITATIVE LEARNING CONTROL OF A LSTM-NMPC CONTROLLER ON PEMFC FOR COMPUTATIONAL COST REDUCTION

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***Abstract*—In this paper, an imitative learning controller is studied to address the problem of high computational cost of a Nonlinear Model Predictive Controller (NMPC) designed for controlling the output voltage of a Proton Exchange Membrane Fuel Cell (PEMFC) stack. A Long Short-Term Memory (LSTM) network is embedded inside the NMPC for providing the required predictions which leads to desired performance in voltage tracking and fuel consumption minimization. However, the long run-time of LSTM-NMPC makes it impractical for real-time implementation. To this end, an imitative-based controller is designed to learn the behavior of the LSTM-NMPC and replace it, resulting in a noticeably lower computational cost while the desired performance is maintained. The generalization and adaptability of the imitative-based controller are also studied in this work. Finally, different simulations are reported for elaborating the process of designing imitative-based controller and the associated considerations.**

***Index Terms*—Imitative learning control, Proton-exchange membrane fuel cell, Model Predictive Control, Data-driven Modeling**

I. INTRODUCTION

PEMFC is a type of fuel-cell power generating system for mobile and stationary applications. Lower operating temperature and pressure ranges, and a proton-conducting polymer electrolyte membrane distinguishes PEMFCs from Solid-oxide Fuel-cells (SOFC) [1]. As it is shown in Figure 1, the hydrogen is delivered to the anode side and split into protons and electrons. The electrons are transferred to the cathode side through an external load circuit to generate the output current of the system. At the cathode side, oxygen reacts with the protons permeating through the polymer electrolyte membrane and form water molecules. Generated output power and voltage of the fuel-cell stack are the first variables of interest which are mainly controlled by the hydrogen fuel flow and the instantaneous current of the system [2]. The fact that the system equations of PEMFC are highly non-linear with several input and output variables makes PEMFC difficult to be modeled. So far, several methods have been proposed to control the voltage and power of the fuel cell ranging from model-based to non-model-based approaches [3].

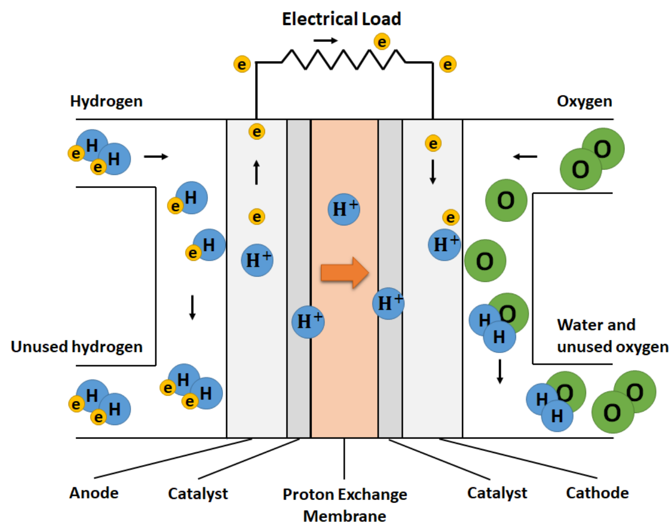


Fig. 1: Schematic of PEMFC operation [4]

In our previous work [4], a Long-Short Term Memory (LSTM) network was designed and embedded inside the NMPC as the control-oriented model to predict the output voltage of a 6-kW stationary PEMFC. Embeding a data-based model inside the NMPC instead of using highly nonlinear dynamic equations increases the accuracy of the controller to predict the system behavior [5]. The superiority of the LSTM-NMPC was shown compared to the linear MPC with an Auto-Regressive Exogenous (ARX) model as the predictor. Due to the highly nonlinear essence of the PEMFC dynamic equations, the linear MPC was not able to predict the voltage reference. Whereas, due to the inclusion of system dynamics and accurate data-driven model, the LSTM-NMPC could capture the nonlinear behavior of the system and follow the voltage reference with an acceptable mean-squared error (MSE). The main shortcoming of the LSTM-NMPC was that because of the recursive structure of the LSTM cells, the computational cost increased substantially compared to both the ARX-MPC and ANN-NMPC methods. Table I compares the computational cost and reference tracking error between these three methods. Although the LSTM-NMPC has the least reference tracking error, its computational cost is far higher than the ANN-NMPC and ARX-MPC, respectively. As a result, it deserved to be investigated whether there is a learning method that can mitigate the LSTM-NMPC computational cost without sacrificing the tracking accuracy.

