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# IDENTIFICATION OF SELECTED ELECTROMECHANICAL SYSTEMS USING ACQUIRED TIME-SERIES DATA

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# Outline

- Introduction: Methods of Modelling Electromechanical Systems
- Data-driven modelling: Neural Network (NN) and Physics-Informed Neural Network (PINN)
- Case study 1: Geared DC Motor
- Case study 2: Double Torsion Pendulum
- Conclusion

# Introduction: Modelling

- The development of an accurate dynamic model is crucial for the purpose of optimization, control, fault detection, diagnosis and prognosis. There are three main modelling approaches: white-box modelling (physics-based or mathematical approach), black-box modelling (pure data-driven approach), and grey-box modelling (hybrid or physics-informed data-driven approach)

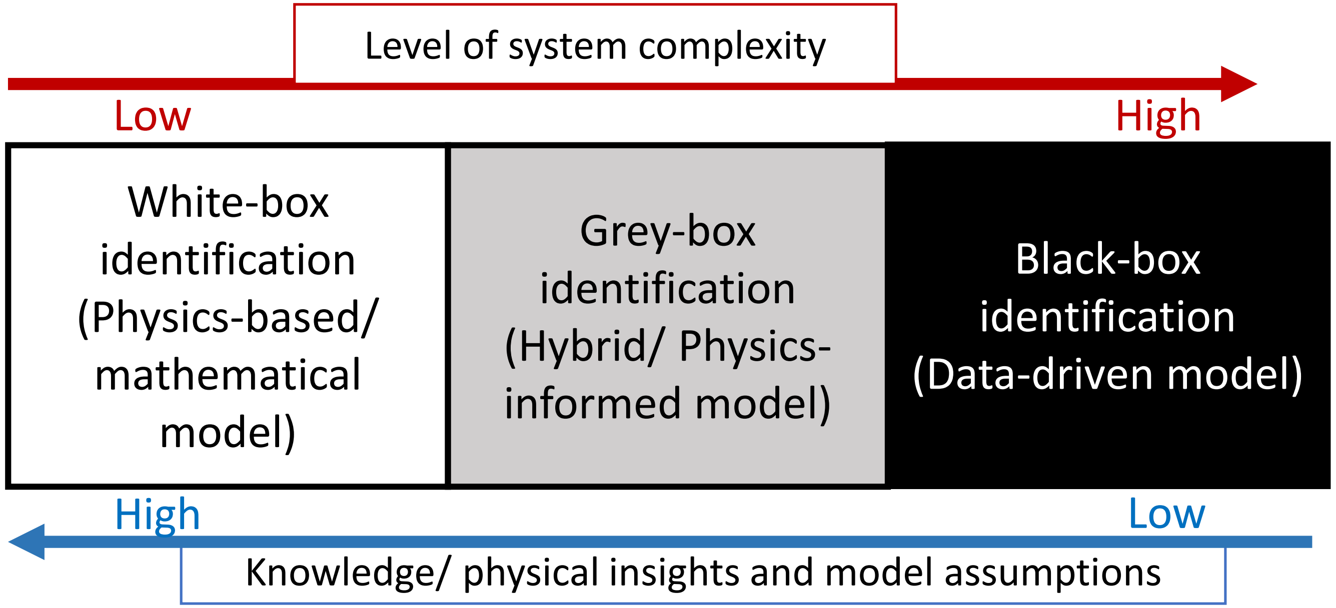



Fig. 1: Dynamic modelling approaches

# Introduction: Modelling

White-box identification (Physics-based/ mathematical model)

Grey-box identification (Hybrid/ Physics-informed model)

Black-box identification (Data-driven model)

Based on first principles, subject to high bias and difficult to apply when dealing with complex electromechanical systems

Based on time-series data. They also rely on a model structure, and a training/learning algorithm. Some common machine learning tools for data-driven modelling or identification include neural networks (NN), sparse identification of nonlinear dynamics (SINDy), and symbolic regression (Symreg).

# Data-Driven Modelling: NN and PINN

- Neural networks (NNs) such as multilayer perceptron (MLP) and recurrent neural networks have been used for diverse engineering applications; their success can be linked to advancements in sensors, computational platforms, and network architectures. Nevertheless, NNs have a few challenges, which include model variance with new datasets, large and quality data required, and its structure lacks physical meaning.
- These challenges can be handled by a physics-informed neural network (PINN). The basic concept of PINN is the use of physical laws described by ordinary or partial differential equations while training a neural network to solve supervised learning problems. Furthermore, PINN gives the flexibility of estimating the unknown states or variables of a system like its frictional behaviour, and it can also be used in identifying the parameters of a mathematical model.

