LSTM for forward and inverse kinematic modeling for trajectory tracking of Soft Continuum arm

NUEN 689: DEEP LEARNING FOR ENGINEERS - PROJECT

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1. Introduction

Rigid robots have demonstrated exceptional performance in various applications where human interaction is virtually nonexistent. They have shown performance similar to that of humans in specific tasks, such as navigating rough terrain. However, due to their rigid nature, both humans and rigid robots have struggled to achieve the large deformations required to navigate through narrow gaps. Moreover, their ability to absorb energy is significantly limited, making them vulnerable to malfunctions during operations. Similarly, their rigid nature discourages human-robot interaction as it poses a danger to humans.

This problem has been countered by soft robots, which provide the necessary compliance while maintaining the structural rigidity needed for the application. Soft robots have shown compliance both with humans and their environment. For instance, soft exoskeletal systems and non-invasive surgical devices exemplify this [1]. However, unlike rigid robots, soft materials possess highly nonlinear characteristics, such as anisotropic material properties (stiffness and damping), hysteresis, and stochastic nature. These qualities are extremely challenging to model analytically and are unsuitable for real-time applications due to their high computational costs.

However, the advancement of machine learning has demonstrated that sufficiently complex models can effectively learn stochastic and nonlinear relationships. Generative AI can learn the distribution of images and generate completely new, meaningful images that have never existed before. By leveraging these capabilities, AI has been explored for modeling the kinematics and dynamics of soft robots [2], [3]. The promising results suggest that learned models can outperform analytical approaches [4], [5].

In this project, we explore an LSTM model for learning the forward and inverse kinematics of a soft continuum arm made of pneumatic muscle actuators [5], [6]. This continuum arm has shown promise in applications such as grasping and mobile robots, although closed-loop control is challenging due to inaccurate models [7], [8]. The project's goal is to develop models that are sufficiently accurate for trajectory tracking. Data collection is achieved

Figure 1:Soft quadruped, Soft snake and a Soft gripper

through simulation data due to the scarcity of real-world data. Then, we develop, train, and fine-tune the model to obtain the best model. The following sections present the problem statement, methodology, and the results of the proposed model.

2. Problem Definition

Due to the soft nature, the robot shows highly non-linear behavior due to the non-linear material and structural properties such as anisotropic stiffness and damping. Moreover, data revealed that hysteresis and deadzone not only depend on the direction but also on the operating parameters. Therefore, developing an analytical model for real-time operation is highly challenging. Hence, an approximator such as neural networks could be used to estimate the complex functions. However, non-linear properties are well approximated with more information, such as the state history. Therefore, literature suggests that Long-Short-Term Memory (LSTM) networks keep the history of previous states in order to predict the next state.

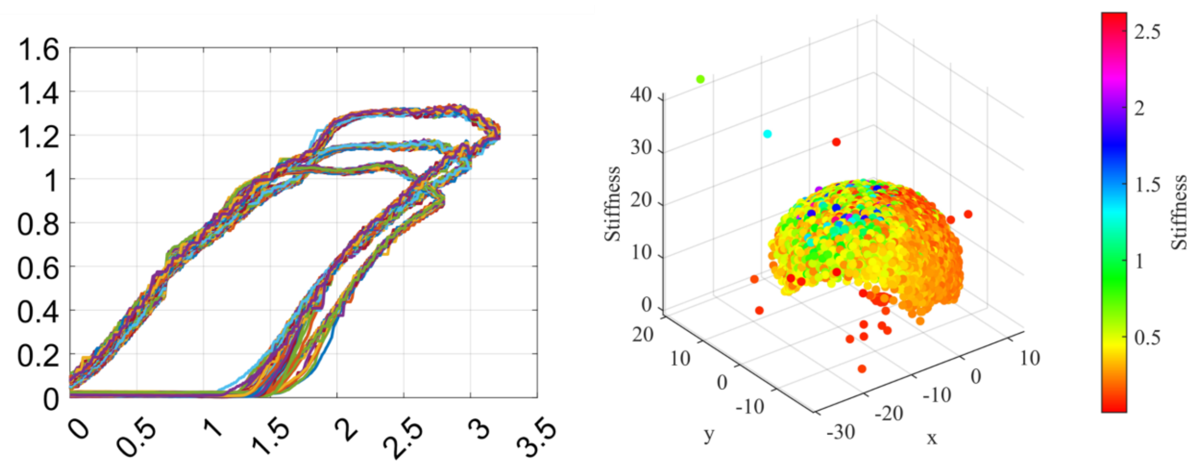


Figure 2: The operating speed depends on the hysteresis of a continuum arm (left). Stiffness variation of a continuum arm in the workspace

Objectives

1. Sample trajectories from the workspace of the continuum arm and preprocess them for training.
2. Develop, train, and tune LSTM models to obtain accurate forward and inverse kinematic models.
3. Validate the model performance by conducting trajectory tracking.

3. Methodology

The continuum arm has three pneumatic muscle actuators (PMAs) that serve as its actuators. However, due to its mechanical construction (inextensible backbone), the continuum arm exhibits only two degrees of freedom within a spherical workspace. The PMAs require a pressure of 0.5 to 3 bar to operate the arm, and this input variable is designated as $\boldsymbol{p}$. In the project, we aim to predict the tip position $\boldsymbol{r}$, given $\boldsymbol{p}$ and a possible model of the inverse relationship.

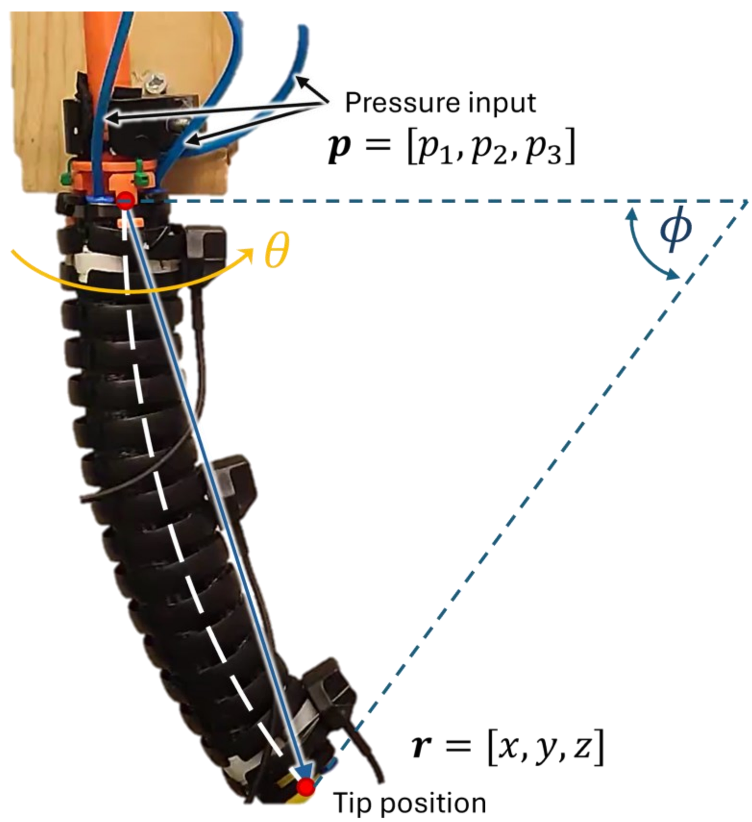


Figure 3: Schematic diagram of the continuum arm

1. Kinematic Model

The continuum arms presented in this project have an inextensible backbone that generates constant curvature bending. Due to that, the model of the arm kinematics is simply derived from a constant curvature arc. The arc is parameterized by two variables known as *configuration space variable*, θ and ϕ, which represent the bending direction and the bending angle. The mapping function between *the task space variable and the configuration variables is given in the following equations, which are used in the current progress to develop the* LSTM pipeline.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} -\frac{\cos(\theta)\cos(\phi)L}{\phi} + \frac{\cos(\theta)L}{\phi} \\ -\frac{\sin(\theta)\cos(\phi)L}{\phi} + \frac{\sin(\theta)L}{\phi} \\ \frac{\sin(\phi)L}{\phi} \end{bmatrix}$$