Imitation learning is a branch of supervised learning in which the main agenda is to train an agent to mimic a desired behavior [6]. If the controller can be replaced by a neural network model to mimic all the controller interactions, the computational cost will be reduced while keeping the reference tracking accuracy unchanged. In other words, Machine Learning (ML) in the imitation of MPC leads to a unified structure which guarantees the real-time performance of the system by reducing the computational time [7]. Using ML in imitation of MPC is divided into two categories: 1- online imitation, 2- offline imitation. In the offline method, the controller inputs and outputs are collected, then fitted to a data-driven model to imitate the behavior of the controller. In the online imitation method, the controller regularly switches between ML and the controller subsystems for updates based on the performance error compared to a predefined threshold [8]. The reason that the offline imitation technique has been used more than the online approach is that the main advantage of the offline method is reducing the computational cost, while the online method requires more onboard computational cost due to the simultaneous optimizer online updating [9].

As the most common ML methods which have been employed in MPC imitation, Artificial Neural Network (ANN) and Deep Neural Network (DNN) are more promising. Choosing between ANN and DNN structures has a direct relation with the complexity of both system and controller. DNN is mostly used in more complex systems including the higher number of states, inputs, and outputs [10]. The study in reference [11] indicated that computational cost of an offline imitative DNN function is approximately 100 time faster than online MPC. Offline MPC imitative method has been widely used in the automotive control systems (ACS) and robotics ranging from the chassis control to the manipulators reference tracking [12]. To the best of authors' knowledge, there are only few studies in literature for using imitative ML on the fuel cell systems. Authors in [13] combined the imitation learning with the reinforcement learning method to propose a comprehensive control technique for stack temperature to tackle the problem of the coordinated control of the water pump and radiator of a stationary PEMFC. Performance analysis of PEMFCs is divided into several categories including dynamic analysis, durability, stack State of Health (SOH), and estimating the Remaining Useful Life (RUL) [14]. One of the cardinal features of stationary PEMFCs which is used in the performance analysis is the voltage prediction. The voltage tracking of the physics-based simulation PEMFC models is done based on an arbitrary predefined reference which subsumes all the transient operating ranges [14].

In this paper, to reduce the computational cost of the LSTM-NMPC while maintaining the reference tracking accuracy, an imitation-based controller is designed using input and output data of LSTM-NMPC. The effect of two different generic voltage references is investigated on the generality of the resulted imitative-based controller. Furthermore, the performance of the imitative-based controller and the original LSTM-NMPC are compared assuming that the plant fuel and air flow actuators are saturated due to aging. It should be noted that in this research switching between on and off modes of the PEMFC is not considered and it is assumed that the system has reached its stable operating condition.

The structure of this paper is as follows: Section II briefly describes the specifications of the PEMFC studied in this work. Section III is devoted to describing the structure and process of designing the imitative-based controller. In Section IV, two problems in the process of designing and implementing the imitative-based controller are discussed. The first problem is choosing an appropriate voltage reference for having a generalized imitative controller. The second problem is related to the adaptability of the offline imitative-based controller to new conditions which happen due to the saturation of fuel and air flow actuators. Finally, the results covering the aforementioned two problems are reported and discussed in Section V.

II. Fuel Cell Model Specifications

The PEMFC stack model which is used in this paper is a stationary type with the rated power of 6 kW including a 100 V-dc power generating circuit. The dynamic equations of the stationary PEMFC stack were derived based on the real MATLAB-Simscape NetStack-PS6 model [15]. The nominal voltage and current are 45 V and 133.3 A, respectively. The total number of cells is equal to 65. Detailed specifications of the PEMFC stack were provided in our previous work [4].

