



Neural Dynamic Modeling and PSO-Based Identification Trajectory Design for a 2-DOF Robot Manipulator

Chi-Shan Hung¹, Yi-Ming Tien², Yi-Cheng Hsiao², Ping-Huan Cheng², Ming-Yang Cheng^{2,*}

¹Department of Mechanical Engineering, National Cheng Kung University

²Department of Electrical Engineering, National Cheng Kung University

Introduction

As the demand for automation continues to grow, accurate robot dynamics modeling has become increasingly important for motion prediction and high-performance control. Recent advances in AI have enabled learning-based approaches to capture complex robot dynamics beyond conventional analytical modeling. However, as robotic systems become more complex with increasing degrees of freedom, effects such as joint friction, parameter uncertainty, and unmodeled dynamics make accurate simulation increasingly challenging, contributing to the Sim-to-Real gap. Therefore, physics-informed neural network (PINN)-based approaches provide a promising solution by combining physical knowledge with neural networks. In this study, we develop a hybrid PINN model and a PSO-based excitation trajectory method for accurate robot dynamics modeling.

PINN-based Dynamic Model

Deep Lagrangian Networks (DeLaN) are physics-informed models that learn robot dynamics while preserving the structure of Lagrangian mechanics. However, the standard DeLaN formulation does not explicitly account for non-conservative and unmodeled effects, such as joint friction. Therefore, we develop a hybrid inverse-dynamics model (Fig 1) in which DeLaN captures the structured dynamics, a parametric friction model represents joint friction, and a feedforward neural network (FNN) learns the remaining residual dynamics.

