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Physics-informed neural networks for the prediction of robot dynamics considering motor and external force couplings

Key words: Dynamics modeling; Physics-informed neural networks; Motor dynamics; External force modeling; Kinematics

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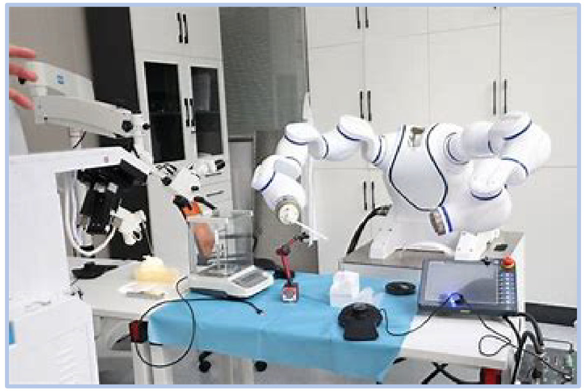
Why accurate robot dynamics matter

- Modern manipulators operate in contact-rich tasks—precision assembly, minimally invasive surgery, human–robot collaboration—where unmodeled nonlinearities and external forces rapidly degrade control accuracy.



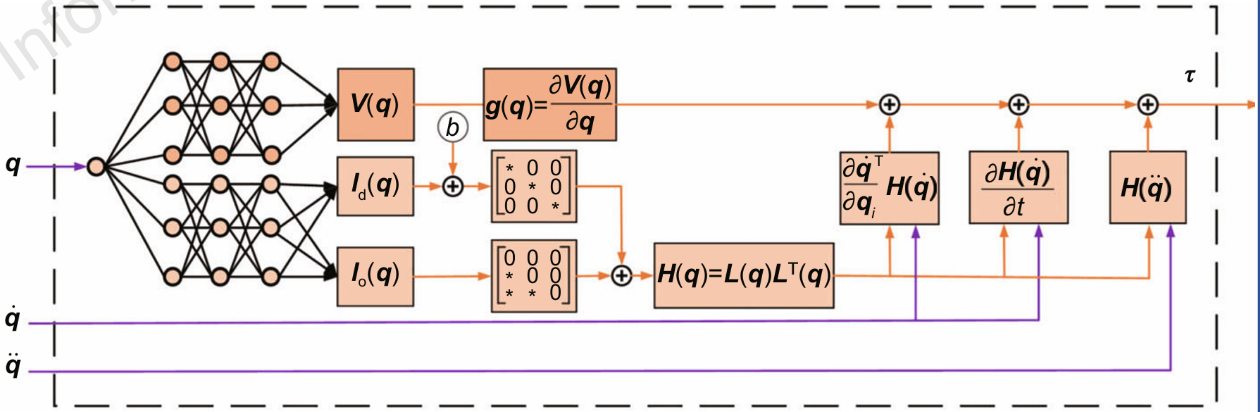
- In modern industry and daily life, the application of robots has become increasingly widespread, spanning various fields such as manufacturing, logistics, healthcare, and service industries.

Motivation & challenges

- **Challenge 1**: Traditional PINNs lack external force modeling → poor accuracy in interaction tasks.
- **Challenge 2:** Industrial robots lack joint torque sensors → hard to obtain precise dynamics data.
- **Goal:** Develop enhanced PINN models with motor dynamics and external force modeling.