Where, L is the length of the module, which is $0.25\ m$. The configuration variable and the actuator variable $\boldsymbol{p}$ is given by the following equations,

$$\theta = \tan^{-1}\left(\frac{\frac{-A\cdot r\cdot\sqrt{3}\cdot(p_2 - p_3)}{2}}{\frac{-A\cdot r\cdot(-p_2 - p_3 + 2\cdot p_1)}{2}}\right)$$

$$\phi = \frac{\sqrt{A^2r^2(p_1^2 - p_2p_1 - p_3p_1 + p_2^2 - p_2p_3 + p_3^2)}}{K}$$

We get the actuator-task variable kinematic relationship by substituting this into the previous equation. Due to the complexity of the equation, it is not mentioned here. However, inverse kinematics doesn't have an analytical solution. Therefore, the only options are optimization or the Jacobian matrix utilization. These methods get more complicated when nonlinear characteristics are embedded in the kinematics/dynamics. Therefore, we need the approximators to approximate the highly nonlinear system.

2. Sampling trajectories

The trajectories are sampled from the task space to generate the training dataset for the model. The samples are generated to cover the entire space of the configuration variables. The initial length of the trajectory is limited to 40 data points, but the final length has increased to 80 during fine-tuning. Moreover, trajectories exhibit significant variation in ϕ, resulting in 3D Cartesian space trajectories. To enhance the robustness of the system, white noise with $\mathcal{N}(0, 0.001)$ is added to the data.

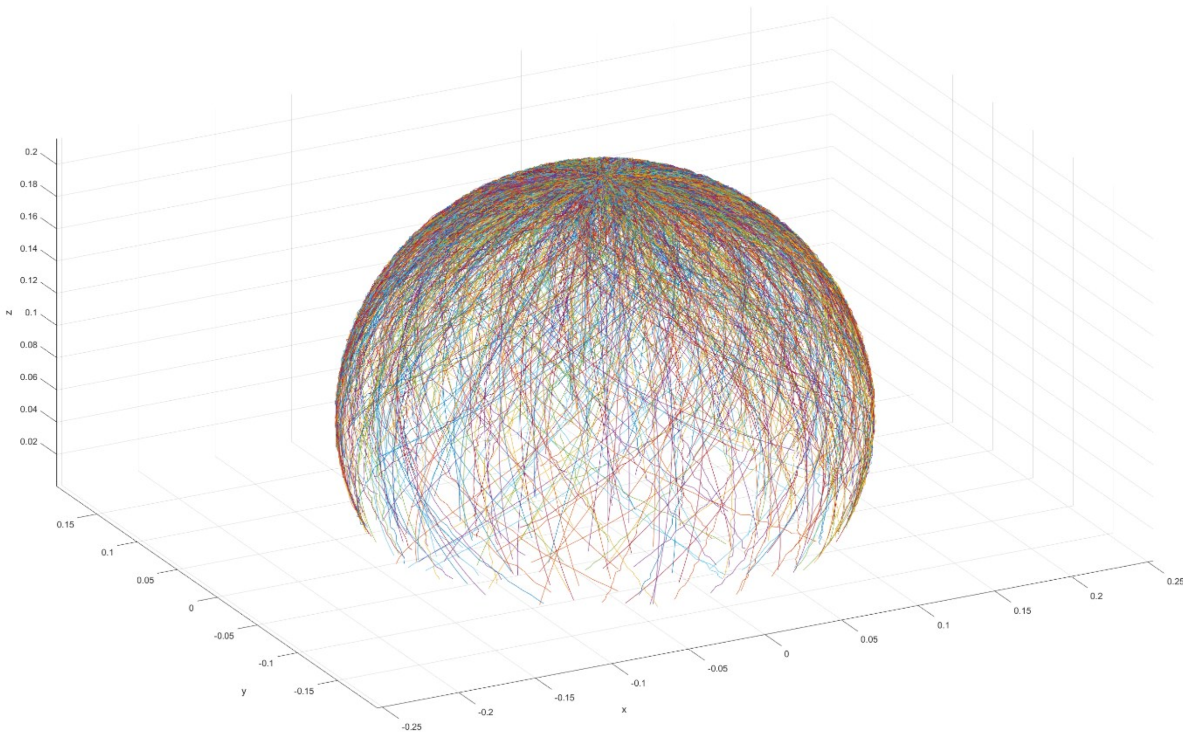


Figure 4: Sample trajectories with noise. Noise only added to a 30% of the dataset

3. Hyper-parameter optimization

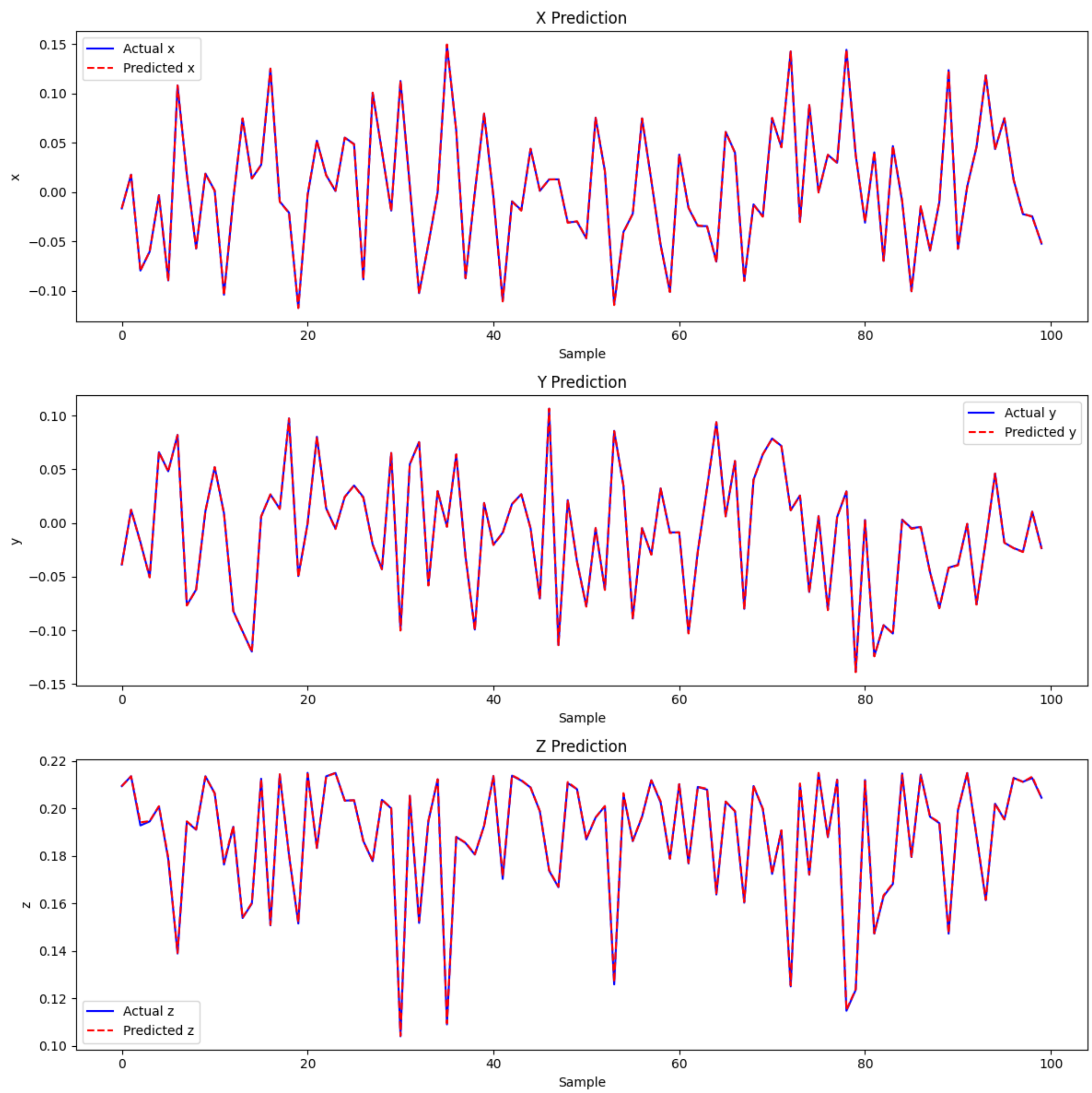
To search for the best architecture of the LSTM network for this application, Bayesian optimization is used. The search range parameters mentioned in the table.

