

Modeling Electrical Motor Dynamics using Encoder-Decoder with Recurrent Skip Connection





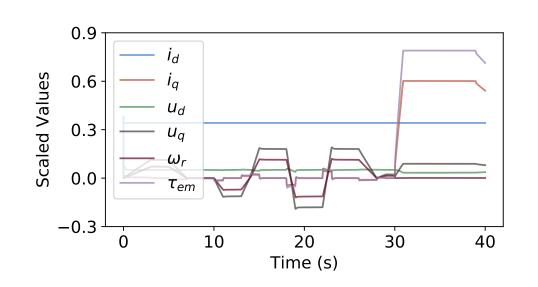
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Modeling Complex Dynamics

- Traditionally, electrical motor dynamics modeling relies on physics-based approach.
- Dynamics are dependent on several physical quantities and operating conditions.
- Sensors and estimators used for measuring these quantities come with inherent noise.
- This makes controller design and fault monitoring challenging problems.

PROBLEM STATEMENT

- We explore the feasibility of modeling the dynamics of an electrical motor by following a datadriven approach.
- We focus on modeling the relationship between input and output quantities of an induction motor.



Real world sample

Simulated sample

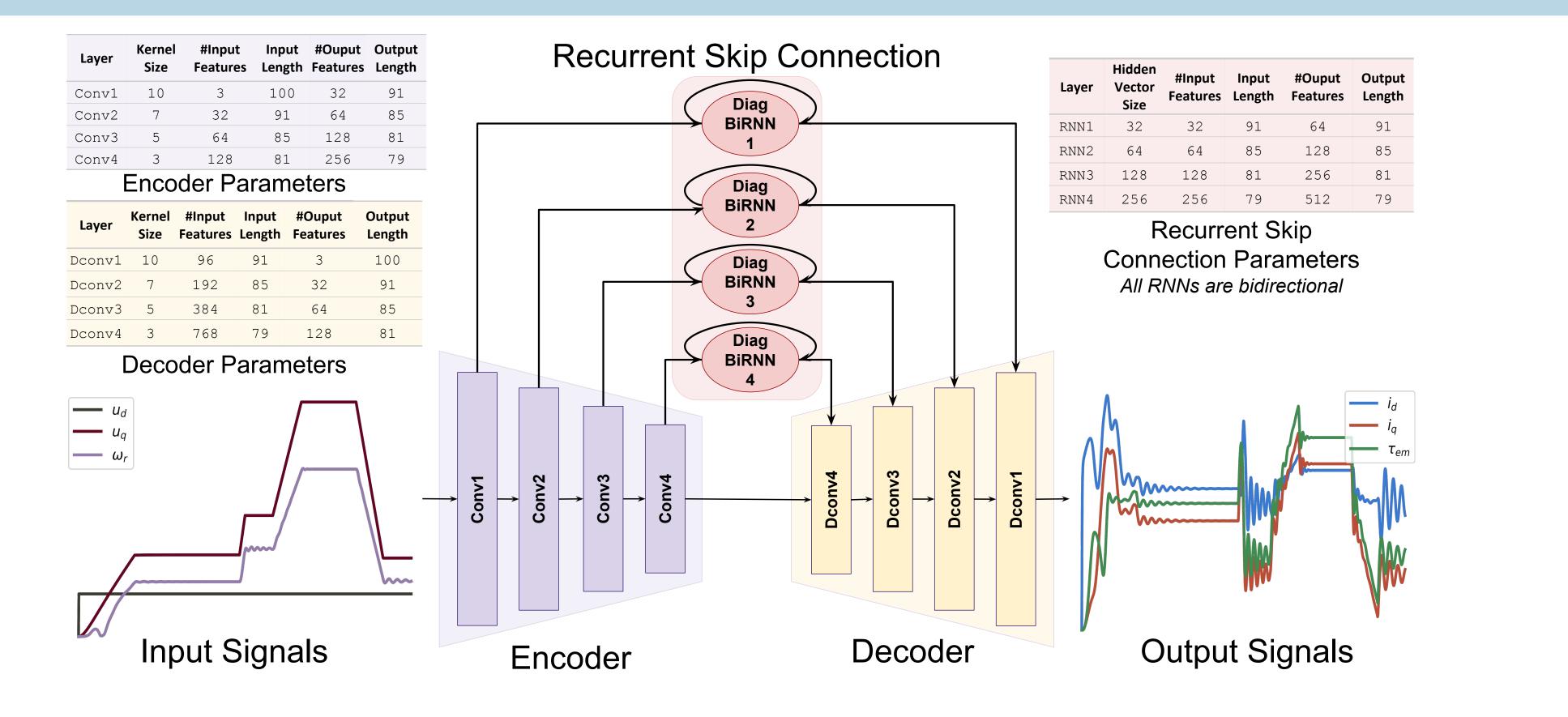
Related Work

- Physics of electrical motors and controller design [1,
- State space model of an induction motor [3].
- Electrical motor dynamics modeling using analytical mechanics [4].
- Competitive performance of CNNs on sequential tasks $\lfloor 5 \rfloor$.
- Independent Recurrent Neural Network [6].

DATASET

- 4 kW induction motor
- Acquisition rate: 250 Hz
- 7 quantities: $i_d, i_q, u_d, u_q, \omega_r, \omega_s, \tau_{em}$
- Simulated data: 100 hours, training: 70% and validation: 30%
- Raw data: 1207 seconds, no ω_s , 10 operating conditions, training: 20%, and testing: 80%