Physics-informed neural

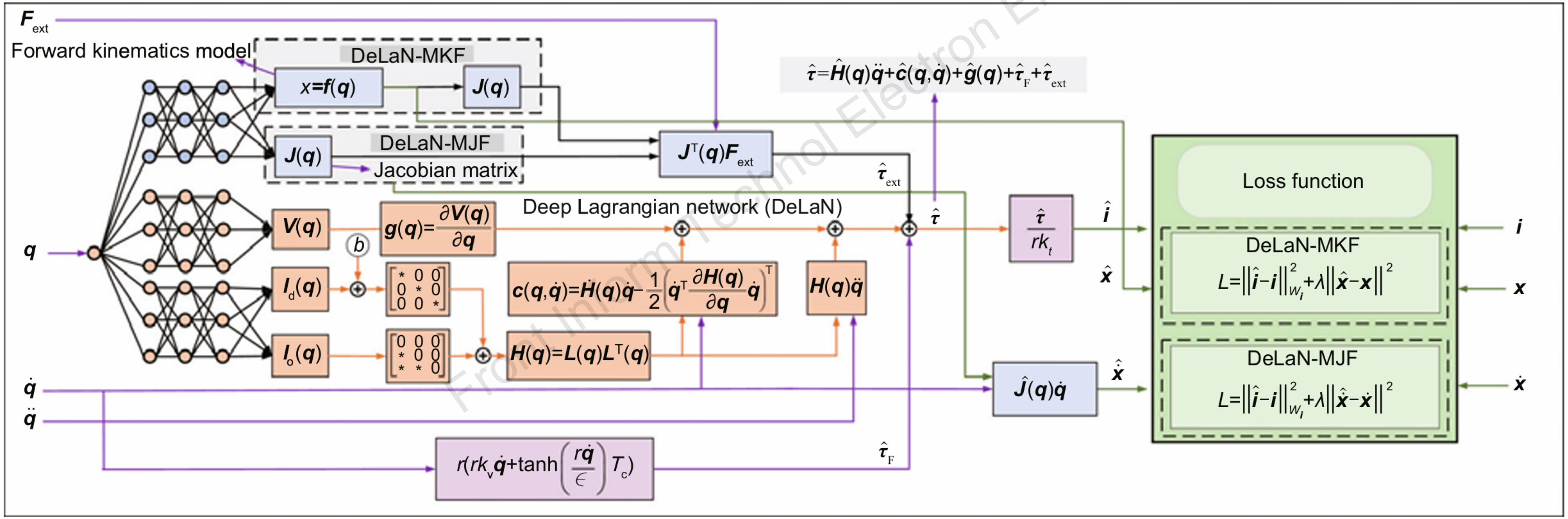
Integrating physical prior knowledge with deep learning enhances interpretability and generalization capability.



Network architecture of DeLaN

Proposed framework

- **Two enhanced PINN models**: DeLaN-MKF and DeLaN-MJF.
- **Integrate** motor dynamics and external force modeling.
- **Two Jacobian estimation methods**: direct and kinematic differentiation.



Network architectures of two hybrid PINN-based models that incorporate motor dynamics and external force modeling into the DeLaN network.

1) Motor dynamics modeling

- Model motor current to joint torque mapping.
- **Friction model** from harmonic drives.
- Learn parameters as network weights.

The UR10e is characterized by a high transmission ratio and harmonic drive, allowing the model to be simplified as

$$\boldsymbol{\tau} = r k_{\mathrm{t}} \boldsymbol{i},$$

Because friction in the UR10e robot originates predominantly from harmonic drives, the joint friction torque becomes

$$\boldsymbol{\tau}_{\mathrm{F}} = r\left(r k_{\mathrm{v}} \dot{\boldsymbol{q}} + \tanh\left(\frac{r\dot{\boldsymbol{q}}}{\epsilon}\right) T_{\mathrm{c}}\right)$$

$$T_{\mathrm{c}} = \begin{cases} T_{\mathrm{c}}^{\mathrm{dir}}, & \text{if } \dot{\boldsymbol{q}} \cdot \boldsymbol{\tau}_j \geq 0, \\ T_{\mathrm{c}}^{\mathrm{rev}}, & \text{if } \dot{\boldsymbol{q}} \cdot \boldsymbol{\tau}_j < 0. \end{cases}$$

2) External force modeling

- **Direct Jacobian Method:** Learn mapping from joint velocity to end-effector velocity.
- **Kinematic Differentiation Method:** Learn forward kinematics, and then differentiate.
- Both integrate external torque via Jacobian transpose.

