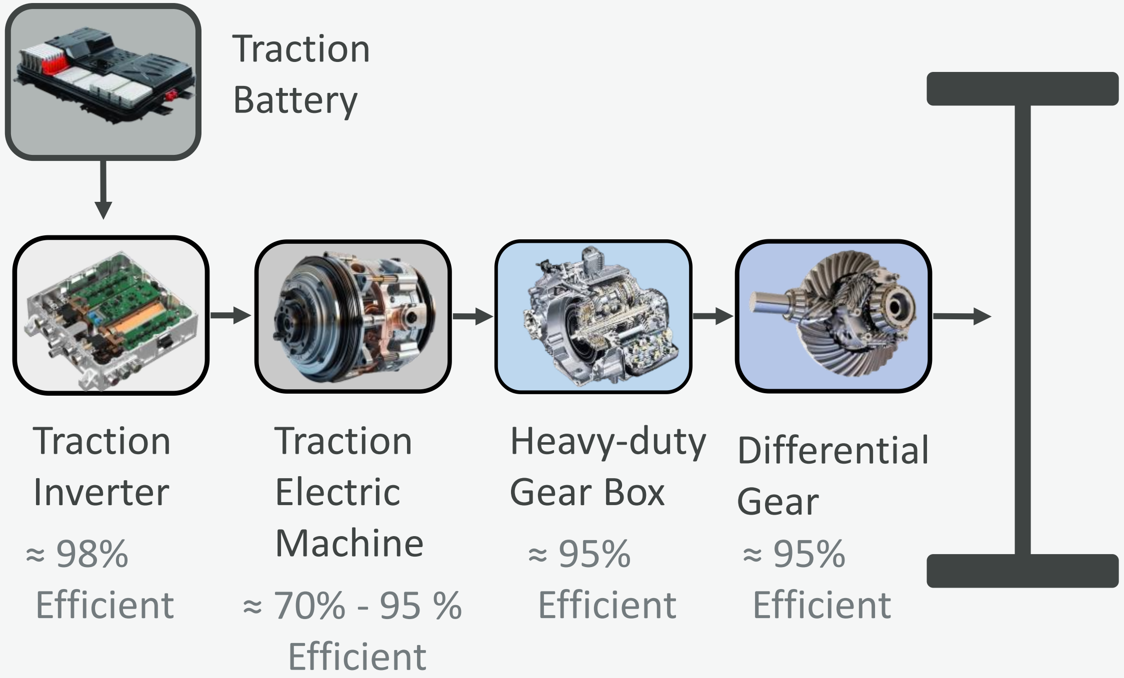
PINN based PMSM Parameter estimation

THE OHIO STATE UNIVERSITY
CENTER FOR AUTOMOTIVE RESEARCH

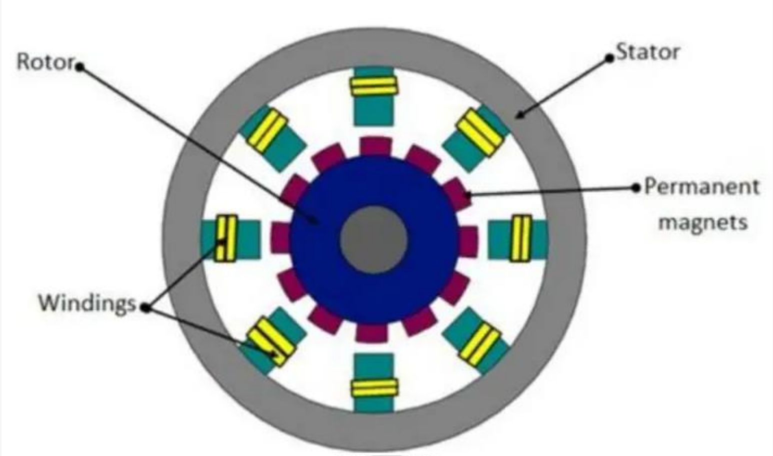
System Overview

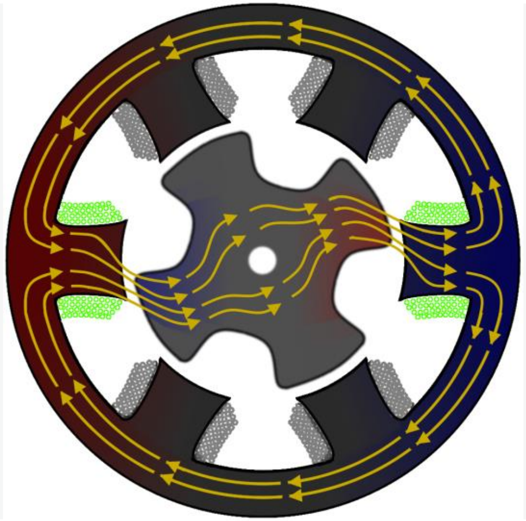


Optimizing the operation of electric machines yields significant efficiency gains.

Permanent Magnet Synchronous Machine (PMSM)

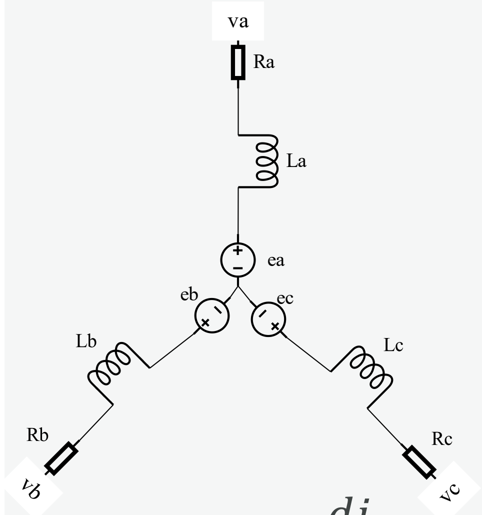
- Stator winding becomes electromagnet when current passes.
- Electromagnet insert force on permanent magnets to rotate it
- Drive control is responsible for generating the required current for electromagnets to produce the required torque