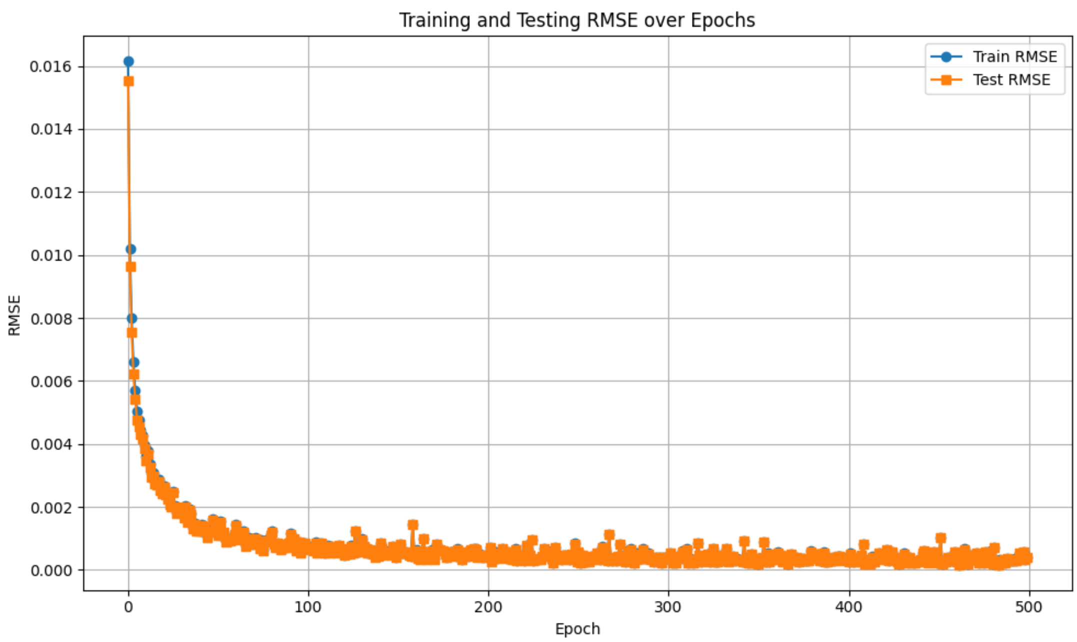
No. Seeds	30	**Trials**	50
LSTM Layer	[1, 4]	**LSTM Nodes**	[16, 128]
NN Layers	[1, 4]	**NN Nodes**	[8, 128]
Lr	[0.0001, 0.01]		

4. Results

Initial training was conducted for the configuration-task variable kinematics. This indicates that the training pipeline is correct. The following figures show the training and testing performances.

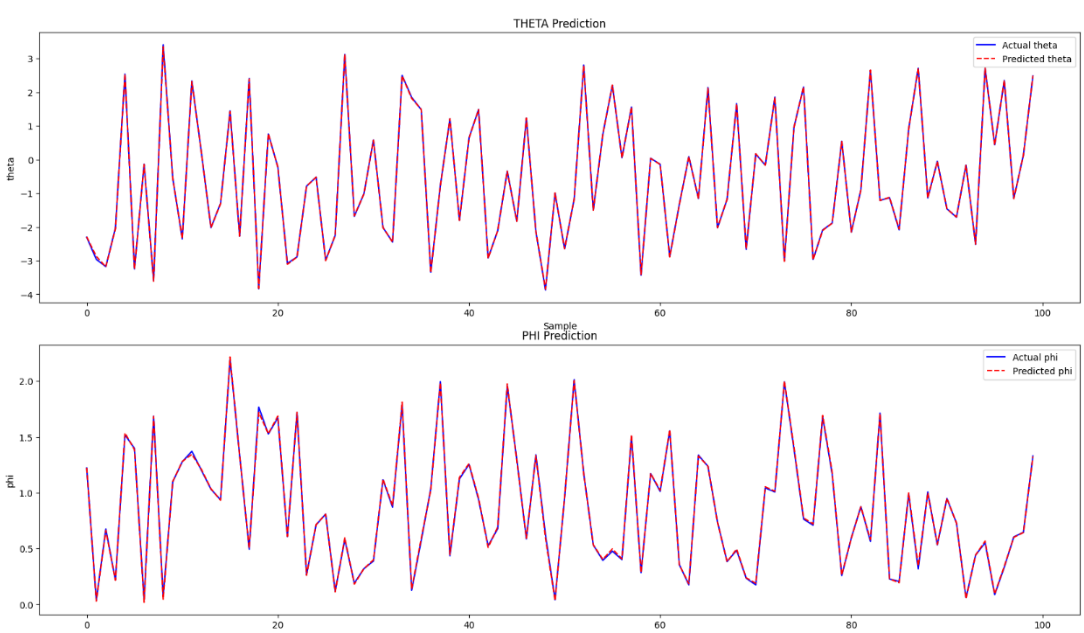
Lookback	10	**LSTM inputs**	2
LSTM Layers	1	**LSTM nodes**	30
NN layers	[1]	**NN out**	3

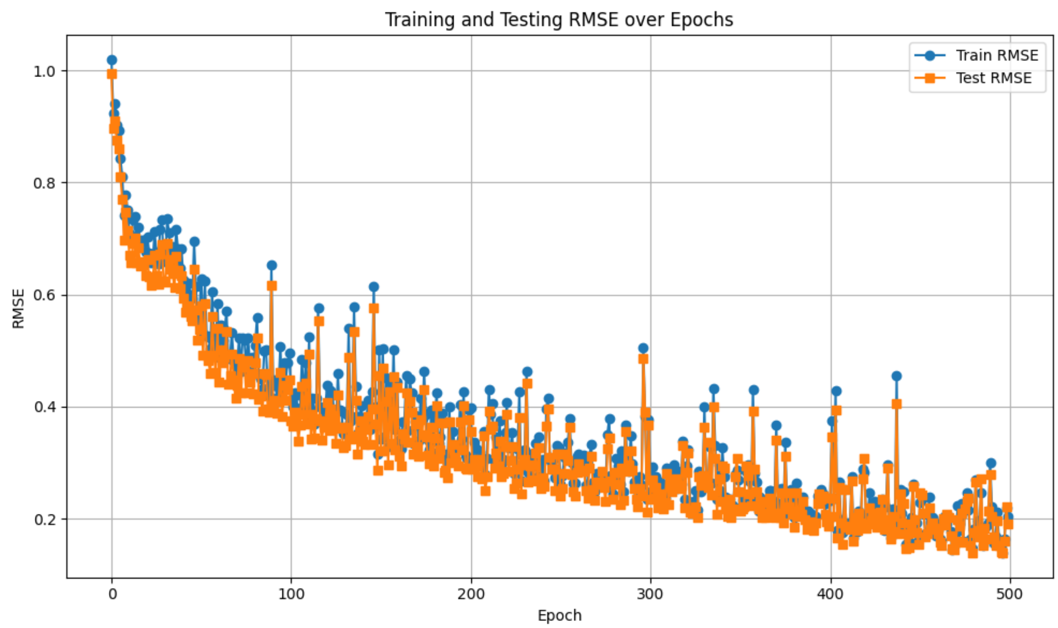




The validation and training show proper training and convergence to a reasonable value. The error seems to be very insignificant. The challenging model is the inverse configuration-task kinematics. The following results present the performance of the training of a particular LSTM model.