# Data-Driven Modelling : NN and PINN Model Structure

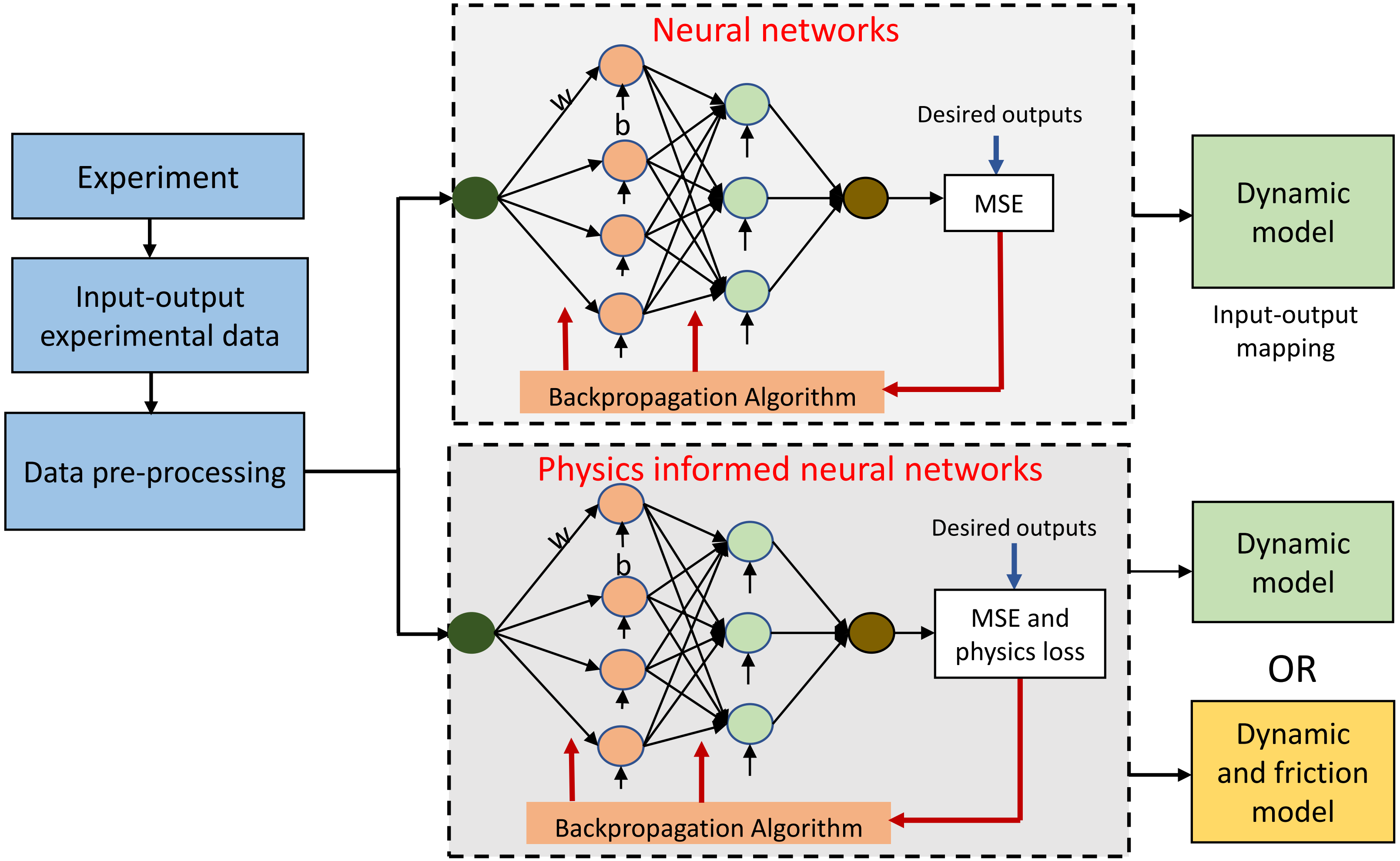



Fig. 2: Data-driven modelling: Structure of NN and PINN

# Case Study 1: Geared DC Motor

## Experiment and data acquisition

- We acquired experimental input and output data from a sourced geared 12V DC Motor (SG555123000-10K). The input to the physical system is a time-varying PWM signal, while the system output is the motor speed which was measured through an encoder.