PMSM Modeling

3 Phase AC System

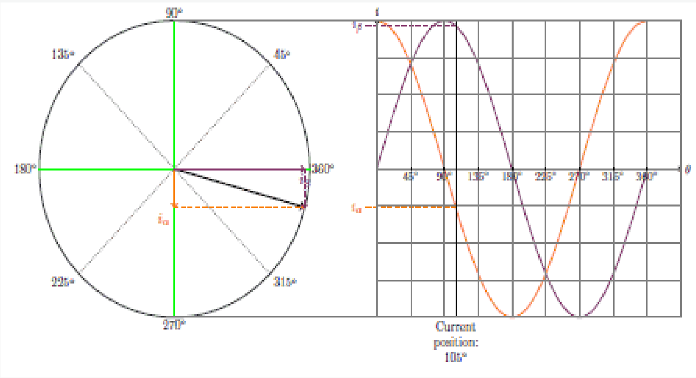


$$v_a = R_s i_a + L_a \frac{di_a}{dt} + e_a$$

$$v_b = R_s i_b + L_b \frac{di_b}{dt} + e_b$$

$$v_c = R_s i_c + L_c \frac{di_c}{dt} + e_c$$

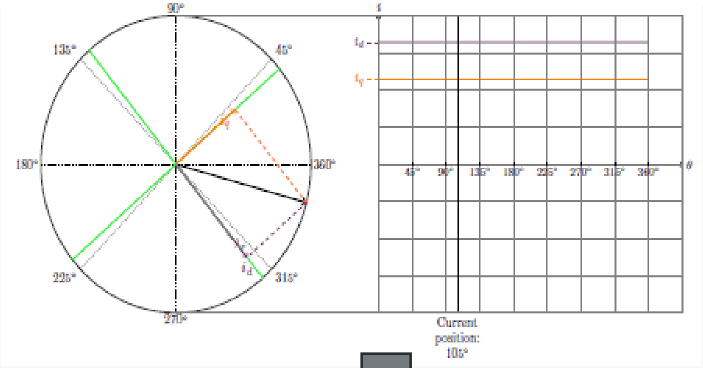
2 Phase Equivalent AC System



v^{abc}, i^{abc} → Transformation Matrix → $v^{\alpha\beta}$, $i^{\alpha\beta}$

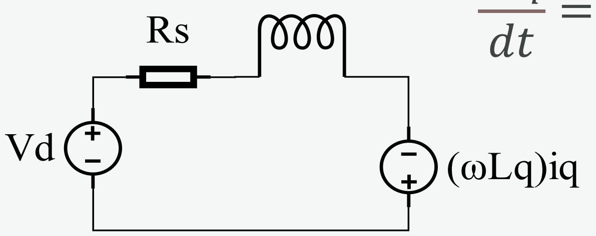
Clark Transformation

Equivalent DC System

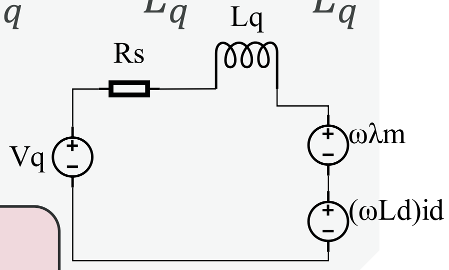


$v^{\alpha\beta}$, $i^{\alpha\beta}$ → Transformation Matrix → v^{dq}, i^{dq}

$$\frac{di_d}{dt} = \frac{V_d}{L_d} - \frac{R_s i_d}{L_d} + \frac{\omega L_q i_q}{L_d}$$



$$\frac{di_q}{dt} = \frac{V_q}{L_q} - \frac{R_s i_q}{L_q} - \frac{\omega L_d i_d}{L_q} - \frac{\omega \lambda_m}{L_q}$$



Park Transformation

PMSM Control

For the EV application, PMSM control should provide torque efficiently

Dynamics

$$\frac{di_d}{dt} = \frac{V_d}{L_d} - \frac{R_s i_d}{L_d} + \frac{\omega L_q i_q}{L_d}$$

$$\frac{di_q}{dt} = \frac{V_q}{L_q} - \frac{R_s i_q}{L_q} - \frac{\omega L_d i_d}{L_q} - \frac{\omega \lambda_m}{L_q}$$

$$T_e = \frac{3}{2} p\left(\lambda_m i_q - \left(L_d - L_q\right) i_d i_q\right)$$

$i_d = 0$ provides the quick solution for the control, but it is not optimal

Controller (MTPA)

Global Constraint (for All T_e values)

Given T_e :

$\boxed{i_d^2 + i_q^2 = i_s^2 < i_{s,max}^2}$ Current constraint

$\boxed{v_d^2 + v_q^2 = v_s^2 < v_{s,max}^2}$ Voltage constraint

Local Constraint (for current T_e value)

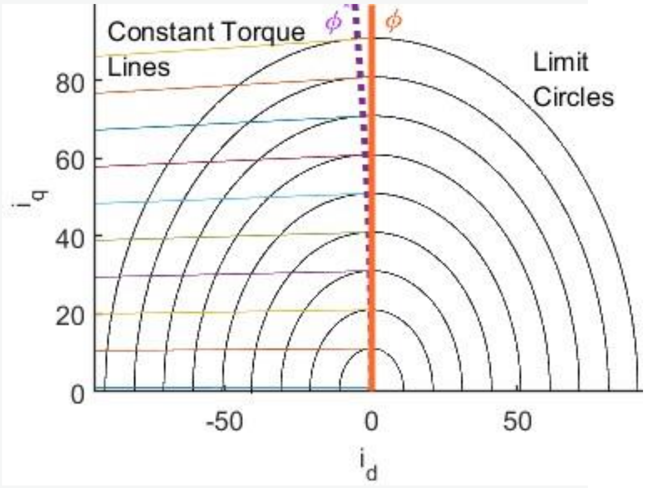
Given fixed T_e :

$$i_q = \frac{k_1}{k_2 + i_d} \qquad \begin{cases} k_1 = \dfrac{T_e}{3p(L_q - L_d)} \\ k_2 = \dfrac{\lambda_m}{(L_q - L_d)} \end{cases}$$

Optimal Trajectory

$$\phi^* = \frac{\lambda_m i_d}{L_d - L_q}$$

ϕ Shows $i_d = 0$ trajectory and ϕ^* shows MTPA trajectory



Deviation between ϕ^* and ϕ increases as the requested torque increases.

It shows that values PMSM parameter values are essential

Parameter Observability

For the given dynamic system

$$\frac{d}{dt}x = f(x,u), y = h(x)$$

where $x \in R^n$ is a vector of state variables, u$\in R^m$ is input vector, y is output vector and f and h are state and output functions, respectively.