Lookback	10	**LSTM inputs**	3
LSTM Layers	3	**LSTM nodes**	[45 45 45]
NN layers	[47 35 26]	**NN out**	2

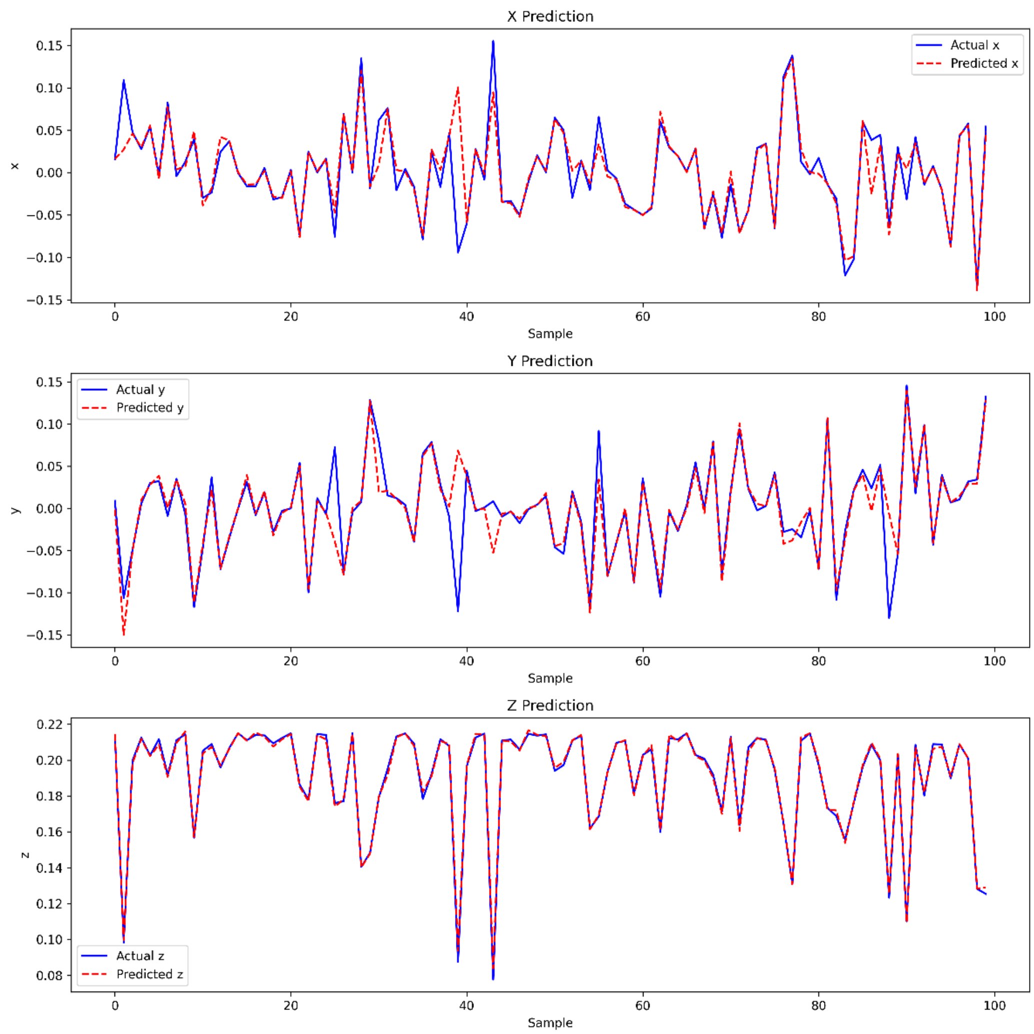




The inverse model's training is challenging. However, a particular LSTM model can learn the relationship with acceptable error.

The actuator-task model is critical in real-world applications, as we control the actuator directly. The forward modeling results are as follows. The forward model is particularly used to simulate the robot in control loops. However, these analytical models are challenging to the

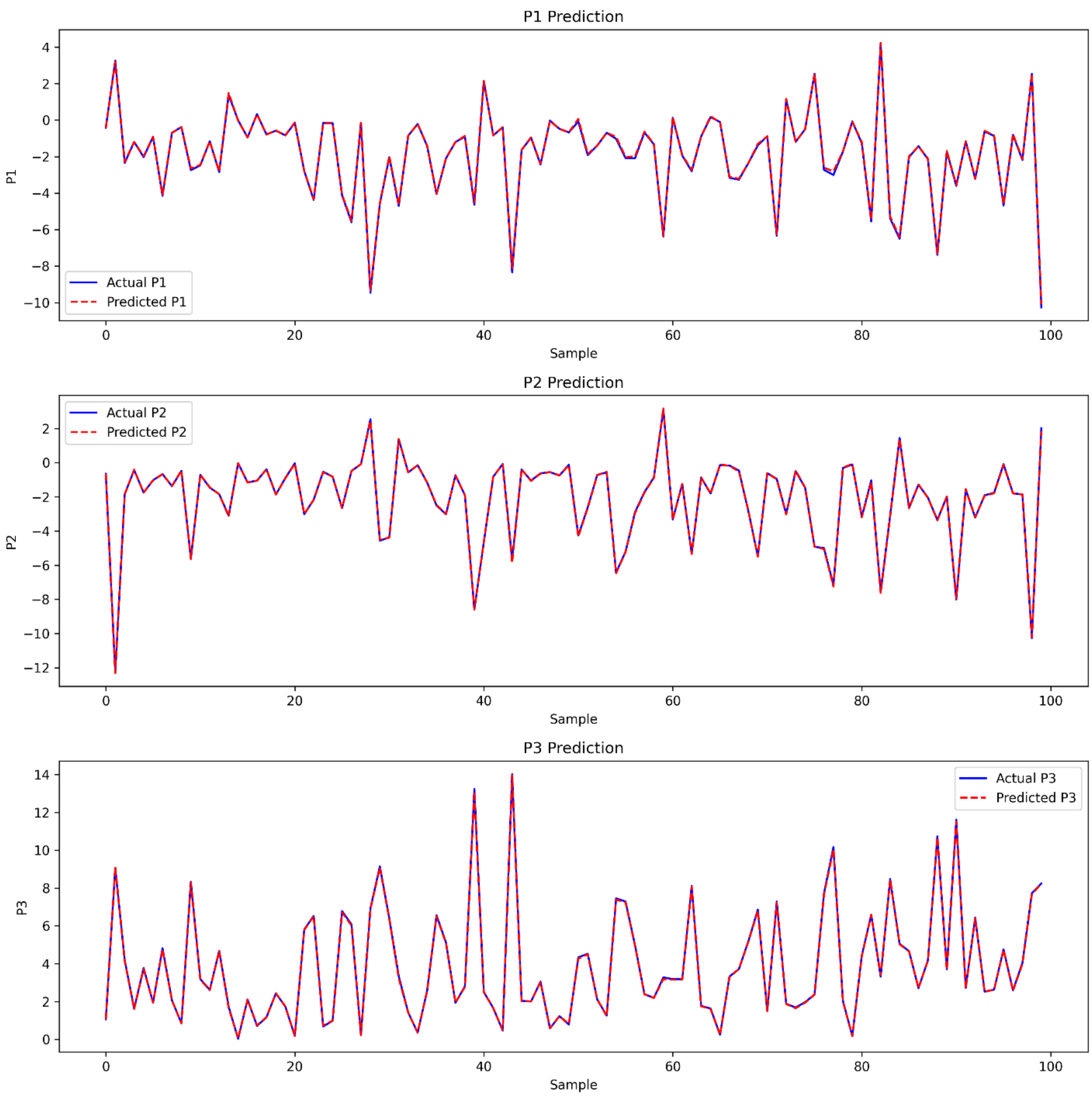
Lookback	10	**LSTM inputs**	3
LSTM Layers	4	**LSTM nodes**	[103 103 103 103]
NN layers	[47 72 88]	**NN out**	3


