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Paper Title: Constrained Optimization-Based Neuro-Adaptive Control (CONAC) for Synchronous Machine Drives Under Voltage Constraints

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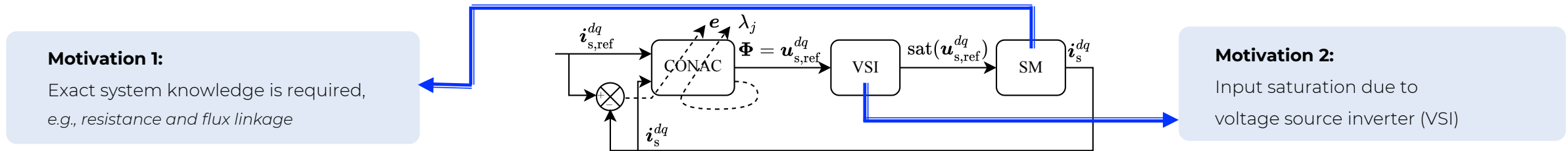
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Background

$$\text{Saturation (VSI)} \quad \text{sat}(\mathbf{u}_{s,\text{ref}}^{\text{dq}}) = \mathbf{R}_s^{\text{dq}} \mathbf{i}_s^{\text{dq}} + \omega_p \mathbf{J} \boldsymbol{\psi}_s^{\text{dq}} + \frac{d}{dt} \boldsymbol{\psi}_s^{\text{dq}}$$

Control input (voltage) State (current) Unknown terms

Resistances Flux linkages



Controller design objectives

- Design **current tracking controller**
- Utilize **ANN to approximate** unknown ideal input (*Motivation 1*)

$$\mathbf{u}^* = \Phi(\mathbf{x}_n; \boldsymbol{\theta}^*) + \boldsymbol{\epsilon}, \text{ and } \mathbf{u}_{s,\text{ref}}^{\text{dq}} = \hat{\Phi} = \Phi(\mathbf{x}_n; \hat{\boldsymbol{\theta}})$$

Unknown ideal control input Actual input (ANN output)

- Derive **ANN weight adaptation law** ensuring stability (weight and error boundedness) and preventing input saturation **using constrained optimization theory** (*Motivation 2*)

$$\frac{d}{dt} \hat{\boldsymbol{\theta}} = ?, \text{ which leads } \hat{\boldsymbol{\theta}} \rightarrow \boldsymbol{\theta}^*$$

Motivation 2:
Input saturation due to voltage source inverter (VSI)

- $\hat{\boldsymbol{\theta}}_i$: estimated weight of i th layer
- $\boldsymbol{\theta}_i^*$: ideal weight of i th layer
- \mathbf{x}_n : artificial neural network (ANN) input
- $\Phi(\mathbf{x}_n; \boldsymbol{\theta})$: ANN function

Constraint formulation

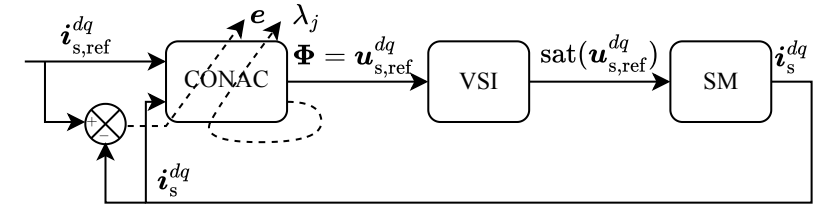
- Constraints are formulated to ensure...

Constraint 1: Stability of adaptation process (weight boundedness)

$$c_{\theta_i}(\hat{\theta}) = \frac{1}{2}(\hat{\theta}_i^\top \hat{\theta}_i - \bar{\theta}_i^2) \leq 0, \quad \forall i \in \{0, 1\} \quad (1)$$

Constraint 2: Input saturation satisfaction

$$c_u(\hat{\theta}) = \frac{1}{2}(\hat{\Phi}^\top \hat{\Phi} - \bar{u}^2) \leq 0 \quad (2)$$



- $\hat{\theta}_i$: estimated weight of i th layer
- θ_i^* : ideal weight of i th layer
- x_n : artificial neural network (ANN) input
- $\Phi(x_n; \theta)$: ANN function