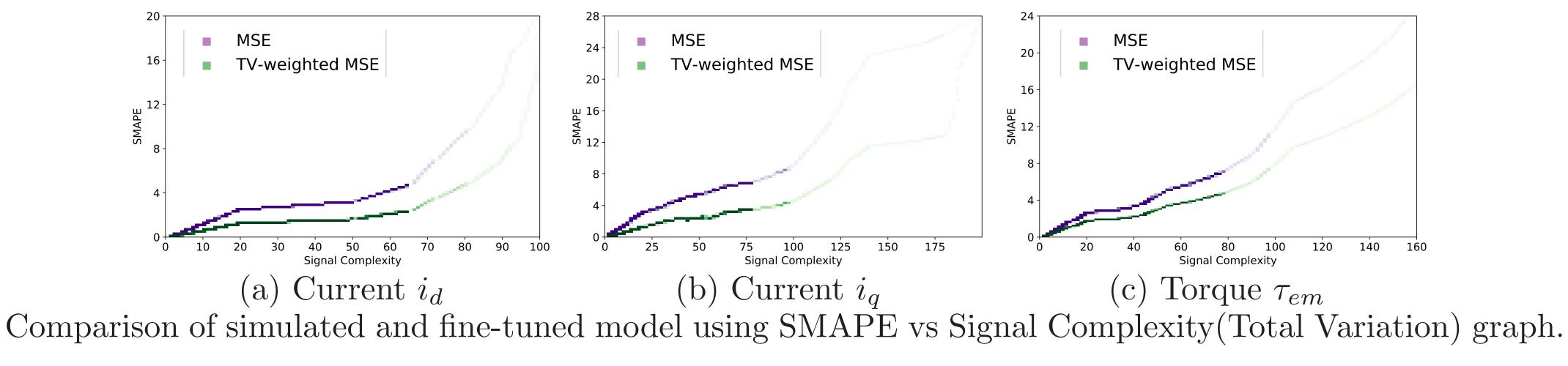
Proposed Architecture

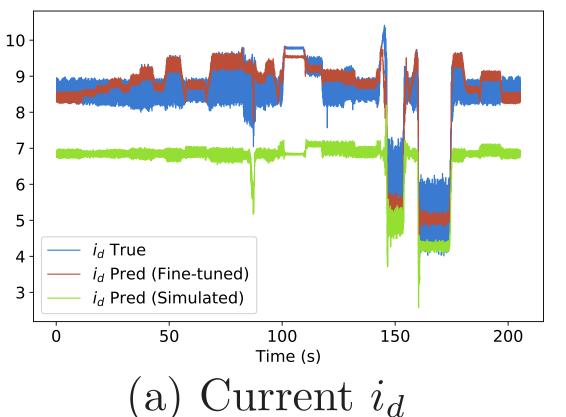


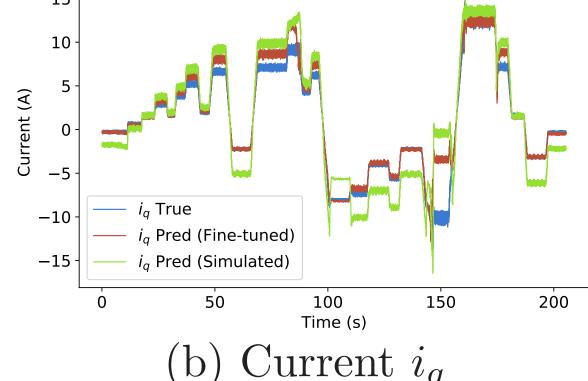
RESULTS

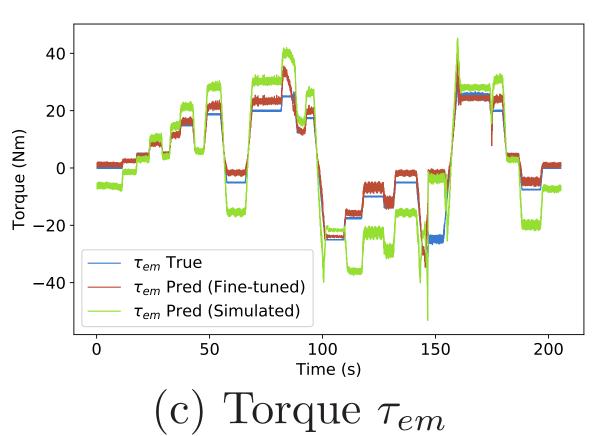
Model	Window Size	Parameters	MAE	SMAPE	R^2
Feed-Forward	20	1118209	78.91	8.53%	-0.39
\mathbf{RNN}	150	12001	78.26	7.76%	-0.35
\mathbf{LSTM}	100	21889	79.58	6.29%	-0.11
CNN	100	650049	79.69	6.13%	-0.14
Encoder-Decoder	100	1096385	81.21	4.57%	0.29
\mathbf{Skip}	100	364801	28.96	3.71%	0.42
RNN-Skip	100	638145	28.18	3.42%	0.43
BiRNN-Skip	100	967105	27.96	3.31%	0.41
DiagBiRNN-Skip	100	618465	26.88	$\boldsymbol{1.09\%}$	0.95

Results for the benchmark and the proposed model variants obtained on the simulated validation set.









Predicted result of one of the experiments from the test set.

Contributions

• New Encoder-Decoder architecture with diagonalized recurrent skip connection to effectively learn time-series relationship between different electrical quantities.

$$h_t = \tanh(w \odot x_t + u \odot h_{t-1} + b)$$

where $w \in \mathbb{R}^M$, $u \in \mathbb{R}^M$, and $b \in \mathbb{R}^M$ are input weights.

• A novel *loss function* that uses fast variations present in the electrical motor signals to avoid model bias.

$$\mathcal{L}_{\text{TV-MSE}} = \frac{1}{N} \sum_{i=1}^{N} \underbrace{\left(\sum_{t=1}^{T-1} |y_t^i - y_{t+1}^i|\right)}_{\text{Total Variation}} \underbrace{\left(\frac{1}{T} \sum_{t=1}^{T} (y_t^i - \hat{y_t^i})^2\right)}_{\text{MSE}}$$

where y_t^i and y_t^i are the values of output and predicted sample i at time-step t, respectively. N is the number of training samples, where each sample is of duration T.

• Two datasets; a large dataset of simulated electrical motor operations and a small dataset of sensor data recorded from the real-world operations of electrical motors.



Visit project page for full paper, code, and dataset

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