III. Imitative Learning Control

For designing the imitative-based controller, a shallow ANN with one hidden layer containing 10 neurons is used. The ANN as the imitative learning controller requires data from the original controller's block to be trained. In this regard, the voltage reference which is applied to the LSTM-NMPC block is used as the input of the ANN. The outputs of the ANN will be the control effort signals of the actuators which are the fuel flow rate, air flow rate, and fuel supply pressure. Figure 2 shows the schematic of imitation learning control that is used in this paper. One aspect of the learning process of imitative-based controller is the offline learning. In other words, the described input and output signals are recorded in one dataset which is used for training the ANN [8]. The trained ANN is then substituted instead of the LSTM-NMPC block and imitates the performance of the controller. The advantage of this approach is the substantial reduction in the running time. However, the offline framework reduces the adaptability

TABLE I: Computational cost and reference tracking error of MPC-ARX, NMPC/ANN, NMPC/LSTM for control of PEMFC

Control Method	Voltage Reference Type	Run time (s)	RMSE of voltage (v)
Linear MPC/ARX	Repeating Sequence Stairs	7.3	1.34
Nonlinear MPC/ANN	Repeating Sequence Stairs	24.4	0.81
Nonlinear MPC/LSTM	Repeating Sequence Stairs	353.4	0.10

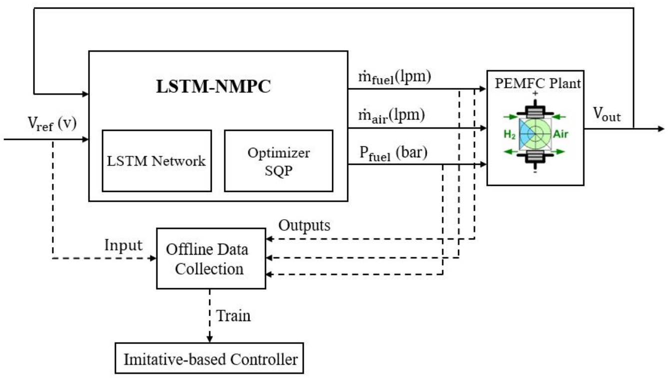


Fig. 2: Schematic of the imitative learning control

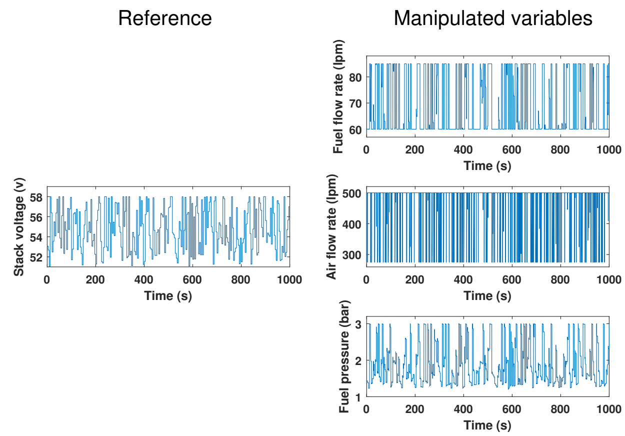


Fig. 3: Manipulated variables with PRS reference for voltage

of the imitative-based controller which will be discussed in the next section.

IV. Generalization and Adaptability of Imitative-based Controller

In this section, two problems are studied for developing an imitative-based controller. The first problem is related to choosing a proper reference signal for exciting the system and NMPC controller. This problem is of high importance since the reference should cover all operating conditions in transient and steady modes to have a general imitative-based controller that can successfully replace the original controller. The second part compares the performance of the NMPC controller and the imitative-based controller in terms of the run-time and adaptability. The results will show that the imitative-based controller runs much faster; however, the major issue of this controller is adaptability to new conditions. A saturation is added to the actuators due to aging as the new condition that the imitative-based controller is not trained for and the controllers results are compared under the new circumstances.

A. Selecting an appropriate reference signal

The imitative-based controller, similar to any other machine learning method, relies on the data used for training. In other words, the designed controller will only be capable of working in the conditions similar to those in the training dataset. This fact highlights the importance of collecting a generalized dataset by applying specific patterns to the reference signal. The Pseudo Random Sequence (PRS) signal is used first with a time period of 4 seconds that permits the system to reach the steady-state mode before the transition to the next reference step. Figure 3 shows PRS or the step sequence input and the corresponding three outputs of the controller.