The theory of observability says, the vector of state variables x is observable if the matrix O is full rank.

$$rank(O) = n$$

Where

$$O = \frac{\partial}{\partial x}L$$

$$L = [\mathcal{L}_f^0 h, \mathcal{L}_f^1 h, \mathcal{L}_f^2 h, \mathcal{L}_f^3 h, \mathcal{L}_f^4 h, \mathcal{L}_f^5 h, \dots \mathcal{L}_f^{n-1} h]$$

$\mathcal{L}_f^k h$ refers to the kth order Lie derivative of output function h .

Parameter Observability

System Dynamics

$$\frac{di_d}{dt} = \frac{V_d}{L_d} - \frac{R_s i_d}{L_d} + \frac{\omega L_q i_q}{L_d}$$

$$\frac{di_q}{dt} = -\frac{R_s i_q}{L_q} - \frac{\omega L_d i_d}{L_q} + \frac{1}{L_q}(V_q - \omega\lambda_m)$$

$$\frac{dR_s}{dt} = 0, \frac{dL_q}{dt} = 0, \frac{dL_d}{dt} = 0, \frac{d\lambda_m}{dt} = 0$$

State Space Function

$$x = [i_d, i_q, R_s, L_q, L_d, \lambda_m]^T$$

$$h = [i_d, i_q]^T \quad u = [v_d, v_q, \omega]^T$$

$$f(x,u) = \begin{bmatrix} \frac{V_d}{L_d} - \frac{R_s i_d}{L_d} + \frac{\omega L_q i_q}{L_d} \\ -\frac{R_s i_q}{L_q} - \frac{\omega L_d i_d}{L_q} + \frac{1}{L_q}(V_q - \omega\lambda_m) \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\mathrm{A} = \begin{bmatrix} -\frac{R_s}{L_d} & \frac{\omega L_q}{L_d} \\ -\frac{\omega L_d}{L_q} & -\frac{R_s}{L_d} \end{bmatrix}$$

Observability Matrix

$$O = \begin{bmatrix} -i_d & 0 & i_d & 0 \\ -i_q & -i_d\omega_e & 0 & -\omega_e \\ R_s i_q - \omega_e L_d i_q & -\omega_e^2 l_d i_d & -R_s\omega_e i_q & -\omega_e^2 L_d \\ R_s i_q + \omega_e L_d i_q & R_s\omega_e i_d & -\omega_e^2 L_q i_q & R_s\omega_e \end{bmatrix}$$

it can be found that O is not full-rank because the second column and the fourth are linearly dependent. it shows that in the steady state; the parameters are not fully observable on the account of rank deficiency.

Learning the EM dynamics is way forward to estimate parameters

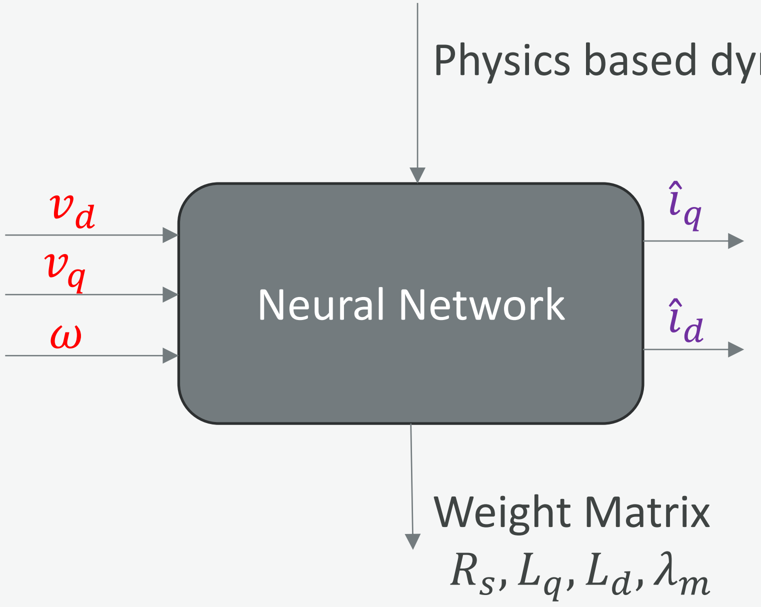
Literature Survey

Technique	Description	Parameters Estimated	Drawbacks
Offline Testing (Standstill Tests)	Uses resistance measurement, back-EMF test, and locked-rotor test	Rs, Ld, Lq, λm	Time-consuming, needs standstill, not suitable for online estimation
Recursive Least Squares (RLS)	Real-time estimation using input-output data	Rs, Ld, Lq	May diverge with noise or parameter drift, not physics-informed
Impedance Spectroscopy	Frequency-swept tests to obtain impedance vs. frequency	Ld, Lq, Rs	Requires expensive equipment, offline only
High-Frequency Signal Injection	Injects HF voltage and analyzes current response	Ld, Lq	Affects normal operation, not always accurate in non salient machines
Fuzzy Logic / Neural Networks	Uses AI-based models trained on data	Rs, Ld, Lq, λm	Needs large training data, poor generalization, lacks physical interpretability
Finite Element Analysis (FEA)	Simulates electromagnetic behavior of motor	Ld, Lq, λm	Computationally expensive, not suitable for online use

Proposed Method

$$V_d = L_d \frac{di_d}{dt} + R_s i_d - \omega L_q i_q$$

$$V_q = L_q \frac{di_q}{dt} + R_s i_q + \omega L_d i_d + \omega \lambda_m$$



- Known Variables
- Unknown Variables
- Estimated Variables

Physics informed neural network helps to learn the system dynamics efficiently.