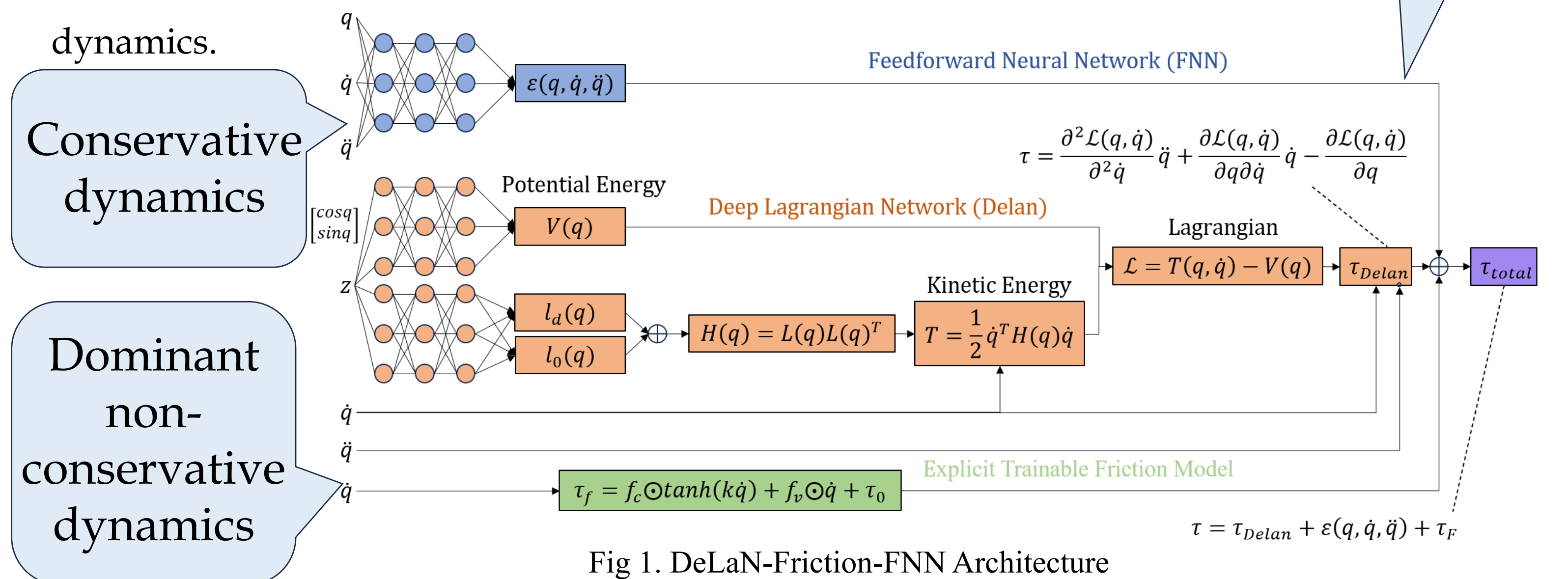


Fig 1. DeLaN-Friction-FNN Architecture

PSO-Trajectory Planning and Constraint Verification

The proposed architecture is evaluated on a self-developed 2-DOF robotic manipulator (Fig 2.). To obtain informative data for dynamics modeling, a particle swarm optimization (PSO)-based excitation trajectory generation method is developed to sufficiently excite the robot dynamics while satisfying workspace constraints. The generated trajectories are applied to both learning-based and identification-based dynamics modeling as shown in Fig 3.