Direct Jacobian

$$\dot{\boldsymbol{x}} = \boldsymbol{J}(\boldsymbol{q})\dot{\boldsymbol{q}}$$

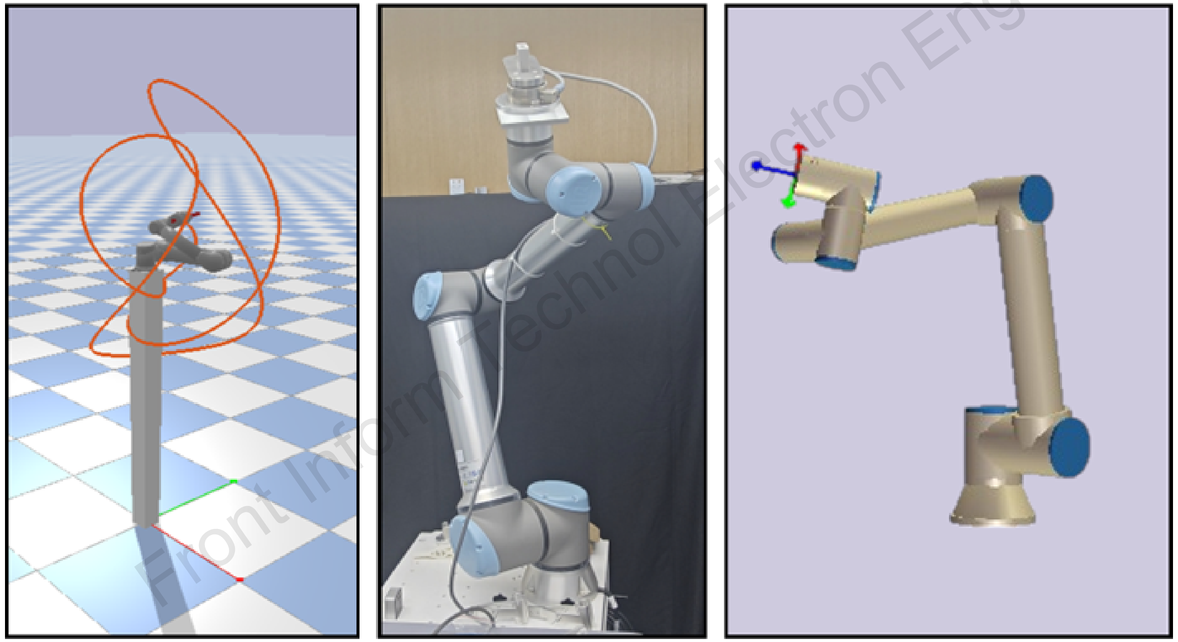
Kinematic differentiation

$$\boldsymbol{x} = f(\boldsymbol{q})$$

$$\boldsymbol{J}(\boldsymbol{q}) = \frac{\partial f(\boldsymbol{q})}{\partial \boldsymbol{q}} = \begin{bmatrix} \frac{\partial f_1}{\partial q_1} & \frac{\partial f_1}{\partial q_2} & \cdots & \frac{\partial f_1}{\partial q_n} \\ \frac{\partial f_2}{\partial q_1} & \frac{\partial f_2}{\partial q_2} & \cdots & \frac{\partial f_2}{\partial q_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial f_m}{\partial q_1} & \frac{\partial f_m}{\partial q_2} & \cdots & \frac{\partial f_m}{\partial q_n} \end{bmatrix}$$

Experimental setups

- **Robots**: UR5 (simulation), UR10e (real + simulation)
- **Tasks**: Material transport, external force scenarios.
- **Metrics**: NMSE, RMSE, R^2.