The other reference input used for exciting the controller is the chirp signal which ranges between 0.1 up to 0.5 rad/s. This signal is also used as it contains all the continuous values between the maximum and minimum boundaries of the output voltage. Moreover, a range of frequencies are applied to the system using this signal. This voltage reference is shown in Figure 4. The imitation-based controllers based on the mentioned two datasets were designed individually and applied to the step sequence and sinusoid references. The results are reported in section IV.

B. Comparison between adaptability of imitative-based and original controllers

As mentioned in the previous section, the imitative-based controller performs well only on the data with the same characteristics as the training samples. Therefore, although the imitative-based controller considerably improves the run-time of the system, any gradual or sudden changes in the system that are not included in the training data lead to inaccurate results for imitative-based controller. Whereas, the LSTM-NMPC shows a better performance since it considers the measured outputs of the system through the feedback. For this part, the actuators are presumed to have aged over time and have less efficiency. Thus, to simulate the aging effect, the outputs of the actuators are assumed to be limited to 40 percent of their actual capacity. This effect can be applied to

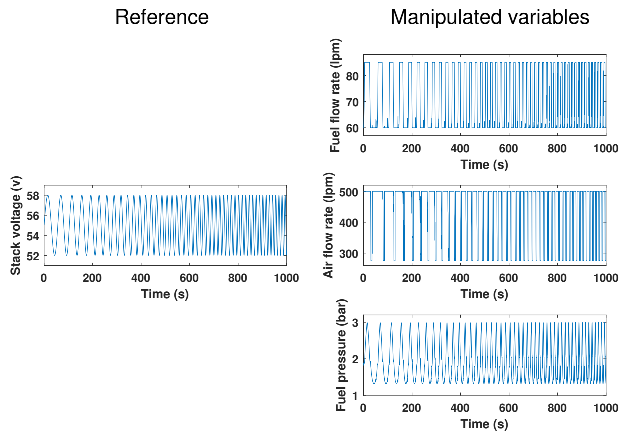


Fig. 4: Manipulated variables with chirp reference for voltage

the LSTM-NMPC by defining new hard constrains while the offline imitative-based controller continues to operate with the same structure and parameters.

V. Results and Discussions

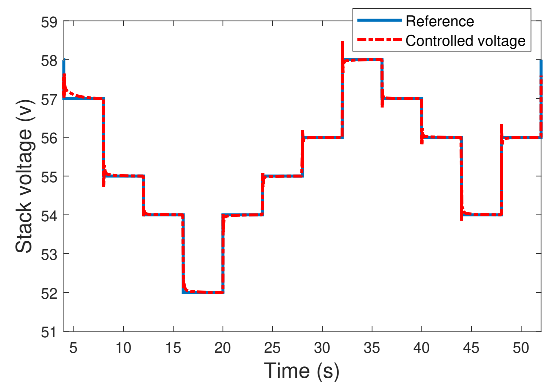
A. Training the imitative-based controller with appropriate data

As discussed in Section IV, collecting the train data is crucial for having an appropriate imitative-based controller and ensure generalization. In this regard, two reference signals, the PRS and chirp signals, are chosen for exciting the controller. Accordingly, two imitative-based controllers are designed and applied to the system. Figure 5 shows the results in response to the step sequence and sinusoid voltage references.

It can be seen in Figures 5a and 5b that the imitative-based controller trained with PRS data performs well on the step sequence reference but is unable to track the sinusoid reference properly. The Root Mean Squared Errors (RMSE) for these two diagrams are 0.07 and 0.20, respectively. For the other case in which the chirp signal has been utilized as the train data in Figures 5c and 5d, both voltage references are tracked and the RMSEs are 0.07 and 0.09, respectively. In the latter case, although the error for the step sequence reference is increased slightly, the error for the sinusoid reference has dropped substantially. This result shows that the chirp signal provides more generality as the resulted imitative-based controller is able to track both kinds of references. Therefore, for the next part, the controller trained with the chirp signal is used.