Problem Formulation

- True values are obtained from the data
- The optimal control problem formulation helps to formulate the loss function

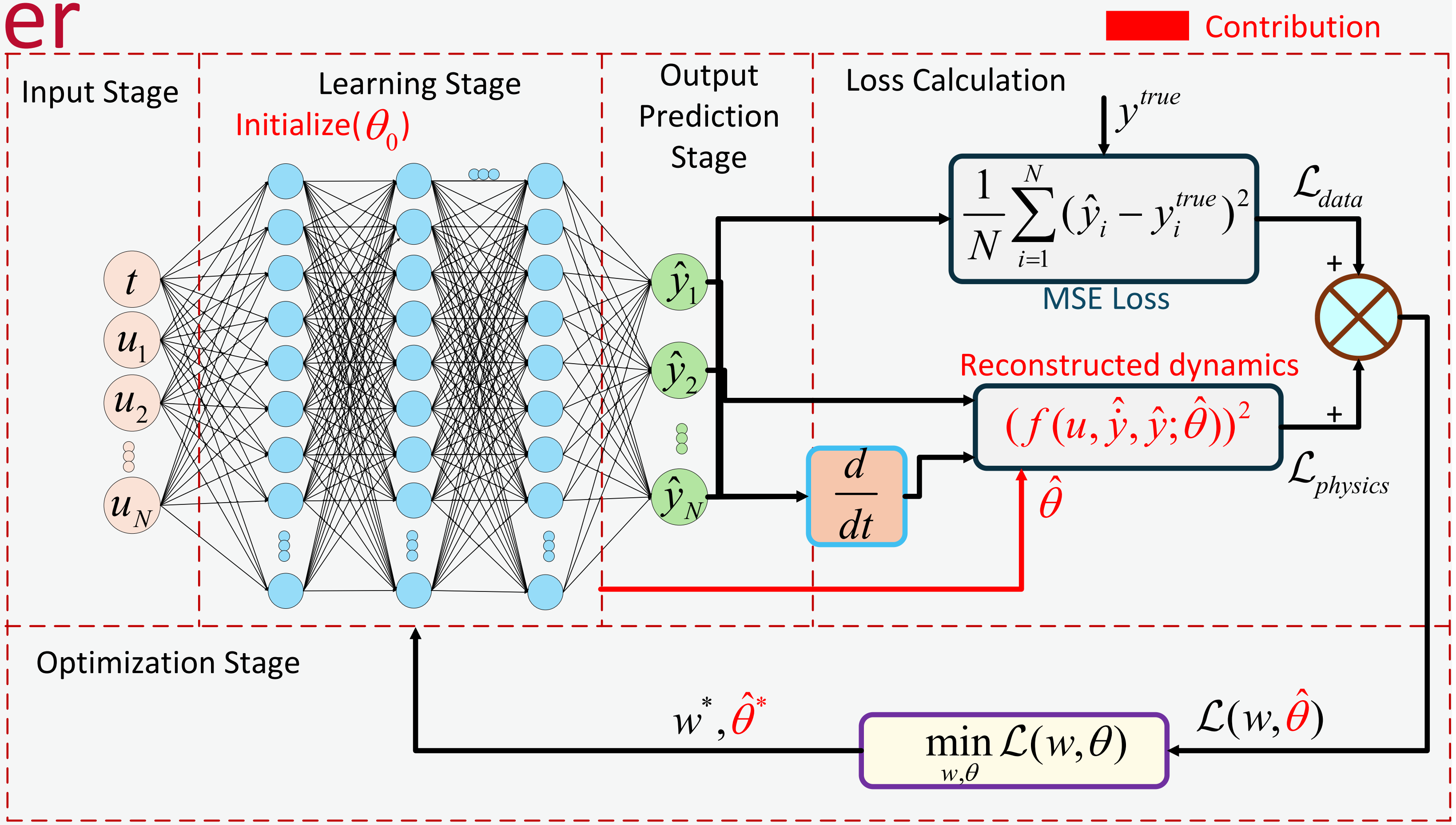
$$\min_{\theta}\left((\hat{\imath}_d - i_d^{true})^2 + (\hat{\imath}_q - i_q^{true})\right)$$

Subject to

$$\begin{cases} v_d^{true} - \left(L_d \dfrac{d\hat{\imath}_q}{dt} + R_s\hat{\imath}_q - \omega L_q\hat{\imath}_q\right) = 0 \\ v_q^{true} - \left(L_q \dfrac{d\hat{\imath}_q}{dt} + R_s\hat{\imath}_q + \omega L_d\hat{\imath}_q + \omega\lambda_m\right) = 0 \end{cases}$$