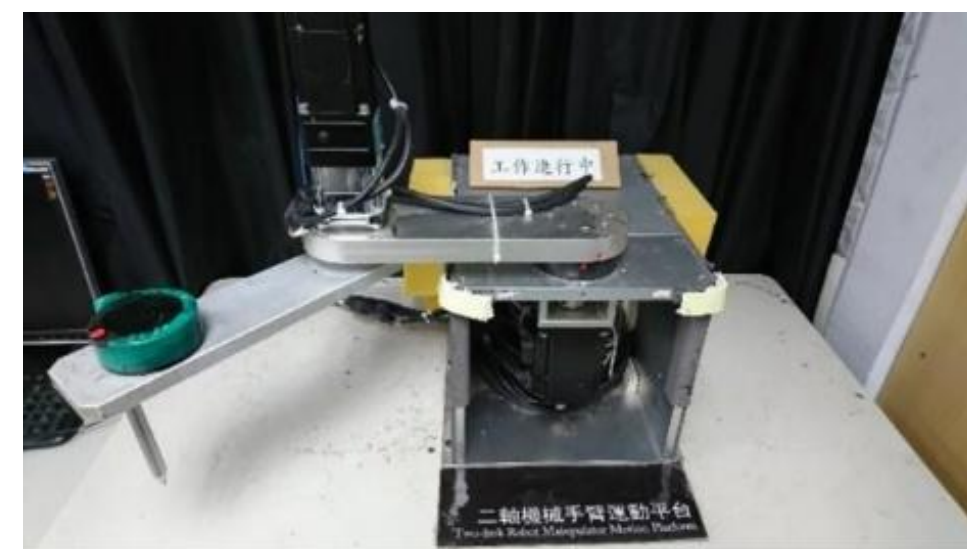


Fig 2. Robotic experimental platform

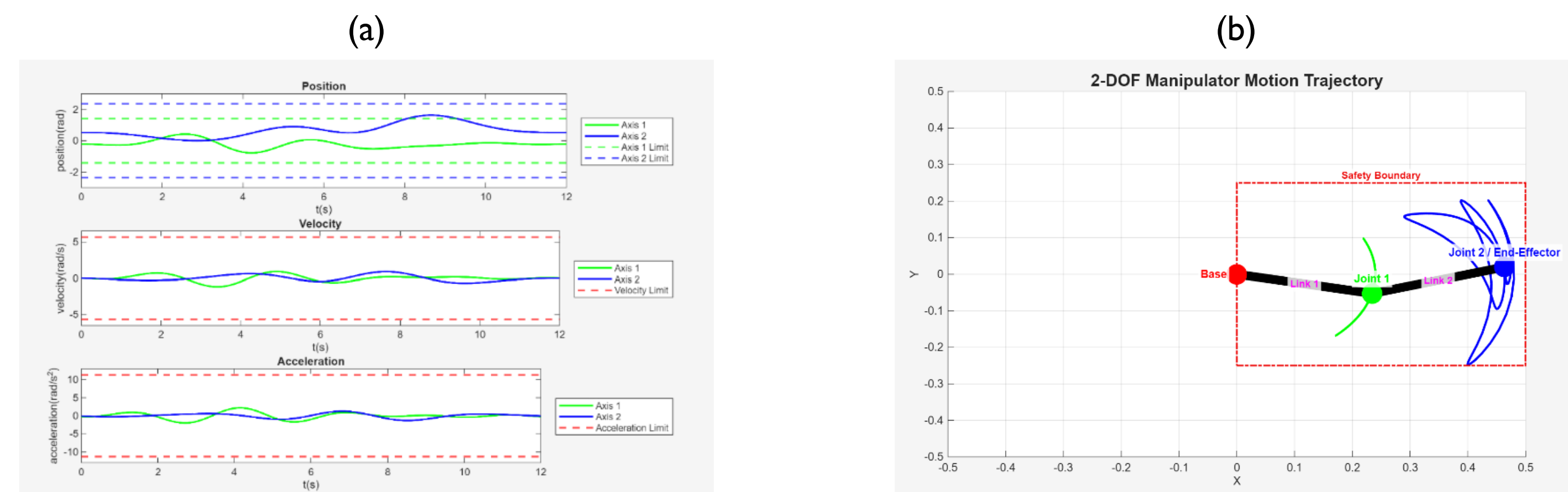


Fig 3. Trajectory validation of the two-axis manipulator planned by PSO: (a). collision-avoidance trajectories of the end-effector (blue) and elbow (green) in Cartesian space. (b). joint-space position, velocity, and acceleration response curves

Torque Prediction Comparison

To evaluate inverse-dynamics modeling performance and generalization, the models are tested on unseen trajectories by comparing the predicted and measured joint torques. Fig. 4 presents the torque prediction performance of the different methods and shows that explicit friction modeling improves DeLaN torque prediction accuracy, while allowing the FNN to learn the remaining residual dynamics yields further improvement. The proposed model achieves the best overall torque prediction performance among the baseline methods considered. Improved performance is maintained on unseen test trajectories. Overall MSE is reduced by approximately 8.5% compared with DeLaN-FNN and DeLaN-Friction, and by 32.8% relative to IDIM-LS.