B. LSTM-NMPC and imitative-based controllers for actuator saturation condition

The imitative-based controller is trained offline in this work which means that, despite online learning, the imitative controller's parameters will not change based on the new



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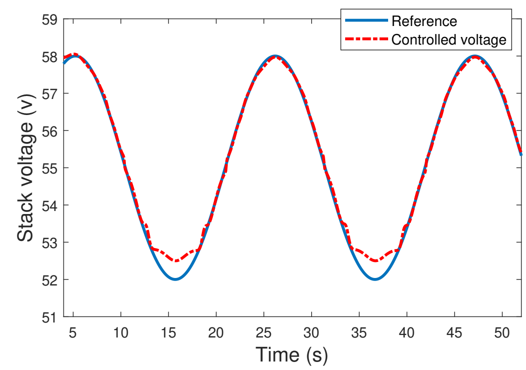

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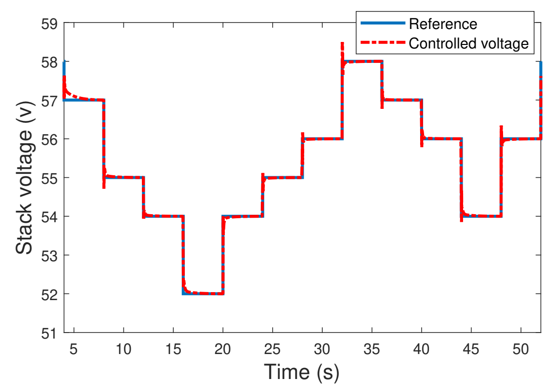

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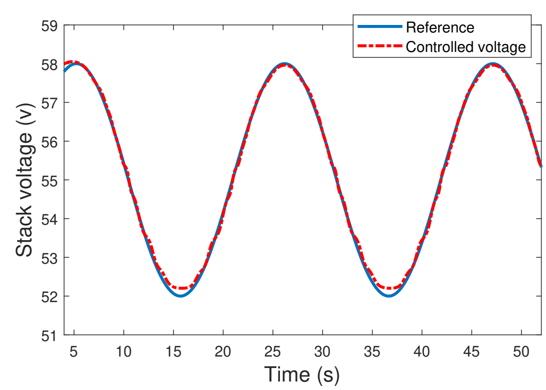
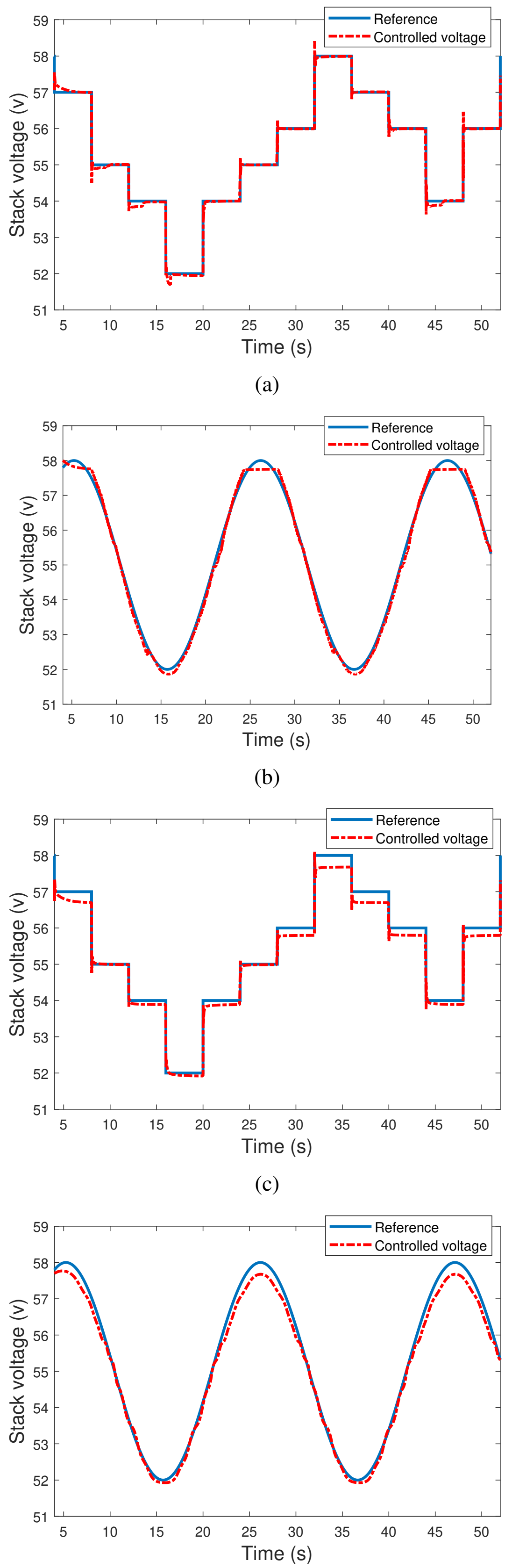