X Prediction
Actual x
Predicted x
x
Sample
Y Prediction
Actual y
Predicted y
y
Sample
Z Prediction
Actual z
Predicted z
z
Sample

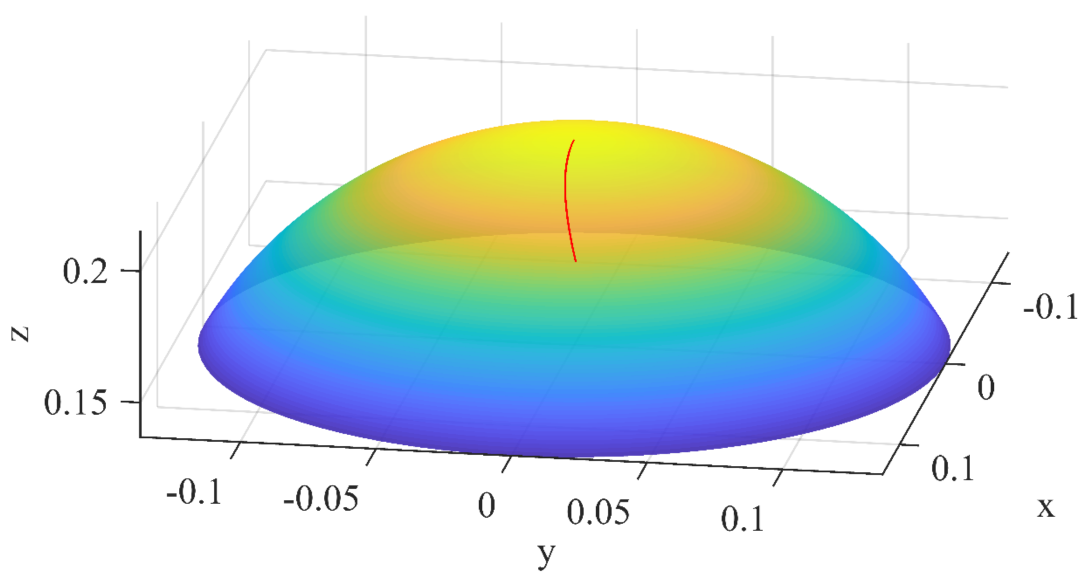

Training and Testing RMSE over Epochs
Train RMSE
Test RMSE
RMSE
Epoch

Training is not perfect. It is understandable that pressure-task kinematics is substantially complex than the other space-kinematics. The following data shows the inverse relationship training performance.

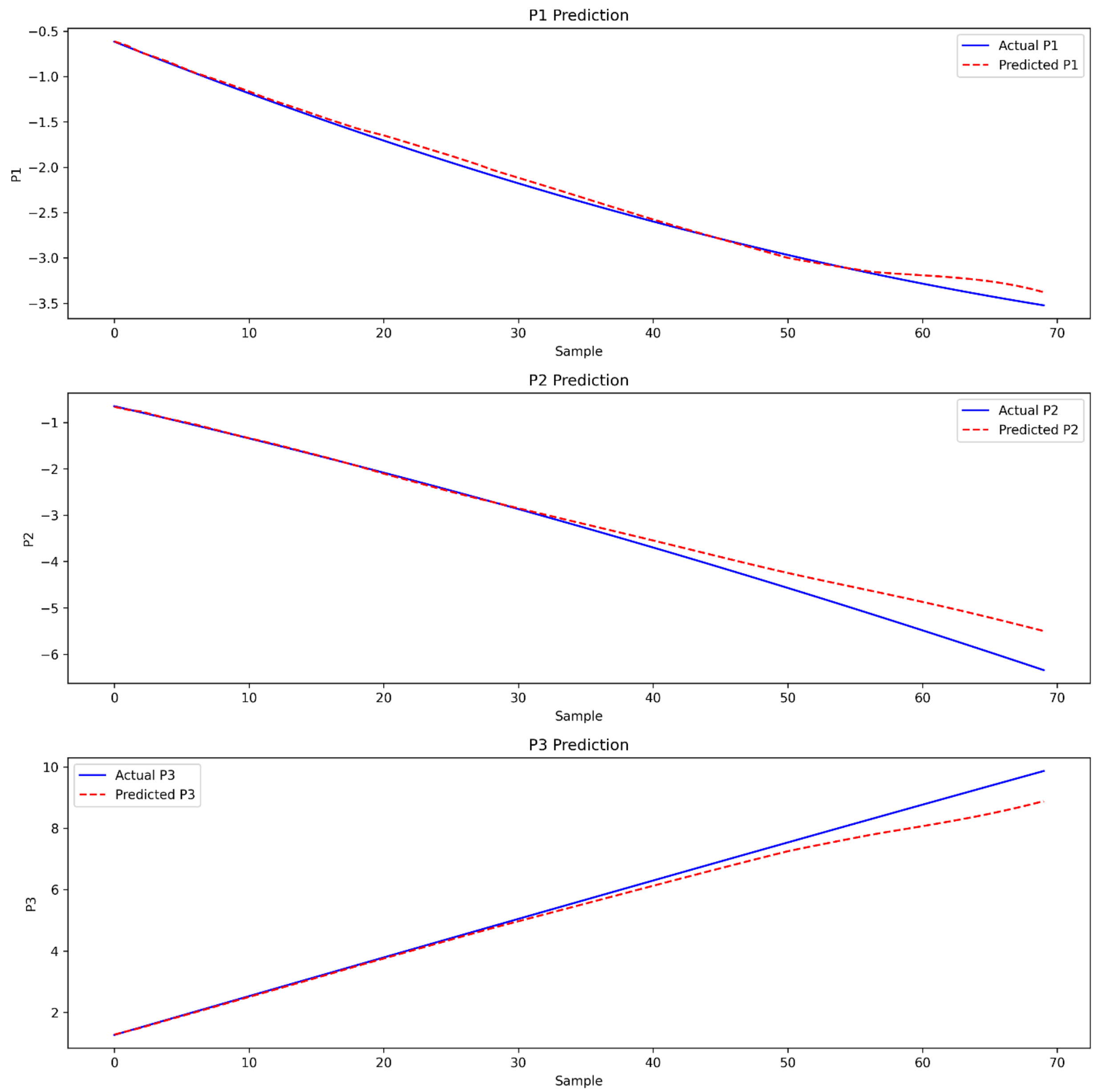
Lookback	10	**LSTM inputs**	3
LSTM Layers	2	**LSTM nodes**	[89 89]
NN layers	[79 111 101]	**NN out**	3



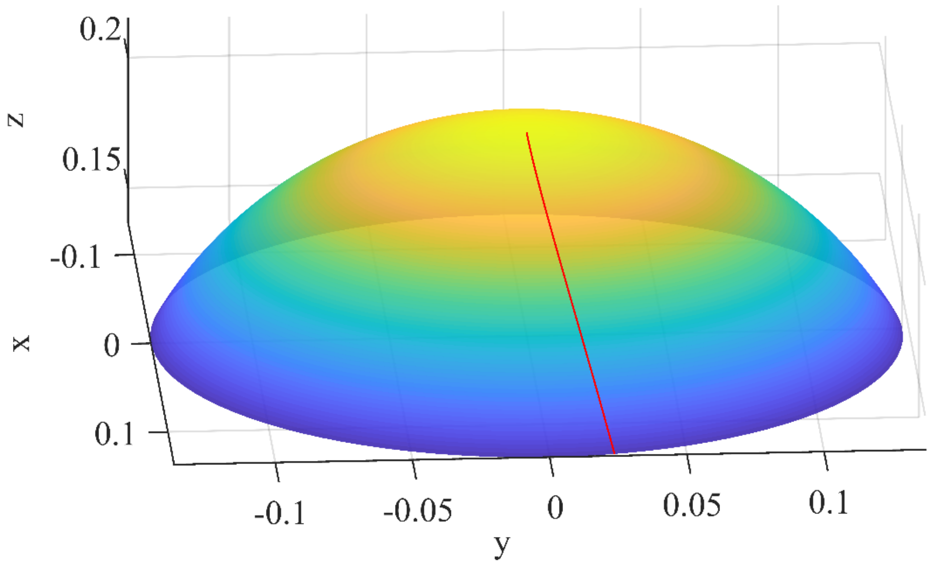
Error seems reasonable and needs to be checked for the trajectory tracking. The initial trajectory is of short length and almost planar.