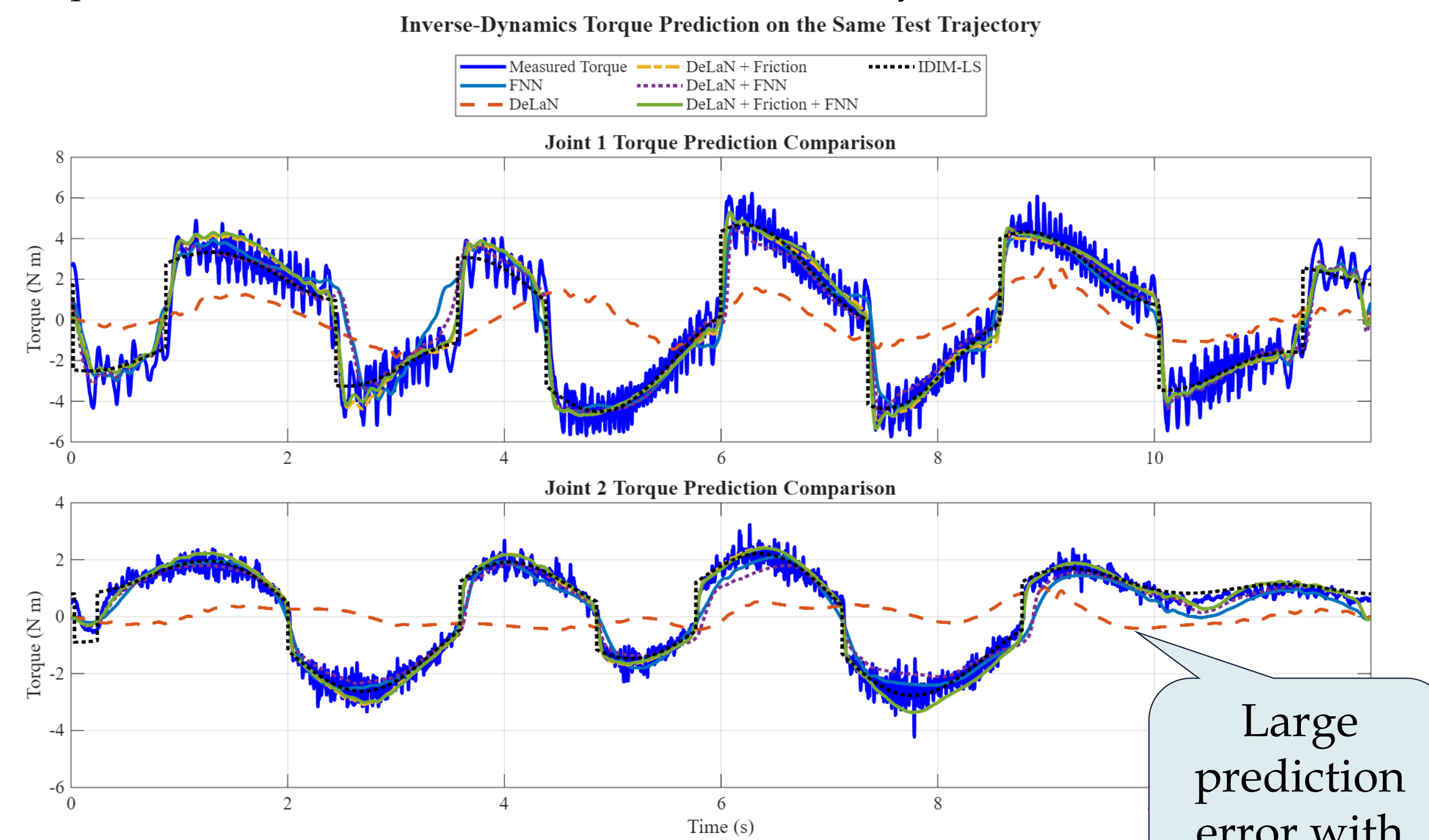


Fig 4. Inverse dynamics torque prediction on the same test trajectory

Table 1. Inverse-dynamics modeling performance

	Inverse Model MSE ($N \cdot m$) ²		Joint 1 R2	Joint 2 R2	Average Relative L2 error
	Joint 1 MSE	Joint 2 MSE			
IDIM-LS	1.007±0.088	0.148±0.059	0.875±0.022	0.938±0.021	29.99%
FNN	2.215±2.166	0.103±0.065	0.734±0.246	0.958±0.025	33.57%
DeLaN	7.913±0.555	2.370±0.510	0.033±0.039	0.018±0.030	98.22%
DeLaN - FNN	0.762±0.298	0.085±0.050	0.905±0.044	0.964±0.020	25.94%
DeLaN-Friction	0.771±0.086	0.078±0.024	0.905±0.017	0.961±0.018	24.23%
DeLaN-Friction - FNN	0.698±0.076	0.078±0.024	0.914±0.017	0.967±0.010	23.53%

Table 2. Relative to total norm ratio of DeLaN-Friction-FNN

Component torque norm / total torque norm	DeLaN/Total	Friction/Total	FNN residual/Total
DeLaN-Friction	0.169023	0.989519	
DeLaN-FNN	0.084123		0.987987
DeLaN-Friction-FNN	0.1509	0.9665	0.0752