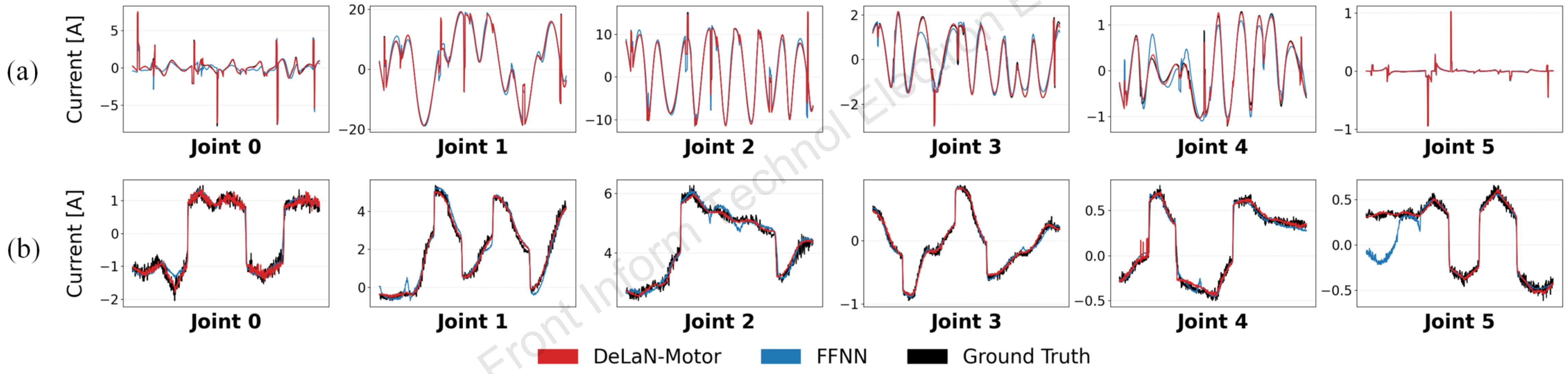


(a) (b) (c)

(a) UR5 robot in the simulation environment, demonstrating a trajectory of the end-effector from the test set; (b) real UR10e robot; (c) UR10e robot in the URsim simulation platform

Results—motor dynamics modeling

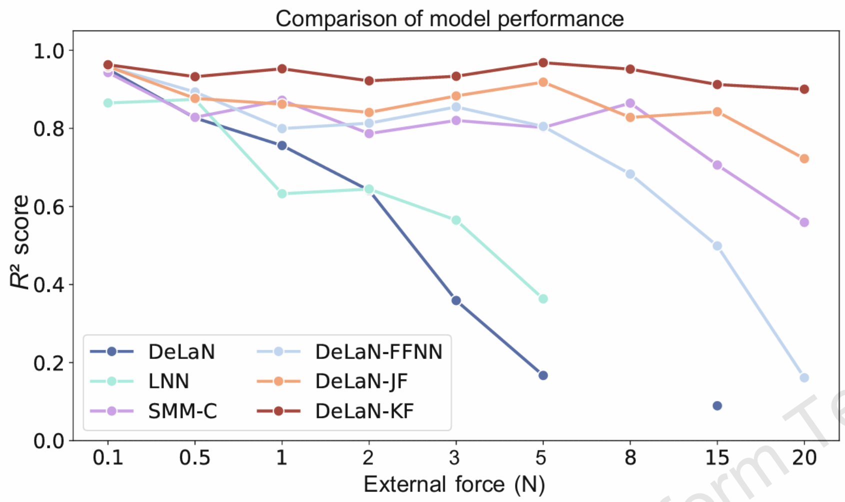
- DeLaN-motor outperforms FFNN in both simulation and real-world.
- Higher R^2 values, lower NMSE across joints.