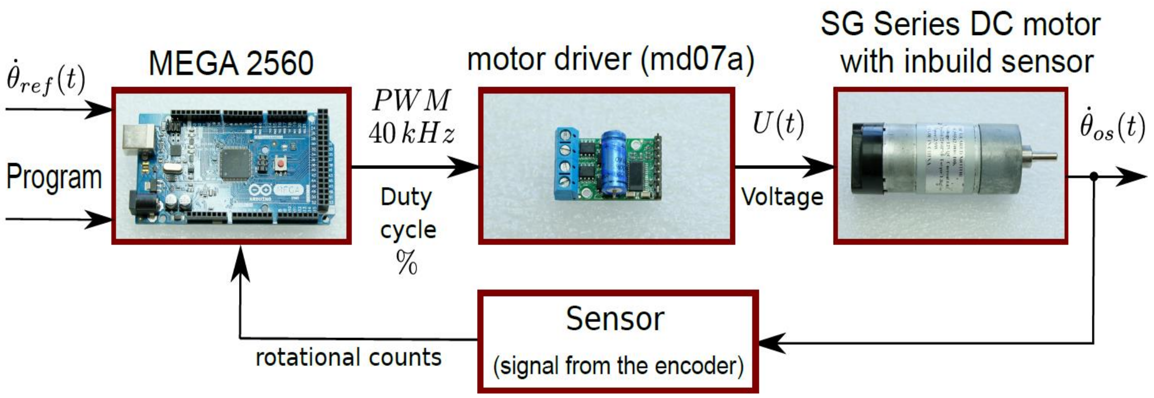



Fig. 3: The experimental setup for data acquisition from a Geared DC Motor

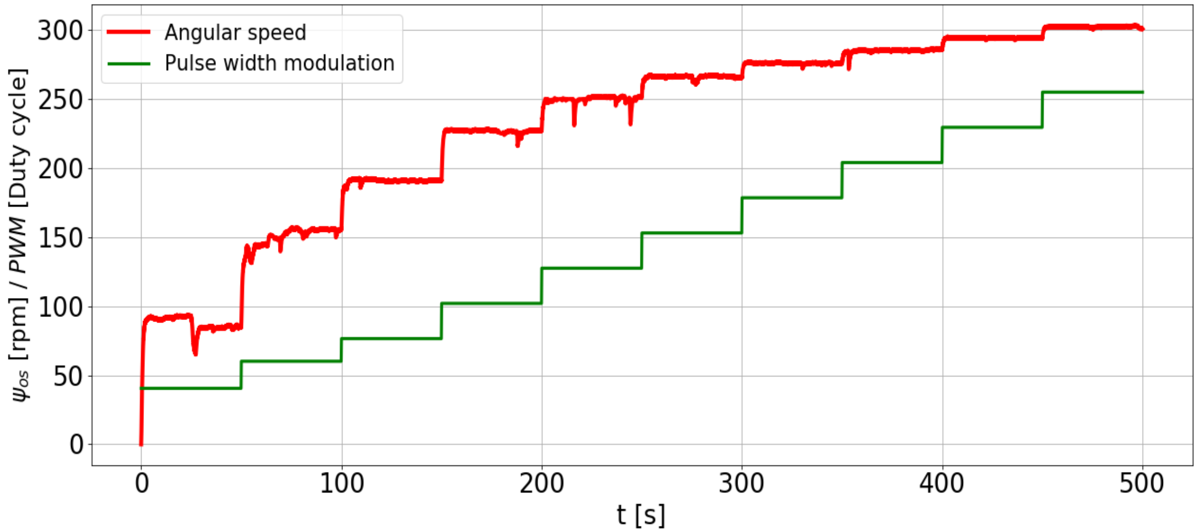



Fig. 4: The experimental setup for data acquisition from a Geared DC Motor

# Geared DC Motor: Physics-based model

- The physics or governing equation of a DC motor can be derived from the operational concept of its mechanical and electrical components using Newton's 2nd law and Kirchhoff's law.