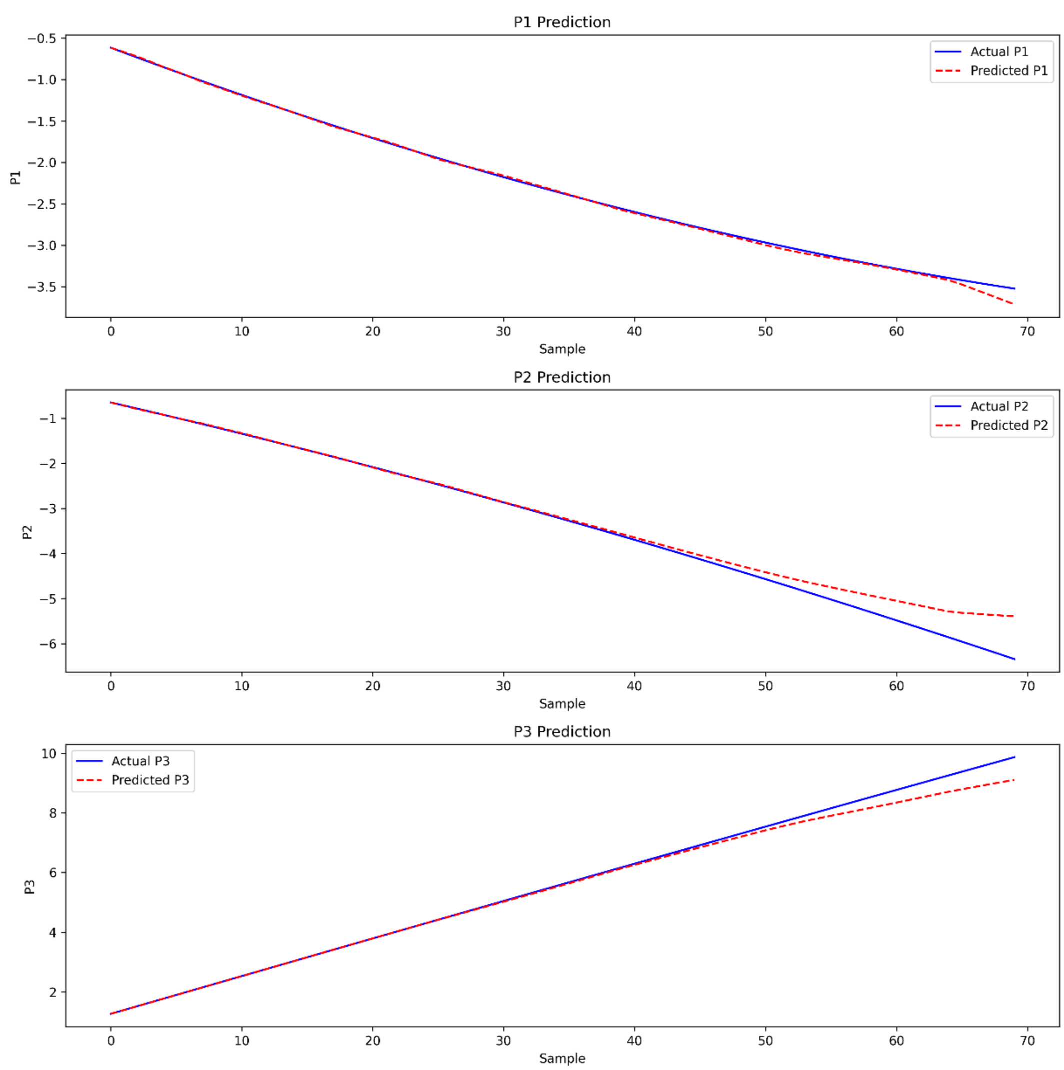


The predicted pressure trajectories are follows.