Constrained optimization problem

- Quadratic objective function $J(\cdot)$ of tracking error $e := i_s - i_{s,ref}$
- By solving the constrained optimization problem, we can obtain estimated ideal control input while satisfying constraints

$$\min_{\hat{\theta}} J(e; \hat{\theta}) = \frac{1}{2} e^\top e,$$

subject to (1) and (2)

Adaptation law derivation

$$\min_{\hat{\theta}} J(e; \hat{\theta}) = \frac{1}{2} e^T e,$$

subject to (1) and (2)

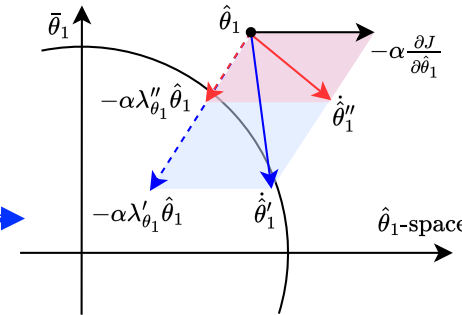
Find Lagrangian
dual problem

$$\min_{\hat{\theta}} \max_{[\lambda_j]_{j \in \mathcal{I}}} L(e, \hat{\theta}, [\lambda_j]_{j \in \mathcal{I}})$$

where $L(e, \hat{\theta}, [\lambda_j]_{j \in \mathcal{I}}) := J(e; \hat{\theta}) + \sum_{j \in \mathcal{I}} \lambda_j c_j(\hat{\theta})$

- Gradient descent/ascent methods are used

$$\begin{aligned} \frac{d}{dt} \hat{\theta} &= -\alpha \frac{\partial L}{\partial \hat{\theta}} = -\alpha \left(\frac{\partial J}{\partial \hat{\theta}} + \sum_{j \in \mathcal{I}} \lambda_j \frac{\partial c_j}{\partial \hat{\theta}} \right), \\ \frac{d}{dt} \lambda_j &= \beta_j \frac{\partial L}{\partial \lambda_j} = \beta_j c_j, \quad \forall j \in \mathcal{I}, \\ \lambda_j &\leftarrow \max(\lambda_j, 0) \end{aligned} \quad (3)$$



Contributions

- No prior **system information** is required
- Adaptation laws are derived based on **constrained optimization**
- Stability** is guaranteed using Lyapunov theory, see Thm. 1 in Paper

$$\|e\| \leq \frac{\bar{u}}{k}, \text{ and } \|\hat{\theta}_i\| \leq \bar{\theta}_i, \quad \forall i \in \{0, 1\}$$

- $\hat{\theta}_i$: estimated weight of i th layer
- θ_i^* : ideal weight of i th layer
- x_n : artificial neural network (ANN) input
- $\Phi(x_n; \theta)$: ANN function
- λ_j : Lagrange multipliers
- \mathcal{I} : Inequality constraint set
- α : learning rate of weights
- β : update rate of Lagrange multipliers

Numerical Validation

- MATLAB/SIMULINK R2024b
- Interior permanent magnet SM's (IPMSM's) flux linkage maps were used
 - Identified from a real machine in laboratory
- IPMSM was operated at the rated mechanical speed

$$\text{sat}(\mathbf{u}_{s,\text{ref}}^{dq}) = \mathbf{R}_s^{dq} \mathbf{i}_s^{dq} + \omega_p \mathbf{J} \psi_s^{dq} + \frac{d}{dt} \psi_s^{dq}$$

- Saturation function is defined as

$$\text{sat}(\mathbf{u}_{s,\text{ref}}^{dq}) = \begin{cases} \bar{u} \frac{\mathbf{u}_{s,\text{ref}}^{dq}}{\|\mathbf{u}_{s,\text{ref}}^{dq}\|}, & \text{if } \|\mathbf{u}\| > \bar{u} \\ \mathbf{u}_{s,\text{ref}}^{dq}, & \text{otherwise} \end{cases}$$