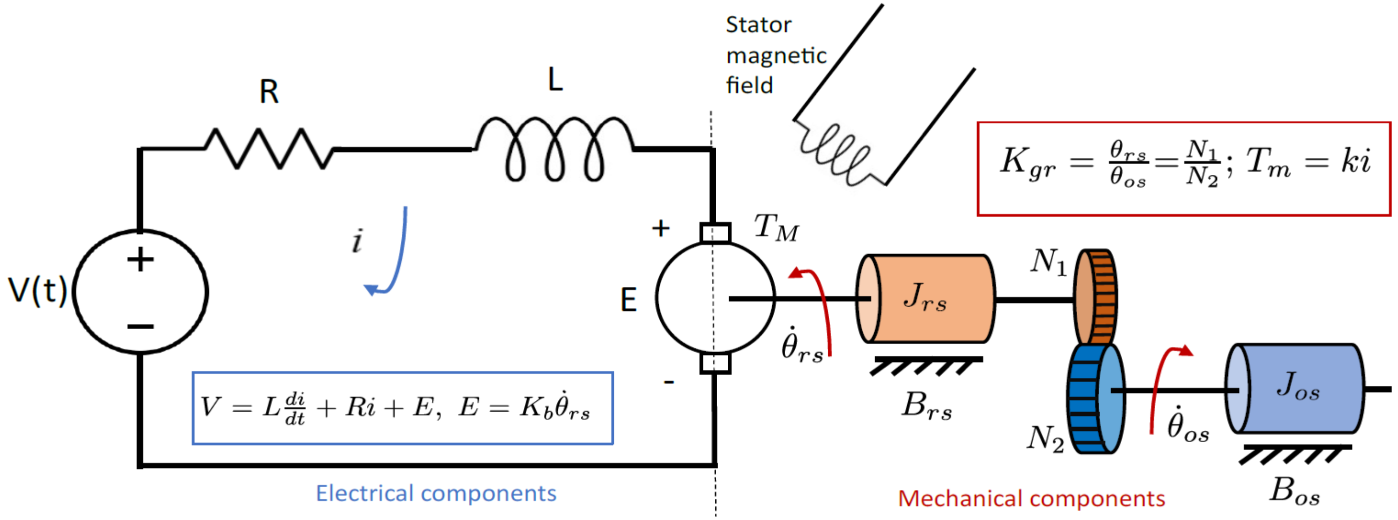



Fig. 5: Schematic of a DC Motor

$$T_m = T_{rs} + \frac{1}{K_{gr}} T_{os}$$

$$T_{rs} = J_{rs}\ddot{\theta}_{rs} + B_{rs}\dot{\theta}_{rs}$$

$$T_{os} = J_{os}\ddot{\theta}_{os} + B_{os}\dot{\theta}_{os}$$

Let : $\dot{\theta}_{rs} = \psi_{rs} \quad \dot{\theta}_{os} = \psi_{os} \quad i = I$

$$\frac{d\psi_{os}}{dt} = \frac{K_{gr}K_m I - K_{gr}[J_{rs}\dot{\psi}_{rs} + B_{rs}\psi_{rs}] - B_{os}\psi_{os}}{J_{os}}$$

$$\frac{dI}{dt} = \frac{V - k\psi_{rs} - RI}{L}$$

# Geared DC Motor: Data-driven model algorithm

- PINN Algorithm Pseudocode

**Table 1: PINN algorithm**

**Import** numpy, pandas, matplotlib and TensorFlow

**Initialize** the known system parameter, $K_{gr}$

**Load** the training and test dataset: Experimental data

**Create** three neural networks ( $NN_1, NN_2$ and $NN_3$ )

**Define**: Input dimension, Number of hidden layers and neurons, and Output dimension

**Add** $J_{rs}, J_{os}, B_{rs}, B_{os}$ *and* $K_m$ as constrained weights or trainable parameters to $NN_1$

**Add** $L, R$ and $K_b$ as constrained weights or trainable parameters to $NN_3$

**Initialize** the weights and biases of $NN_1, NN_2$ and $NN_3$

**For** g=1 to the number of Epochs (20000)

**Get** the prediction of the training dataset

$\hat{\Psi}_{rs} = NN_1(t,v)$ , $\hat{\Psi}_{os} = NN_1(t,v)$ , $\hat{I} = NN_2(t,v)$

**Compute** the derivative of the three networks: $\frac{d\hat{\Psi}_{rs}}{dt}, \frac{d\hat{\Psi}_{os}}{dt}$ and $\frac{d\hat{I}}{dt}$