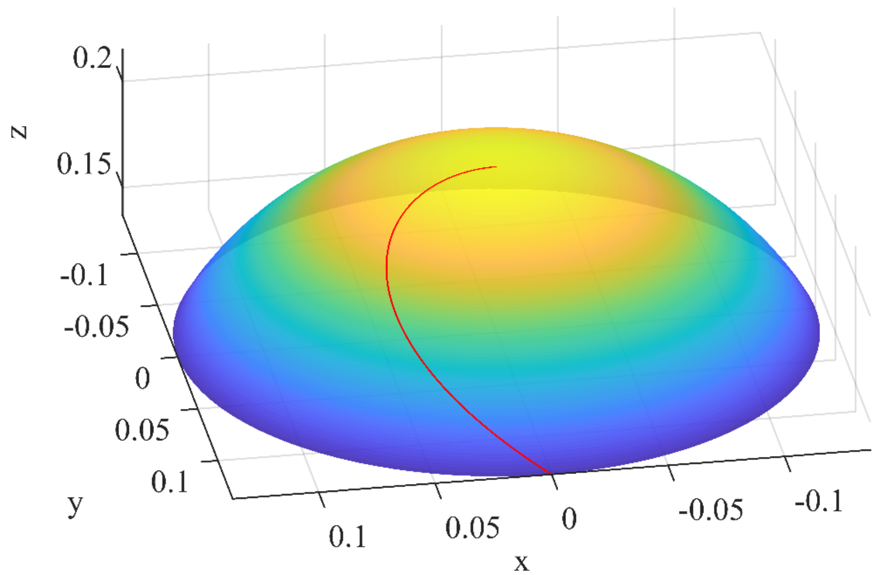


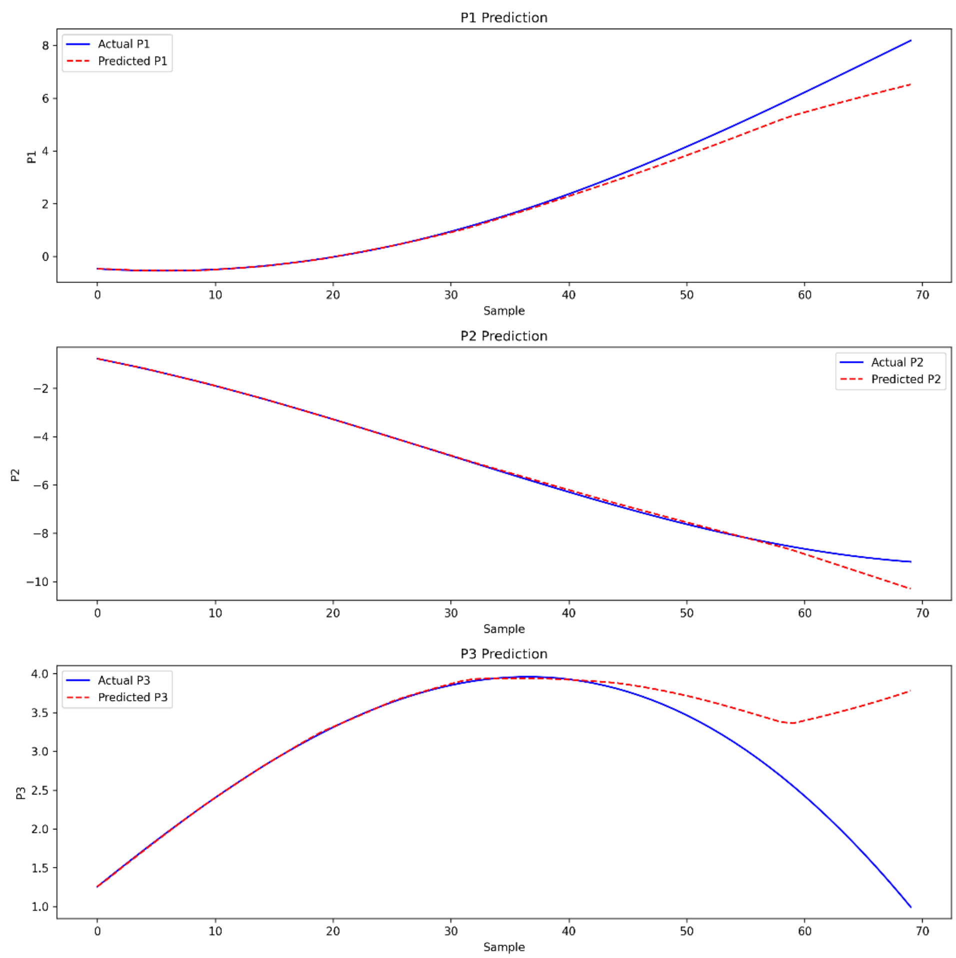
The predictive power is superior at the beginning, although the final data points show a deviation from the desired values. Therefore, another tracking is conducted to evaluate the model. In this experiment, a long trajectory on a plane is selected.


0.2
z
0.15
-0.1
x
0
0.1
-0.1
-0.05
0
0.05
0.1
y

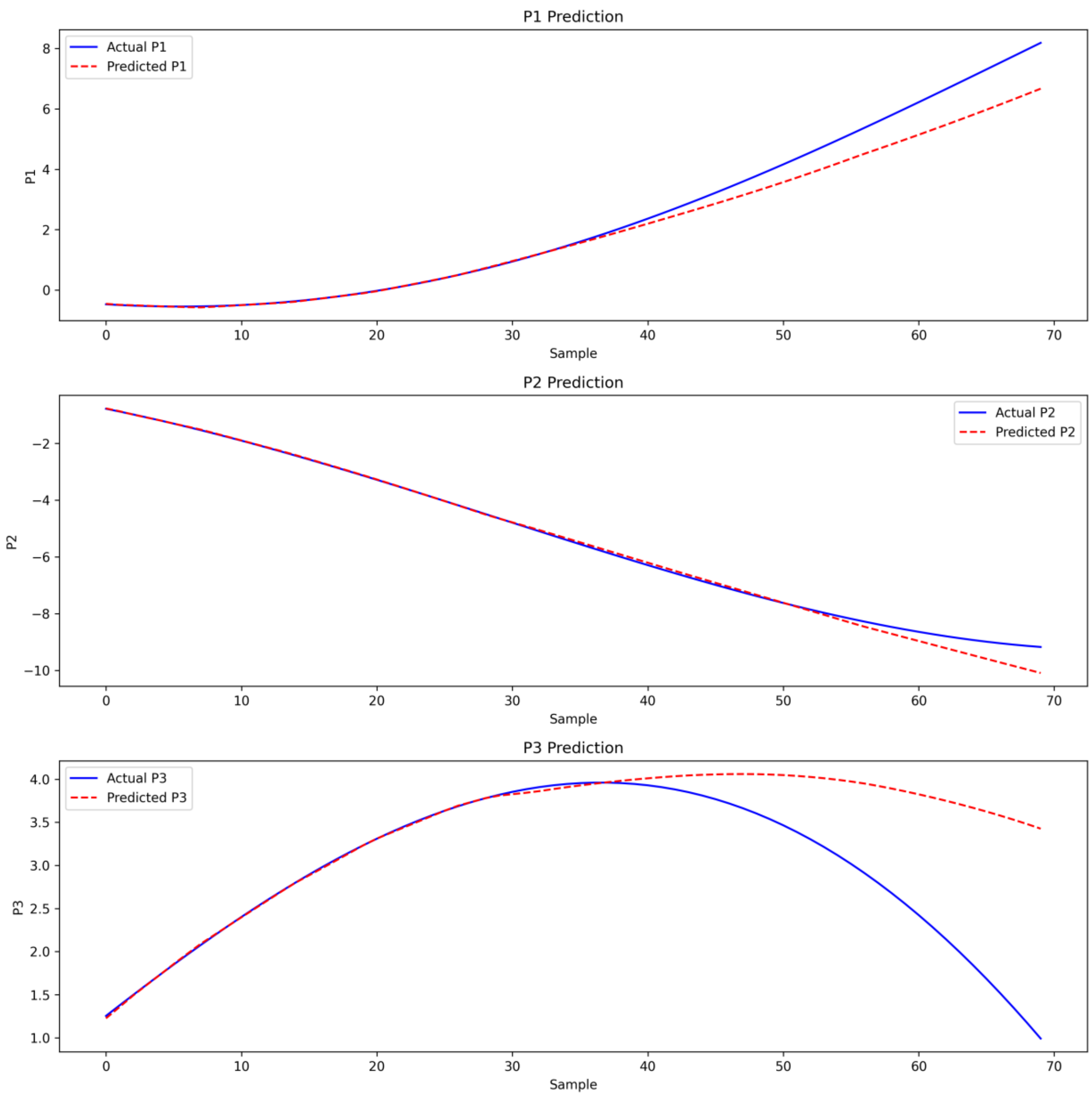

P1 Prediction
Actual P1
Predicted P1
P1
Sample
P2 Prediction
Actual P2
Predicted P2
P2
Sample
P3 Prediction
Actual P3
Predicted P3
P3
Sample

Results indicate good agreement as the previous experiment. In order to evaluate the robustness of the, out-of-plane trajectory is tracked.





The LSTM model is struggling to track the pressure trajectory. Variation of the variable appears to be difficult to achieve. Therefore, a fine-tuning with more data that has significant out-of-plane trajectories. Training was conducted with decaying learning rate for stable learning.



The model was able to identify the trajectory direction. However, the model is still unable to track it. This indicates that the model needs further training and hyperparameter tuning.

5. Conclusion

The ML models have shown potential to approximate nonlinear systems. The LSTM model has specifically demonstrated exceptional performance in approximating time-dependent robotics applications. In this work, we have investigated the pure LSTM model's performance in approximating forward and inverse models of a soft continuum arm. The results indicate that the models are able to learn the behavior of the robots. However, further training and fine-tuning are required for real-world applications.