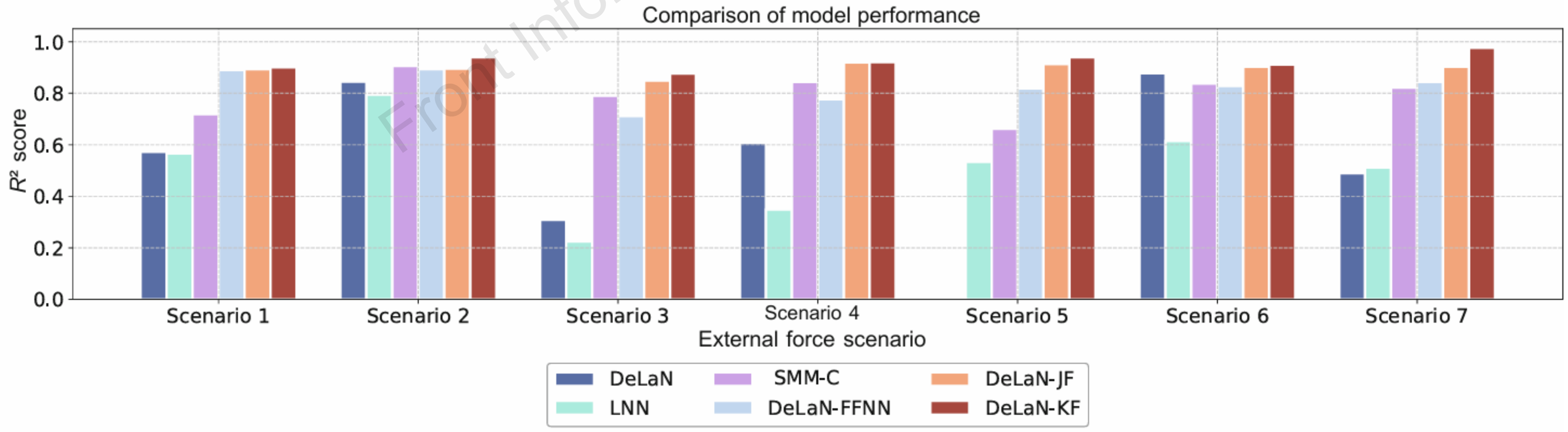
Inverse dynamics learning performance under zero external force

Results—external force modeling performance

- **DeLaN-KF and DeLaN-JF** maintain high R^2 under varying forces.
- **Baselines DeLaN and DeLaN-FFNN** fail when force>8 N.



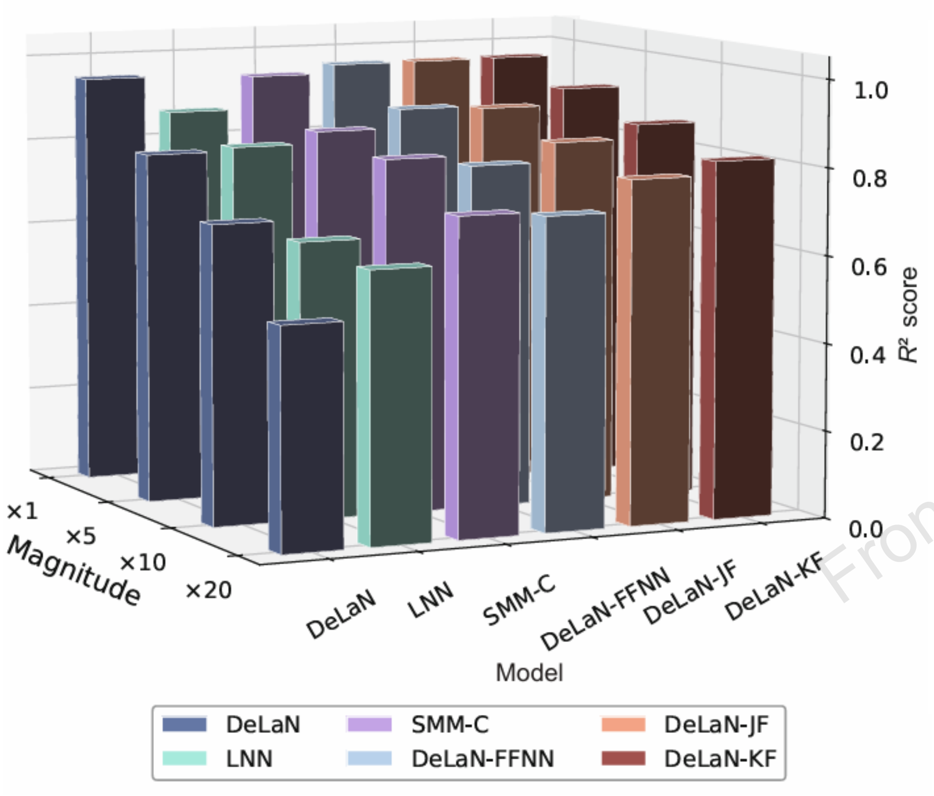
R^2 for joint torque prediction varied with force magnitude.