Control Performance Validation

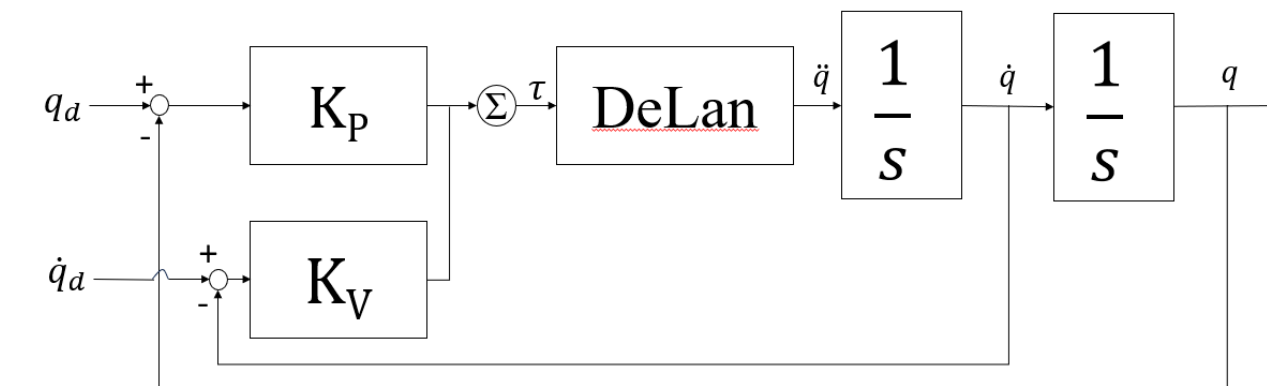


Fig 5. Simulation environment control architecture

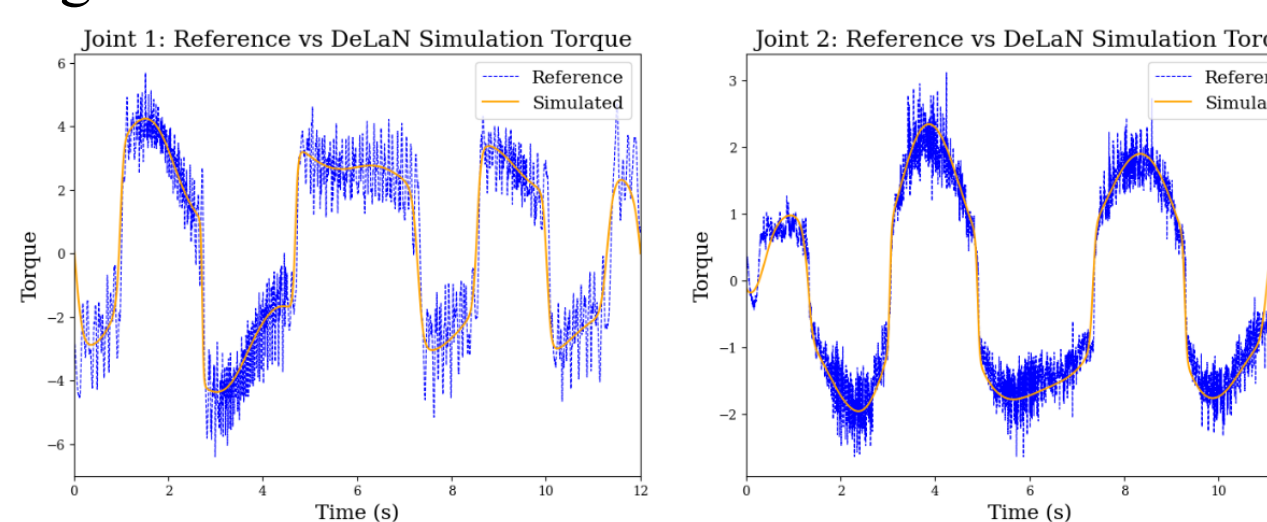


Fig 6. Control simulation results: Measured vs DeLaN-simulated joint torques

To evaluate the control-oriented applicability of the learned model, a closed-loop simulation is constructed using the structured DeLaN dynamics (Fig 5). The extracted inertia matrix and dynamic terms enable inverse- and forward-dynamics calculations. The simulated joint torques follow the trend of the measured torques (Fig 6), demonstrating that the physical structure can support model-based control.

Conclusion

By modeling the dominant friction effects separately, the residual FNN can focus on the remaining unmodeled dynamics while preserving the structured physical representation of DeLaN. Experimental validation on a self-developed 2-DOF manipulator shows that the proposed model achieves the best overall torque prediction performance on unseen trajectories. In addition, the PSO-based trajectory design successfully generates excitation trajectories satisfying joint and workspace constraints for dynamics modeling. The model also enables the extraction of inertia and other dynamic terms, supporting future model-based control applications.