**Compute** the residuals of the system (physics losses) including the losses due to prediction

$$L_1 = \sum_i^N \left( J_{rs} \frac{d\hat{\Psi}_{rs}(i)}{dt} + B_{rs}\hat{\Psi}_{rs}(i) + \frac{1}{K_{gr}} \left[ J_{os} \frac{d\hat{\Psi}_{os}(i)}{dt} + B_{os}\hat{\Psi}_{os}(i) \right] - K_m \hat{I}(i) \right)^2 ,$$

$$L_2 = \sum_i^N \left( L \frac{d\hat{I}(i)}{dt} + R\hat{I}(i) - v_i + k\hat{\Psi}_{rs}(i) \right)^2 ; \; L_3 = \sum_i^N \left( \hat{\Psi}_{os}(i) - \psi(i) \right)^2 ,$$

$$L_{T1} = L_1 + L_3 \; , \; L_{T2} = L_2$$

**Compute** the gradient of the losses $L_{T2}$ and $L_{T2}$ with respect to all the network weights and biases

**Update** the weights and biases of $NN_1, NN_2$ and $NN_3$

**Sum** the losses of the two networks, $L_T = L_{T1} + L_{T2}$

**Print** epoch g and the total loss of the system at epoch g including the value of parameters

**Plot** the prediction of $NN_1, NN_2$ and $NN_3$ with the test dataset

**Print** the value of all the identified parameters ( $J_{rs}, J_{os}, B_{rs}, B_{os}, K_m, L, R$ and $K_b$ ) after the training

**Save** the weights and biases of the $NN_1, NN_2$ and $NN_3$

**End of the Algorithm**

# Geared DC Motor: PINN model results

Table 1: Geared DC Motor Physical Parameters

| $J_{rs}$ | $J_{os}$ | $B_{rs}$ | $B_{os}$ | $K_m$ | L | R | $K_b$ |
|---|---|---|---|---|---|---|---|
| 0.001 | 0.0379 | 1.2539 | 0.3532 | 0.6585 | 0.001 | 1.3798 | 0.3938 |