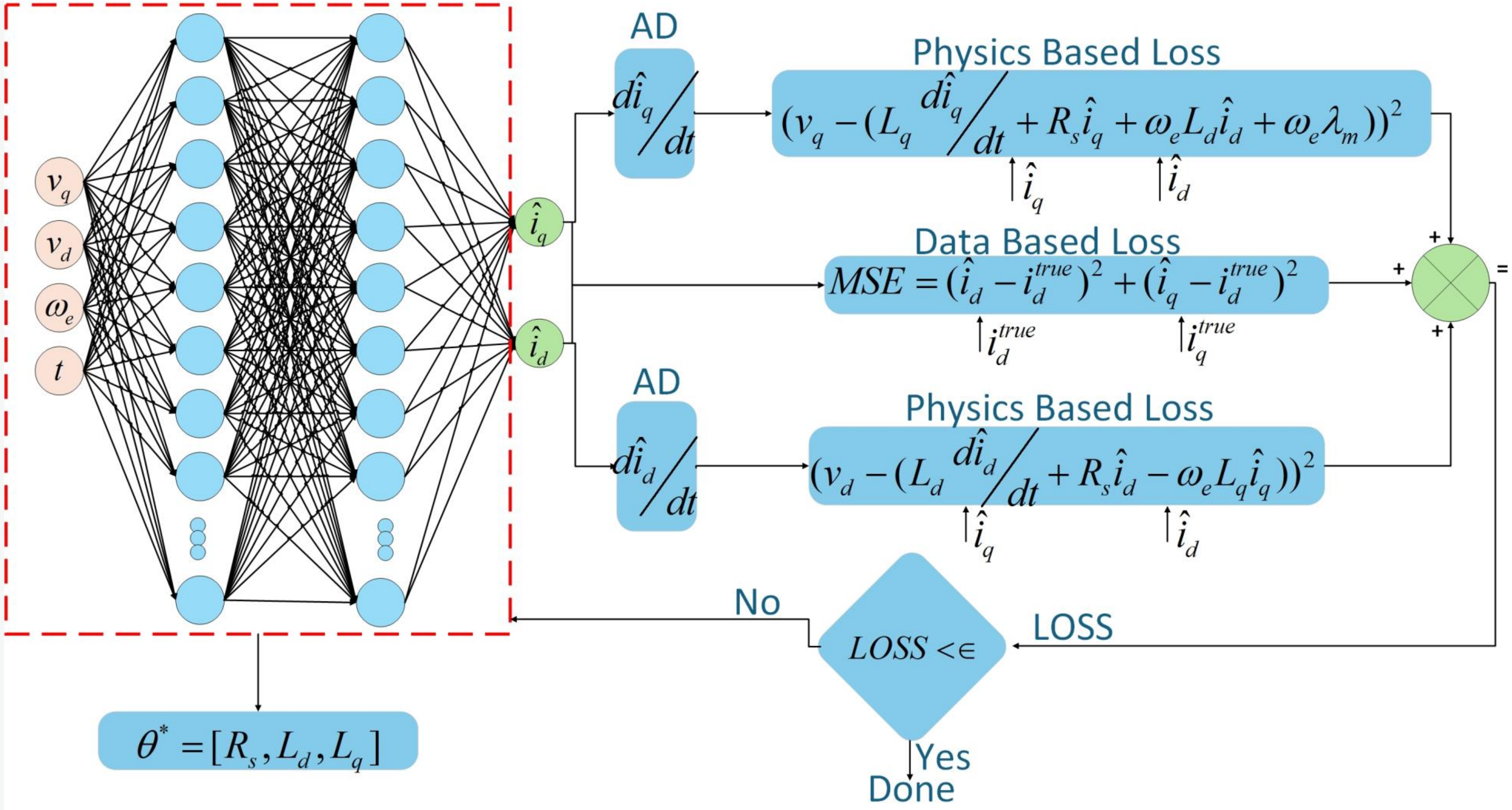
PINN for parameter estimator

- PMSM parameters are initialized and learned along with neural network weights and biases
- This framework can estimate the parameters of rank rank-deficient system

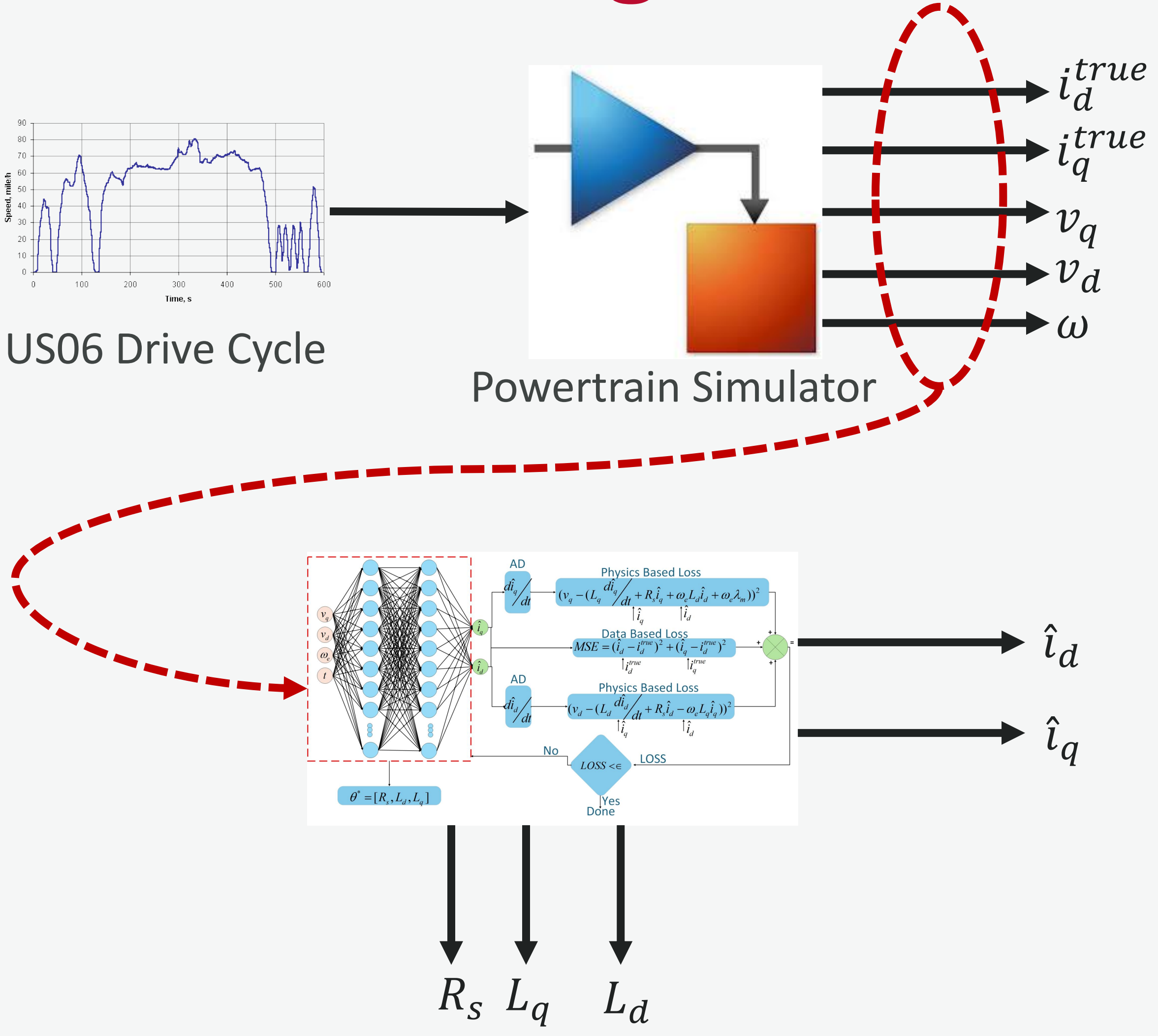


PINN based Parameter Estimator for PMSM

- MSE enforce to learn the dynamics from given data
- Physics based loss makes sure that learnt NN should represents actual dynamics



PINN Training



Algorithm 1 PINN-Based Parameter Estimation for PMSM

Require: Input data $\{v_d, v_q, \omega, t, i_d^{\text{true}}, i_q^{\text{true}}\}$; Number of epochs N; Learning rate ζ

Initialize neural network weights θ

Initialize raw parameters: $\tilde{R}_s, \tilde{L}_d, \tilde{L}_q$

for epoch $= 1$ to N **do**

Compute predicted currents $\hat{i}_d$, $\hat{i}_q$ from neural network

Compute time derivatives $\frac{d\hat{i}_d}{dt}, \frac{d\hat{i}_q}{dt}$ using autograd

Compute physics loss:

$$\mathcal{L}_{\text{phys}} = \left\| v_d - \left(R_s \hat{i}_d + L_d \frac{d\hat{i}_d}{dt} - \omega L_q \hat{i}_q\right) \right\|^2 + \left\| v_q - \left(R_s \hat{i}_q + L_q \frac{d\hat{i}_q}{dt} + \omega L_d \hat{i}_d + \omega \lambda_m\right) \right\|^2$$