6. References

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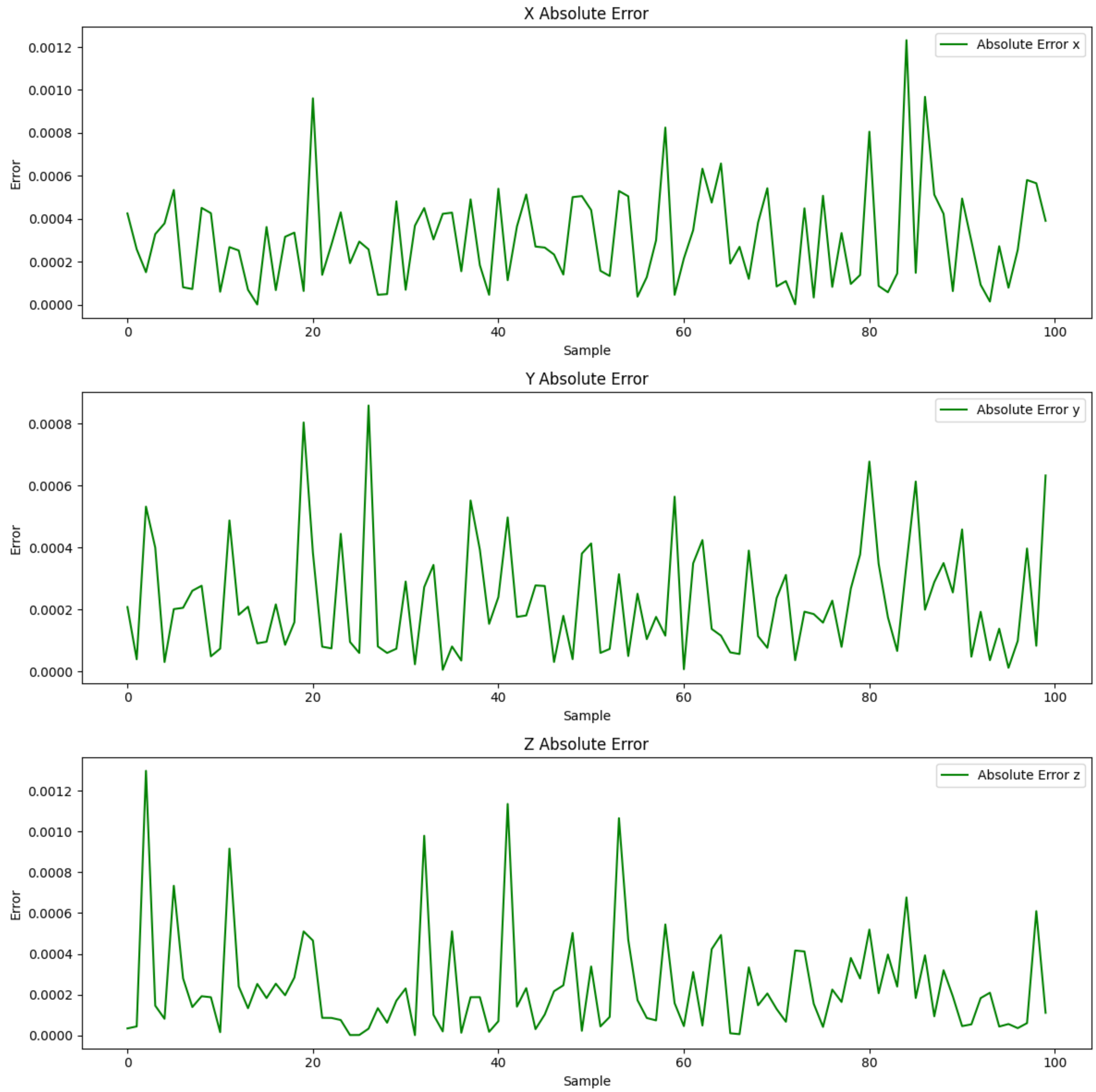
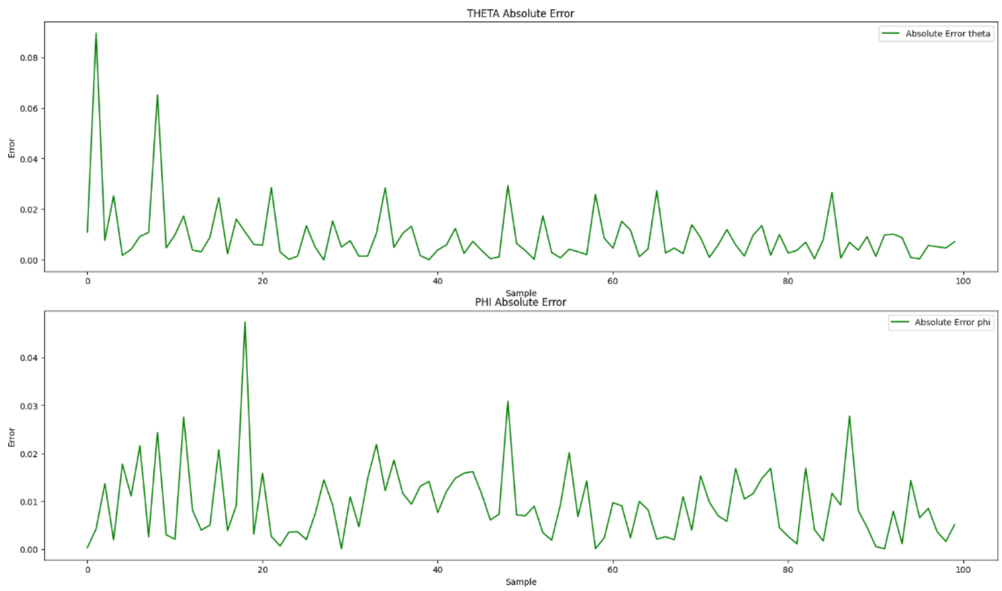
7. Appendices

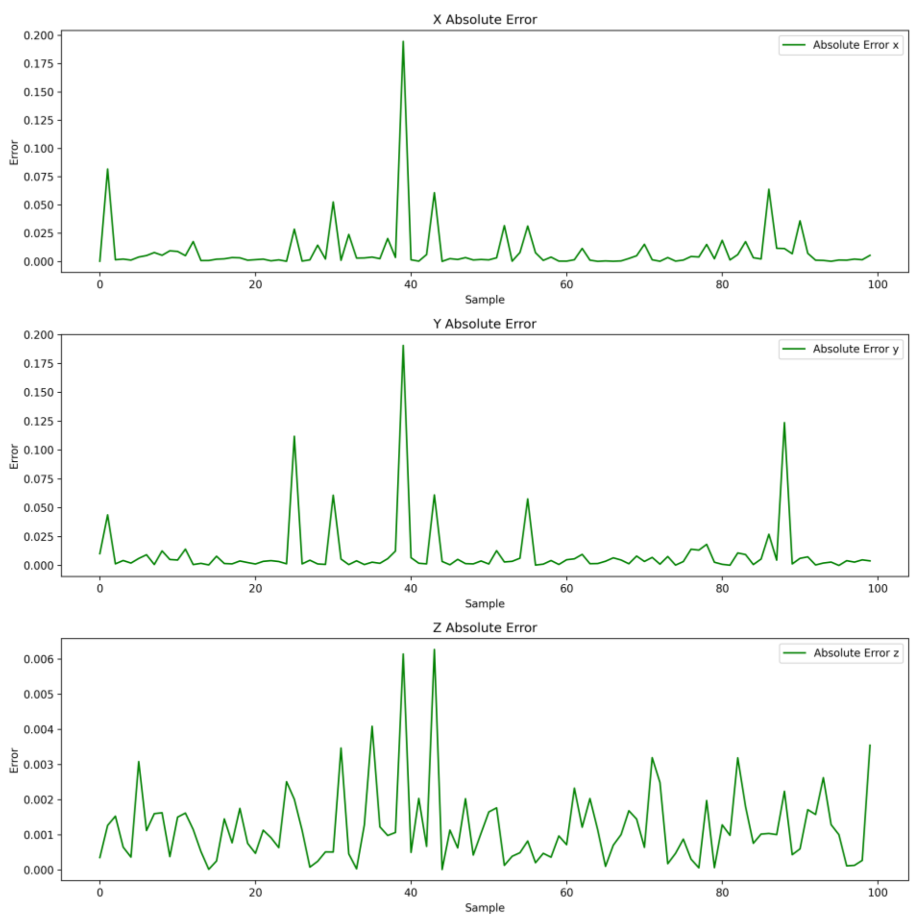
Configuration-task kinematic error



Task-configuration kinematic error



Pressure-Task error



Task-Pressure error