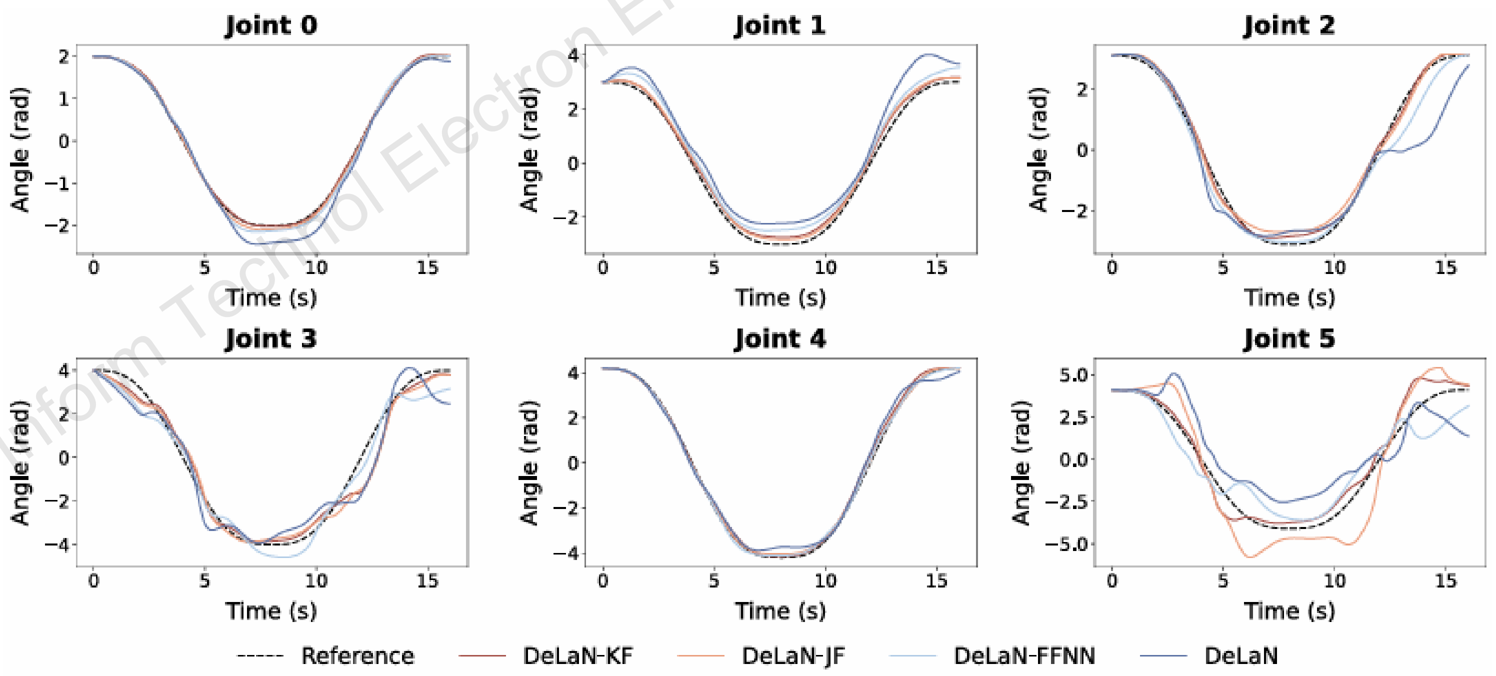
Performance under different external force scenarios

Results—generalization & control performance

- ☐ **DeLaN-KF** shows the best generalization under unseen forces.
- ☐ **DeLaN-KF** also achieves the lowest tracking error in control tests.



Generalization performance evaluation



Trajectory tracking performance

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