Compute MSE loss:

$$\mathcal{L}_{\text{MSE}} = \left\| \hat{i}_d - i_d^{\text{true}} \right\|^2 + \left\| \hat{i}_q - i_q^{\text{true}} \right\|^2$$

Total loss: $\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{phys}} + \mathcal{L}_{\text{MSE}}$

Backpropagate and update parameters:

$$\theta \leftarrow \theta - \zeta \nabla_\theta \mathcal{L}_{\text{total}}$$

Log loss values and parameter estimates

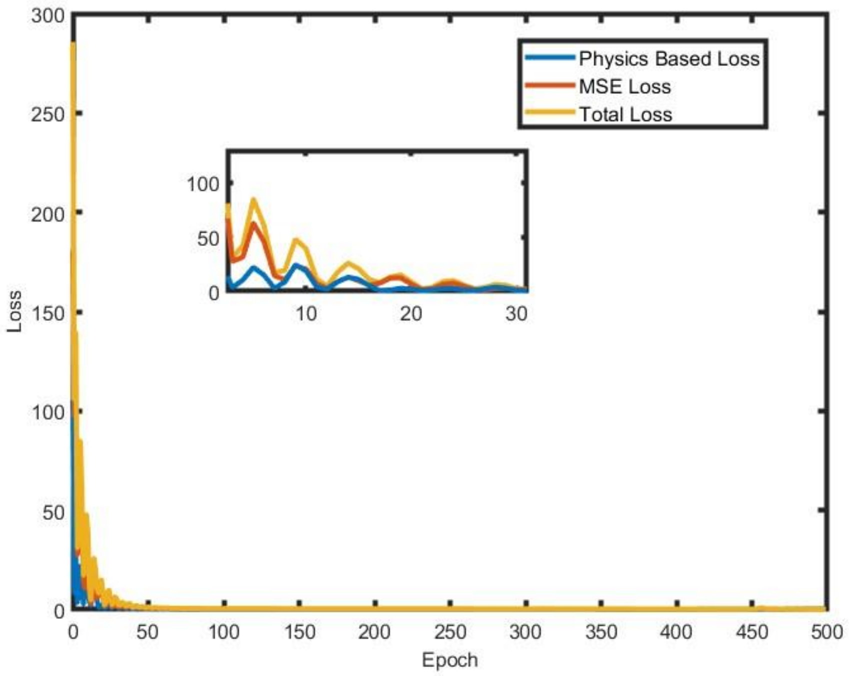
end for

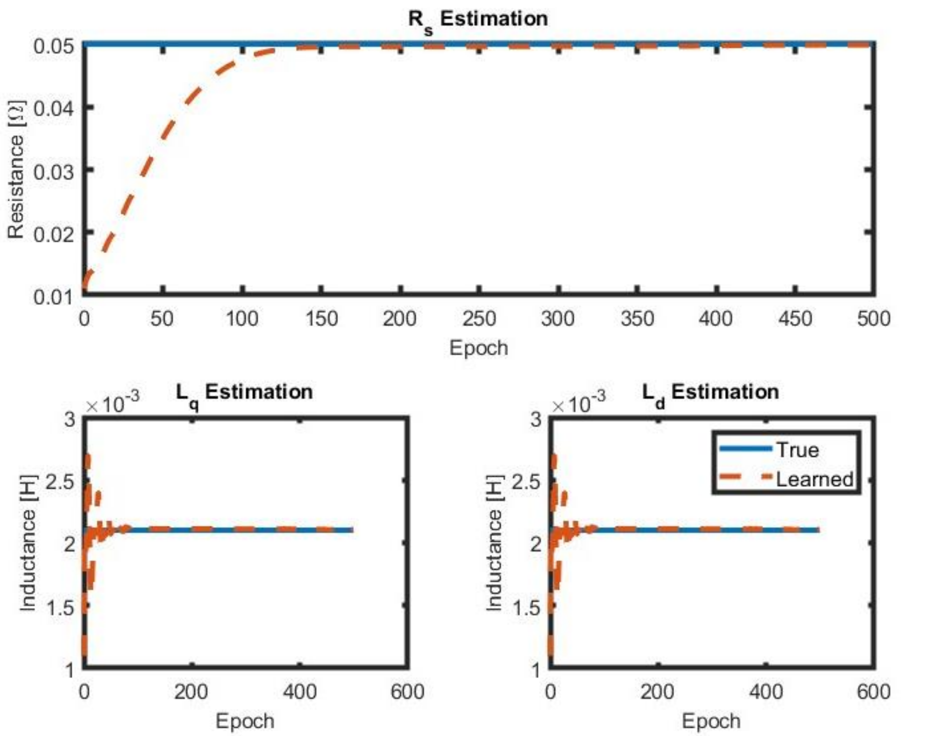
Return: Trained network and estimated parameters R_s, L_d, L_q,