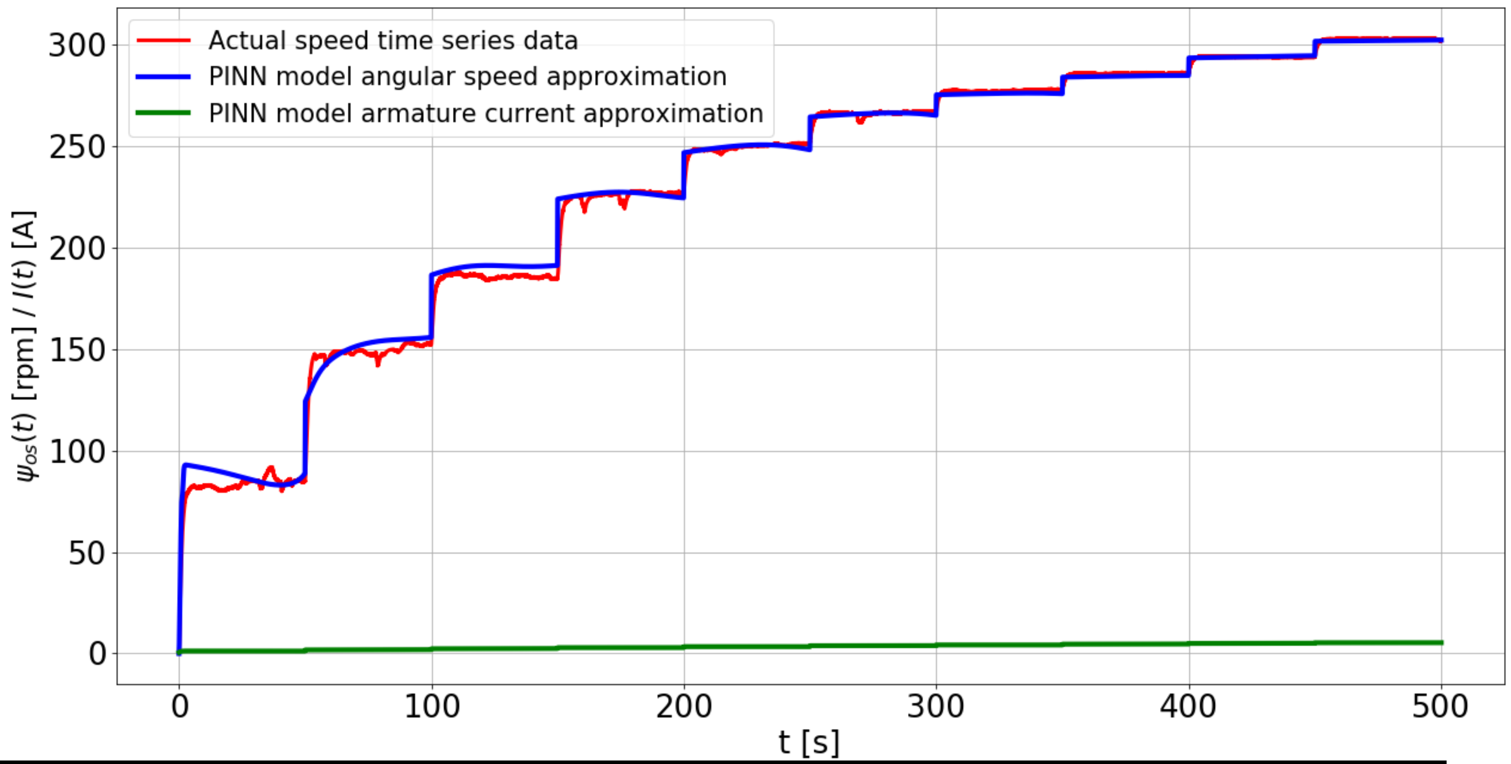



Fig. 6: The angular speed and armature current predictions of the geared DC motor PINN model after step-like increment of reference value

# Case Study 2: Double Torsion Pendulum

- The laboratory test stand is a double torsion pendulum, and our aim is to investigate the planar frictional contact between the column and disk pendulums. A well labelled isometric view of the test stand is shown in Fig. 7. The electronic components that are part of the test stand include NXP microcontroller (FRDM-KL25Z), 2 phase DC stepper motor, DC motor driver SMC64r2, and two HMC15IZ sensors to measure the pendulum's angle of rotation column and disk, power supply (25 V), and a CPU.

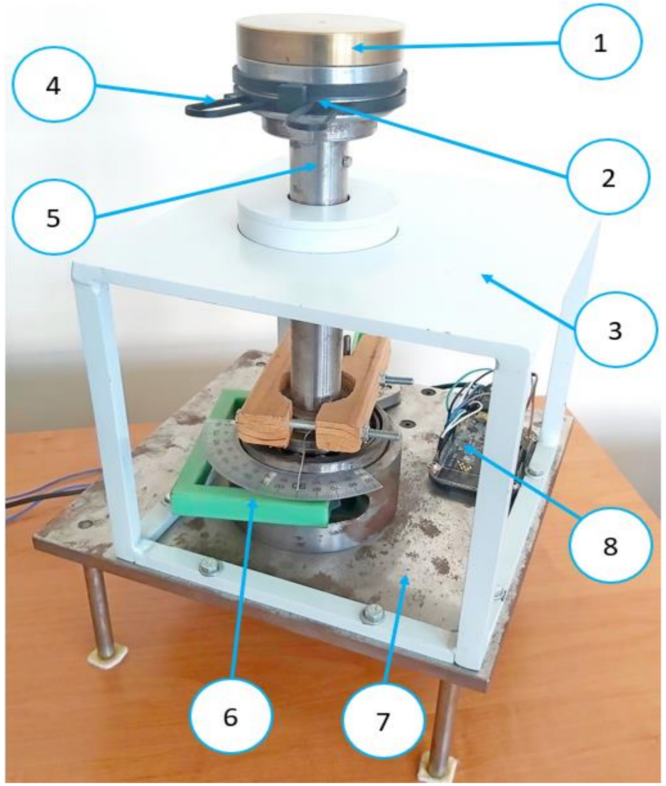



Fig. 7: Isometric view of the double torsion pendulum, where (1) upper free disk (2) friction surface (3) support frame (4) bearing springs (5) column pendulum (6) drive mechanism (7) base (8) microcontroller