Comparative study

- (C1) CONAC with input constraint
- (C2) CONAC without input constraint

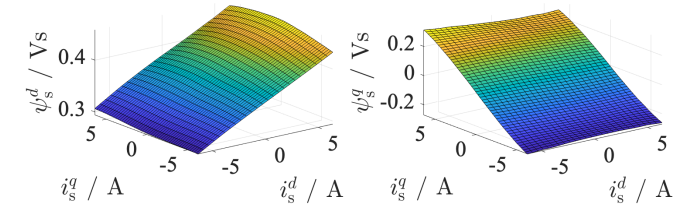
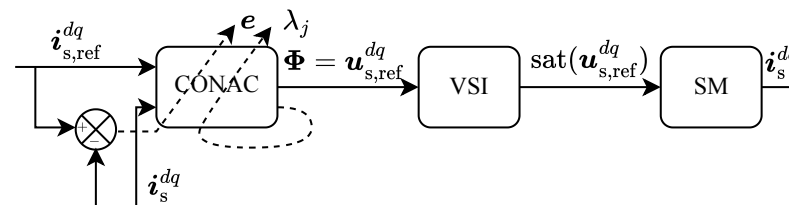


Fig 1. Stator flux linkages of IPMSM at the rated mechanical speed $\omega_{m,R} = 240.855\text{rad/s}$

Table 1. IPMSM parameters

Symbol	Description	Value
$p_{m,R}$	rated mech. power	2.5 kW
$\omega_{m,R}$	rated mech. speed	240.855 rad/s
$m_{m,R}$	rated mech. torque	10.5 Nm
$i_{s,\text{max}}^d$	max d current	4.19 A
$i_{s,\text{max}}^q$	max. q current	4.19 A
u_{max}	max. voltage	340 V
R_s	stator resistance	1.475 Ω

Numerical Validation (Tracking Performance)

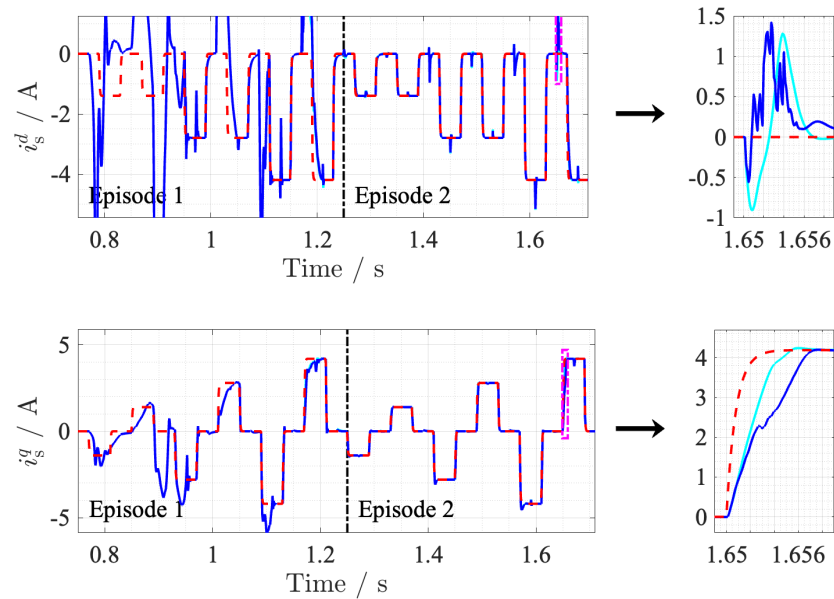


Fig 2. Current tracking results

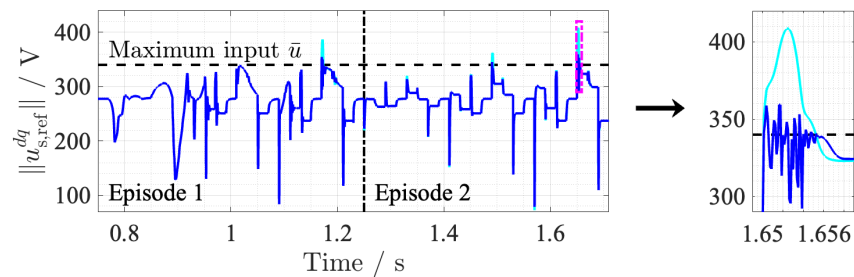


Fig 3. Norm of control input (voltage)