Results: Case 1 $(L_d = L_q) SPMSM$

In surface mount PMSM, $L_d = L_q$

Given: $\lambda_m = 0.192\, wb$



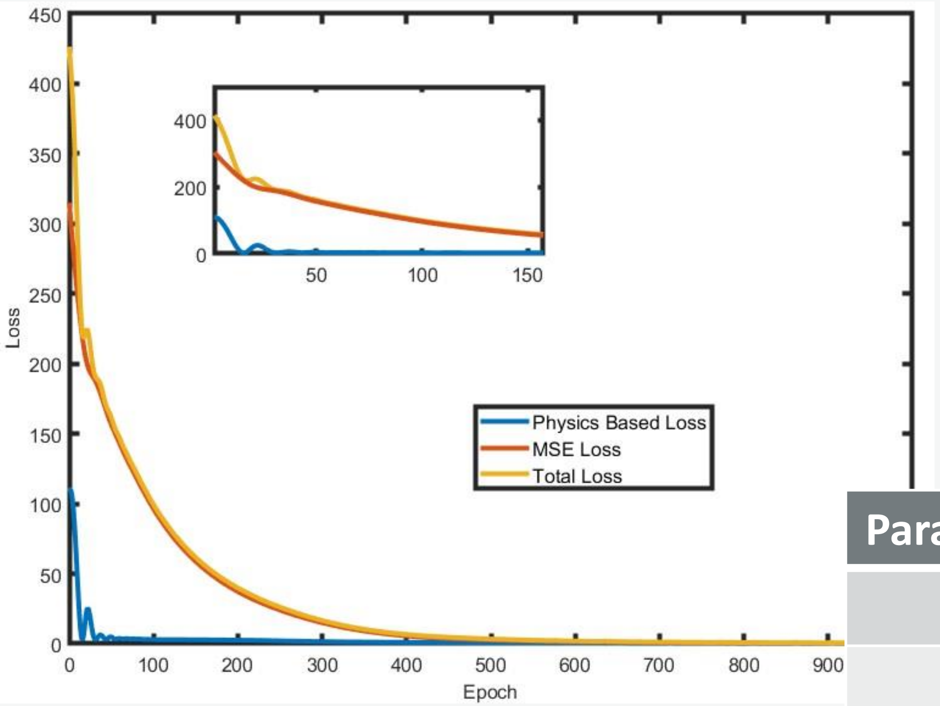


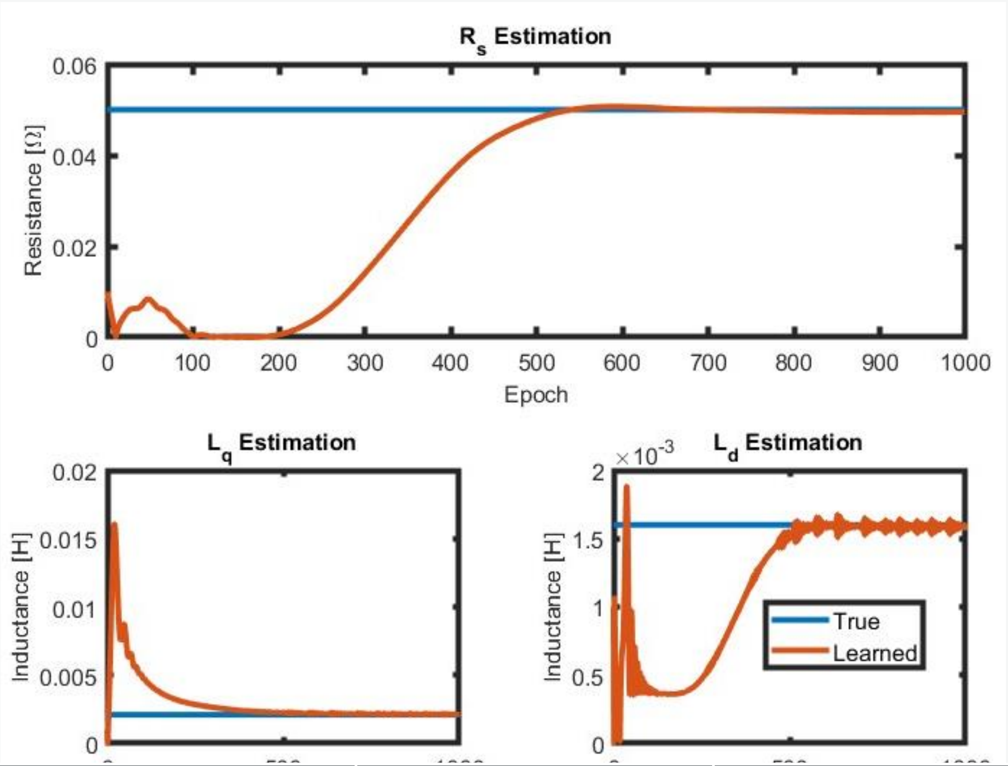
Parameter	Actual Value	Estimated Value	Accuracy [%]
$R_s\ [\Omega]$	0.05	0.0496	99.2
$L_d\ [H]$	0.0021	0.0021	100
$L_q\ [H]$	0.0021	0.0021	100