(d)

Fig. 5: Designing imitative-based controller with different reference signals and testing on step sequence and sinusoid. (a) train reference: PRS, test reference: step sequence; (b) train reference: PRS, test reference: sinusoid; (c) train reference: chirp, test reference: step sequence; (d) train reference: chirp, test reference: sinusoid



(a) (b) (c) (d)

Fig. 6: Imitative-based controller and LSTM-NMPC with aging in PEMFC plant (saturation on the actuators). (a) LSTM-MPC with step sequence reference; (b) LSTM-NMPC with sinusoid reference; (c) Imitative-based controller with step sequence reference; (d) Imitative-based controller with sinusoid reference.

upcoming data. A saturation is added to the fuel flow and air flow rate actuators due to aging. The imitative-based controller designed with chirp reference is used for this part and compared with the LSTM-NMPC performance. Figure 6 shows the results for this part.

Based on these results, the LSTM-NMPC is still able to follow the desired voltage in Figures 6a and 6b. Some distortions are emerged in both diagrams which results in the RMSEs equal to 0.08 and 0.14 for the step and sinusoid references, respectively. However, the imitative-based controller produces less accurate voltage tracking for both references in Figures 6c and 6d. The RMSE is 0.19 for step sequence and 0.22 for the sinusoid reference, which is worse than the original controller or LSTM-NMPC. This result highlights the main drawback of offline learning and the necessity of tuning the data-based methods in real applications as the system changes. However, the run-time of the imitative-based controller is still much less than the LSTM-NMPC. Table II summarizes the results presented in this paper. The cumulative fuel consumption which is minimized as one of the objectives of NMPC's cost function has been kept unchanged for all the cases. In addition, the considerable difference in the run time of LSTM-NMPC and imitative-based controller can be observed. All the simulations and corresponding run times reported in this paper were carried out using an Intel Core i7-9700 CPU with 32 GB installed RAM.

VI. Conclusions

In this paper, the LSTM-NMPC for controlling the output voltage of PEMFC was studied to improve its computational cost by using the imitation learning control methods. First, the reference signal that entered the LSTM-NMPC controller and the manipulated variables signal were collected from the LSTM-NMPC by which a neural network is trained as the imitative-based controller. Two reference signal types, the PRS and chirp signals, were used for exciting the LSTM-NMPC. Based on the generalization criteria, the chirp signal was chosen. Next, the LSTM-NMPC was replaced with the trained imitative-based controller and the same performance with much less running time was achieved. The results show that the imitative learning controller can mimic NMPC with an average error less than 0.1 v, while its computational time was about 50 times less than that of the NMPC.

Furthermore, a change in the system as a result of aging was considered showing that the offline imitative-based controller is prone to such changes. The solution for this problem as a future work is referring back to the LSTM-NMPC for controlling the system and updating the imitative-based controller in an online learning framework; however, this will increase the onboard computational cost.

Acknowledgment

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TABLE II: Computational cost, reference tracking error, and cumulative fuel consumption of the designed controllers

Case study	Run time (s)	RMSE (V)	Fuel consumption (L)
LSTM-NMPC from [4] on step reference	358	0.1036	27.65
LSTM-NMPC from [4] on sinusoid reference	436	0.0645	27.93
Imitative controller trained with PRBS on step reference	7.1	0.0690	27.56
Imitative controller trained with PRBS on sinusoid reference	8.3	0.2042	27.85
Imitative controller trained with chirp on step reference	7.1	0.0719	27.60
Imitative controller trained with chirp on sinusoid reference	8.5	0.0908	28.05
LSTM-NMPC with actuator saturation on step reference	286	0.0805	26.98
LSTM-NMPC with actuator saturation on sinusoid reference	361	0.1409	27.15
Imitative controller with actuator saturation on step reference	7.6	0.1993	27.68
Imitative controller with actuator saturation on sinusoid reference	8.6	0.2264	28.10

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