# Double Torsion Pendulum: Time-series data and physics-based model

- Time-series data

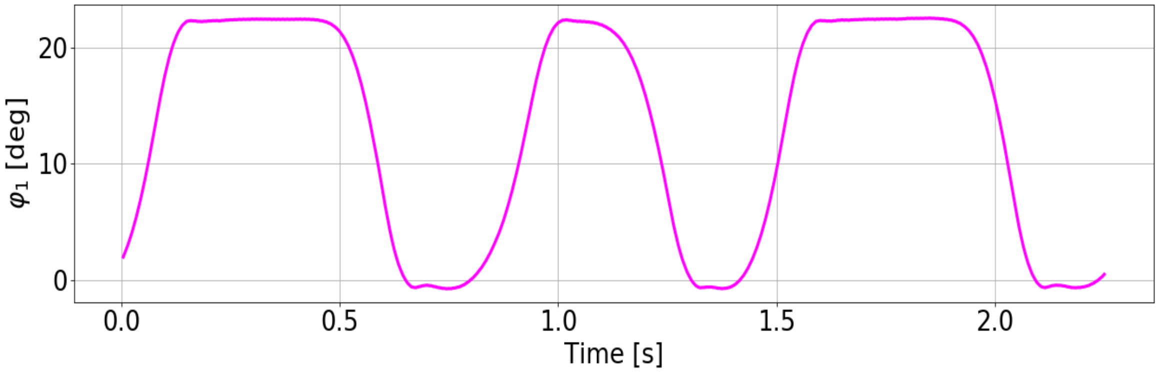



Fig. 8: Time-series response of the column pendulum

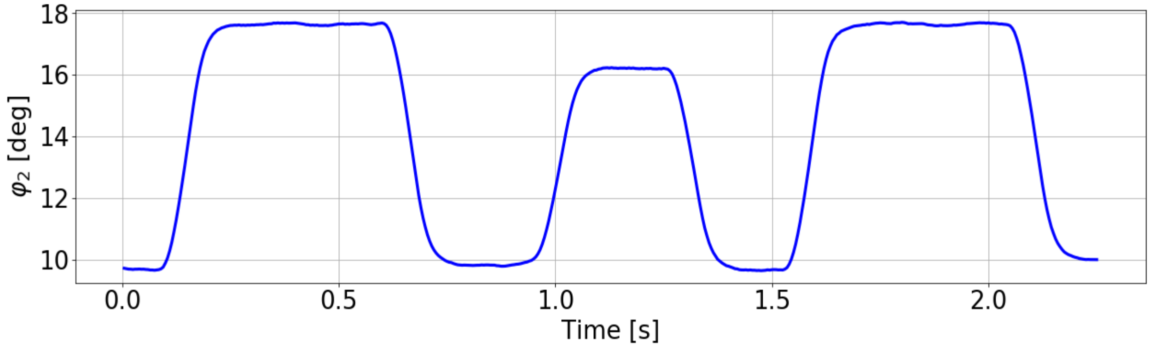



Fig. 9: Time-series response of the disk pendulum

- Physics-based model

$$\tau = J_2\varphi_2 + \tau_f$$

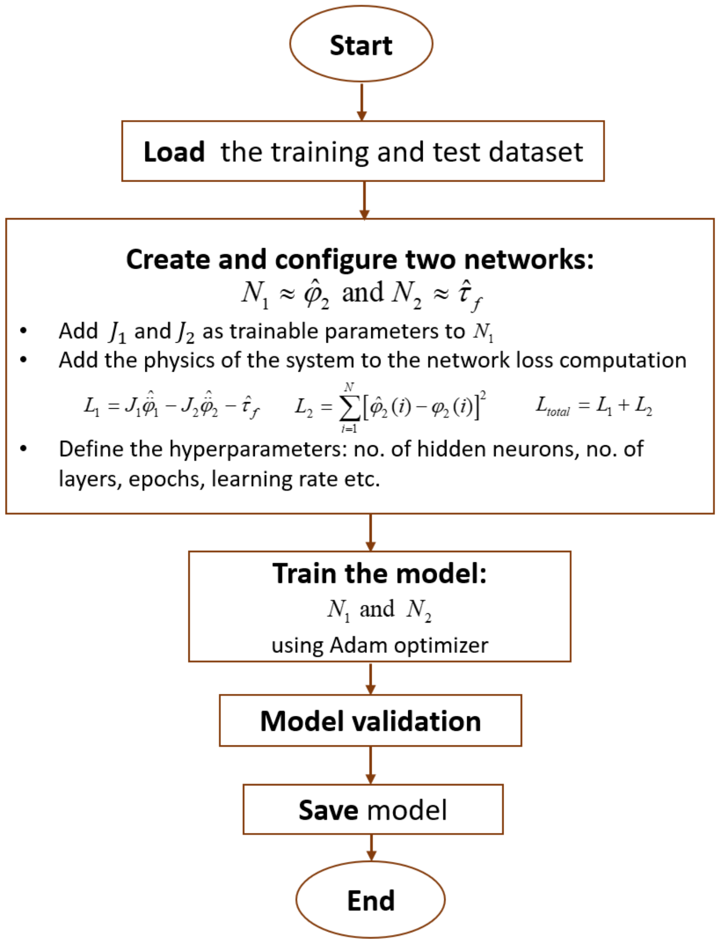
Where $\tau = J_1\varphi_1$

$$J_1\varphi_1 = J_2\varphi_2 + \tau_f$$

$\tau$ is the torque of the column pendulum, $J_1$ and $J_2$ are the moment of inertia of the column and disk pendulum, respectively.