- (C1) CONAC with input constraint
- (C2) CONAC without input constraint
- - - - Reference current

Tracking Performance

- Both controllers demonstrated satisfactory performance
- Performance was improved in Episode 2, $\cong -84\%$
- (C2) achieved slightly higher performance
 - However, it neglected costs that come from saturation

Table 2. Quantitative comparison of performances' L_2 norm

	Episode 1			Episode 2		
	(C ₁)	(C ₂)	%	(C ₁)	(C ₂)	%
$i_s^d - i_{s,ref}^d$	1.835	1.835	+0.0	0.119	0.117	+1.3
$i_s^q - i_{s,ref}^q$	0.597	0.591	+1.0	0.157	0.126	+19.6
$\max(c_u, 0)$	0.297	2.031	-85.9	0.488	3.251	-85.0

Numerical Validation (Constraint Handling)

- (C1) CONAC with input constraint
- (C2) CONAC without input constraint

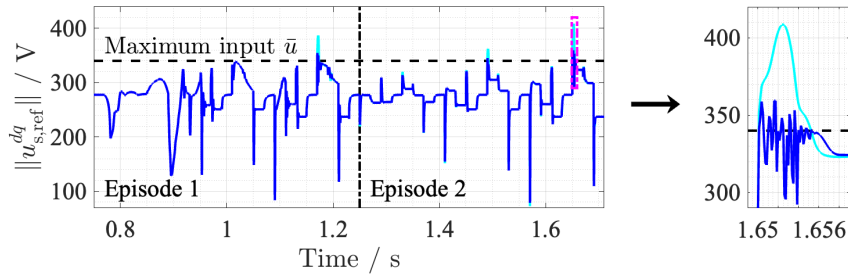


Fig 3. Norm of control input (voltage)

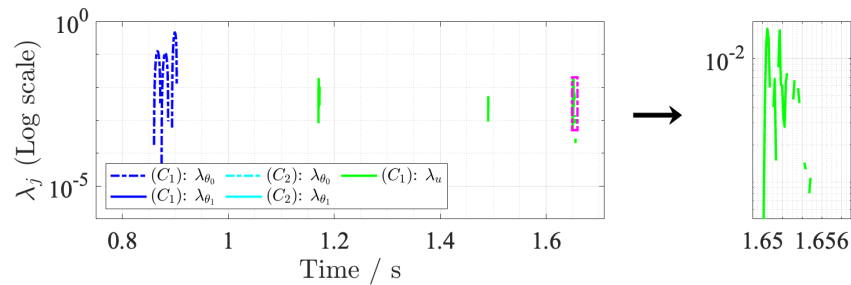


Fig 4. Lagrangian multipliers in logarithmic scale

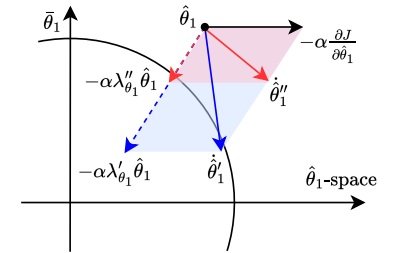
Input Saturation

- Input saturation of (C1) was suppressed
- (C2) exceeded the input limit, $\approx +85\%$

Constraint Handling

- Lagrange multipliers increase to adjust adaptation, see eq. (3)

$$\begin{aligned} \frac{d}{dt} \hat{\theta} &= -\alpha \frac{\partial L}{\partial \theta} = -\alpha \left(\frac{\partial J}{\partial \theta} + \sum_{j \in \mathcal{I}} \lambda_j \frac{\partial c_j}{\partial \theta} \right), \\ \frac{d}{dt} \lambda_j &= \beta_j \frac{\partial L}{\partial \lambda_j} = \beta_j c_j, \quad \forall j \in \mathcal{I}, \\ \lambda_j &\leftarrow \max(\lambda_j, 0) \end{aligned} \quad (3)$$



Conclusion

- CONAC was proposed for SM drives with input voltage saturation
- Stability and constraint satisfaction were ensured via Lyapunov theory
- As future work, the following subjects will be investigated
 - The parameter dependencies of CONAC
 - Real-time implementation to validate the effectiveness and feasibility