Results: Case 2 $(L_d < L_q) IPMSM$

In Interior PMSM, $L_d < L_q$

Given: $\lambda_m = 0.192\, wb$

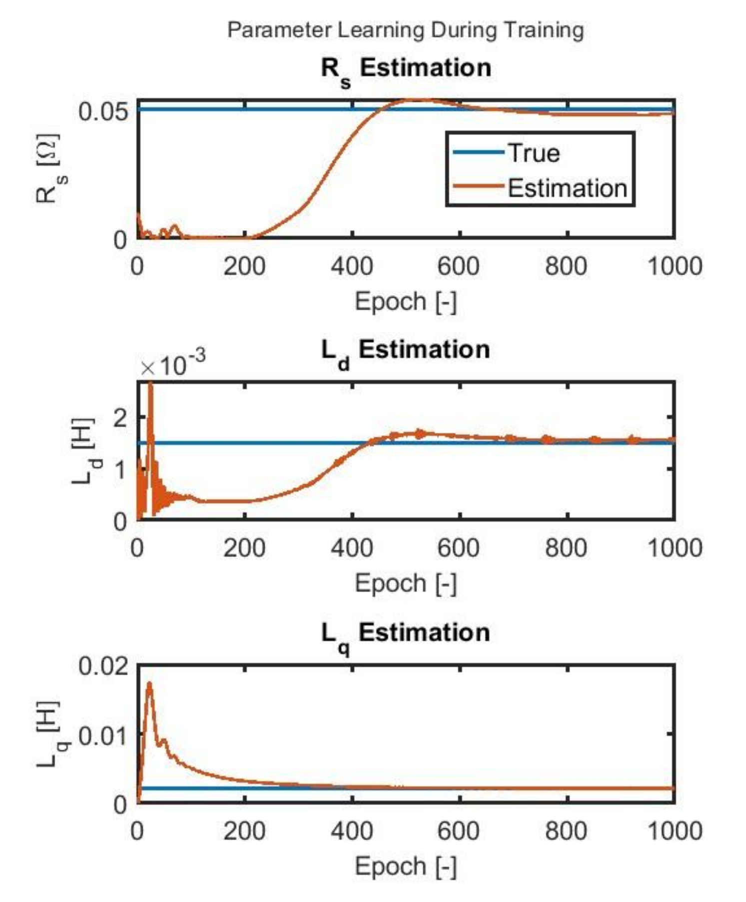




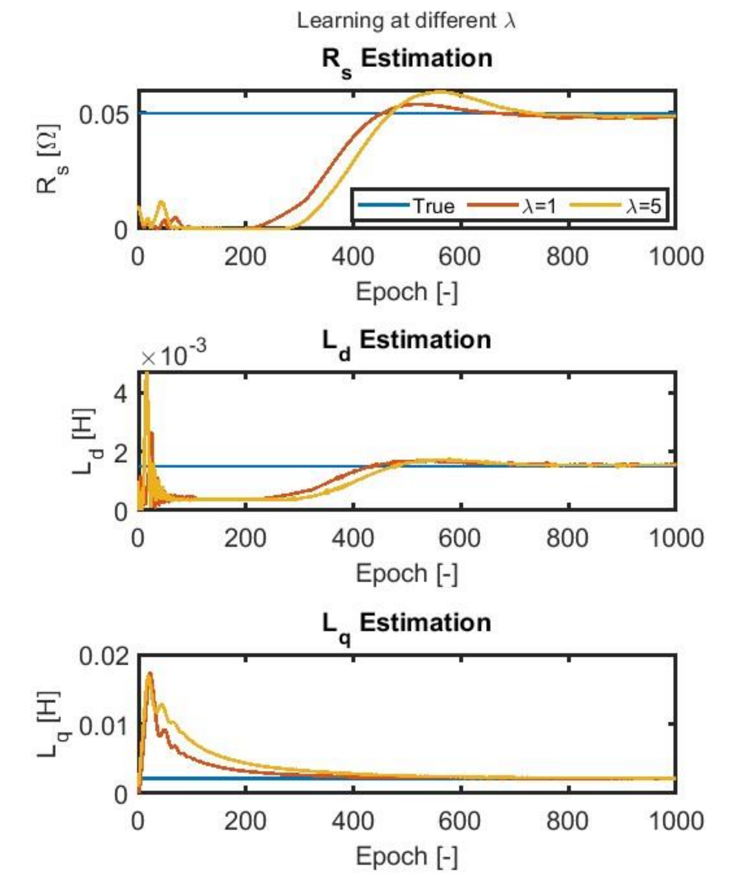
Parameter	Actual Value	Estimated Value	Accuracy [%]
$R_s\ [\Omega]$	0.05	0.0495	99.2
$L_d\ [H]$	0.0016	0.0016	100
$L_q\ [H]$	0.0021	0.0021	100

Simulation Results

- The PINN framework PMSM estimates the parameters correctly.

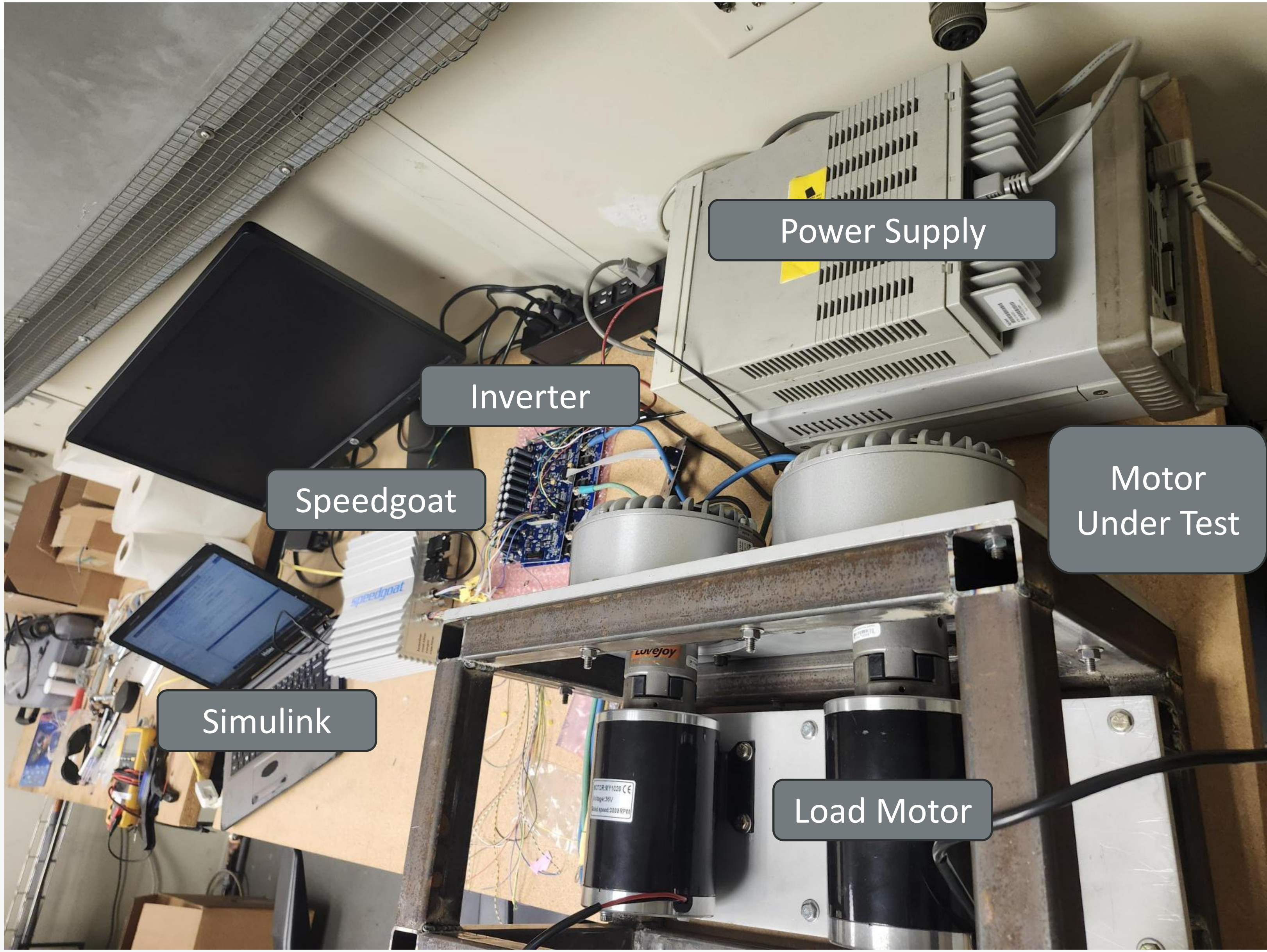


- The parameter with high correlation input to output, converges faster when λ increases



Hardware Setup

- 3kW PMSM parameters are estimated
- Data was recorded under different conditions
- Only resistance and flux linkage is known



Thank you

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