# Double Torsion Pendulum: Data-driven model algorithm

- PINN Algorithm flowchart




- PINN model results

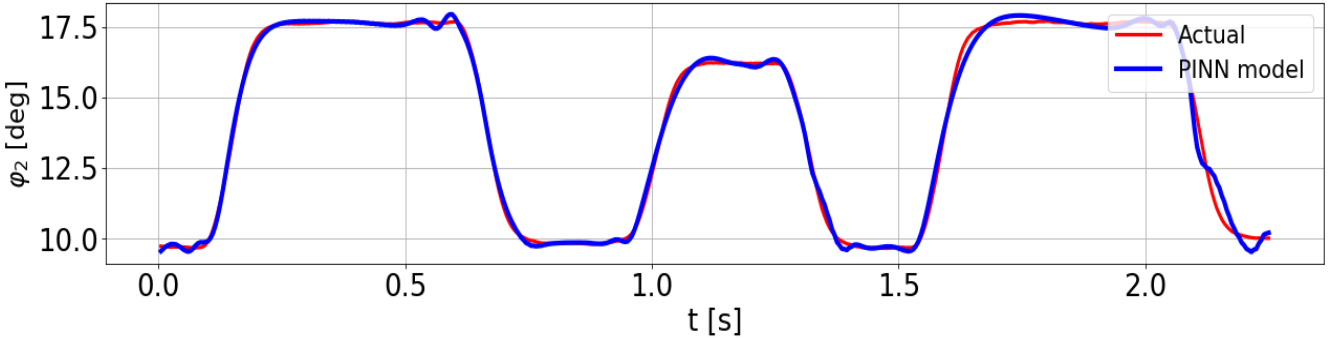



Fig. 10: The time series of the predicted disk pendulum angular position by the PINN model

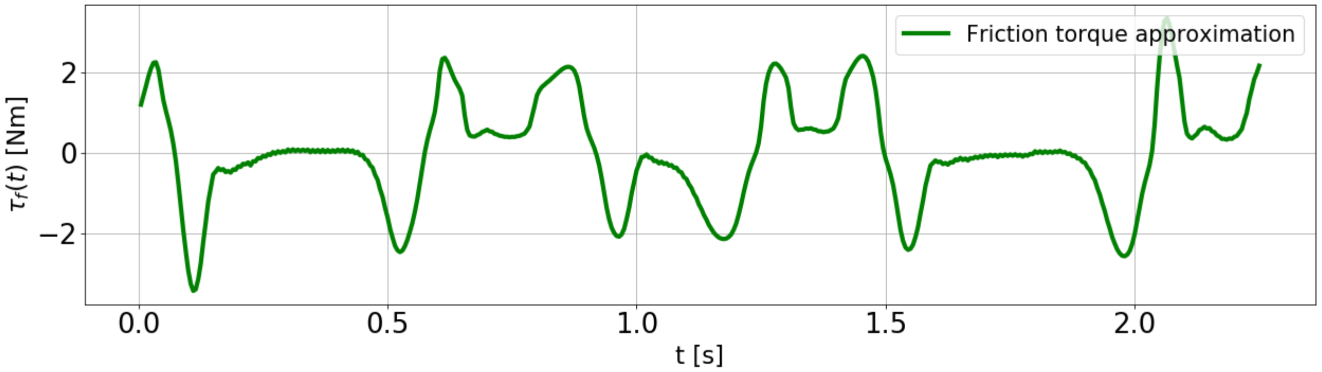



Fig. 11: The time series of the predicted friction torque by the PINN model

# Conclusion

- We have presented the identification of two electromechanical systems: a geared DC motor and a double torsion pendulum system.
- The overall results demonstrate the input-output relation, and the frictional behaviour of an electromechanical system can be estimated using experimental time-series data from the system and a flexible neural network such as PINN.

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# THANK YOU