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

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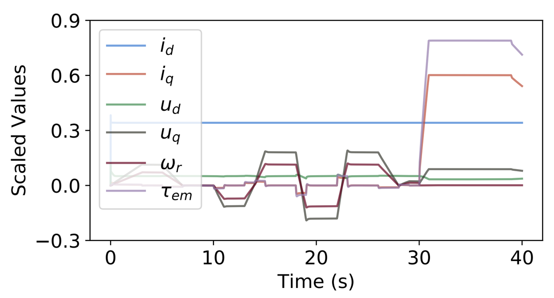
Modelling Complex Dynamics

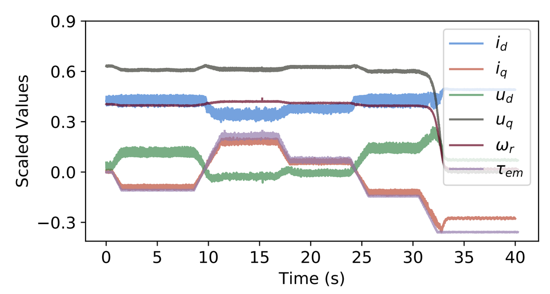
Electrical motor dynamics modeling relies on physics-based approach. Dynamics are dependent on several physical quantities and operating conditions. Sensors and estimators used for measuring these quantities are not accurate. This makes controller design and monitoring a hard problem.

Problem Statement

We explore the feasibility of modeling the dynamics of an electrical motor by following a data-driven approach, which uses only its inputs and outputs and does not make any assumption on its internal behaviour.



Simulated sample



Real world sample

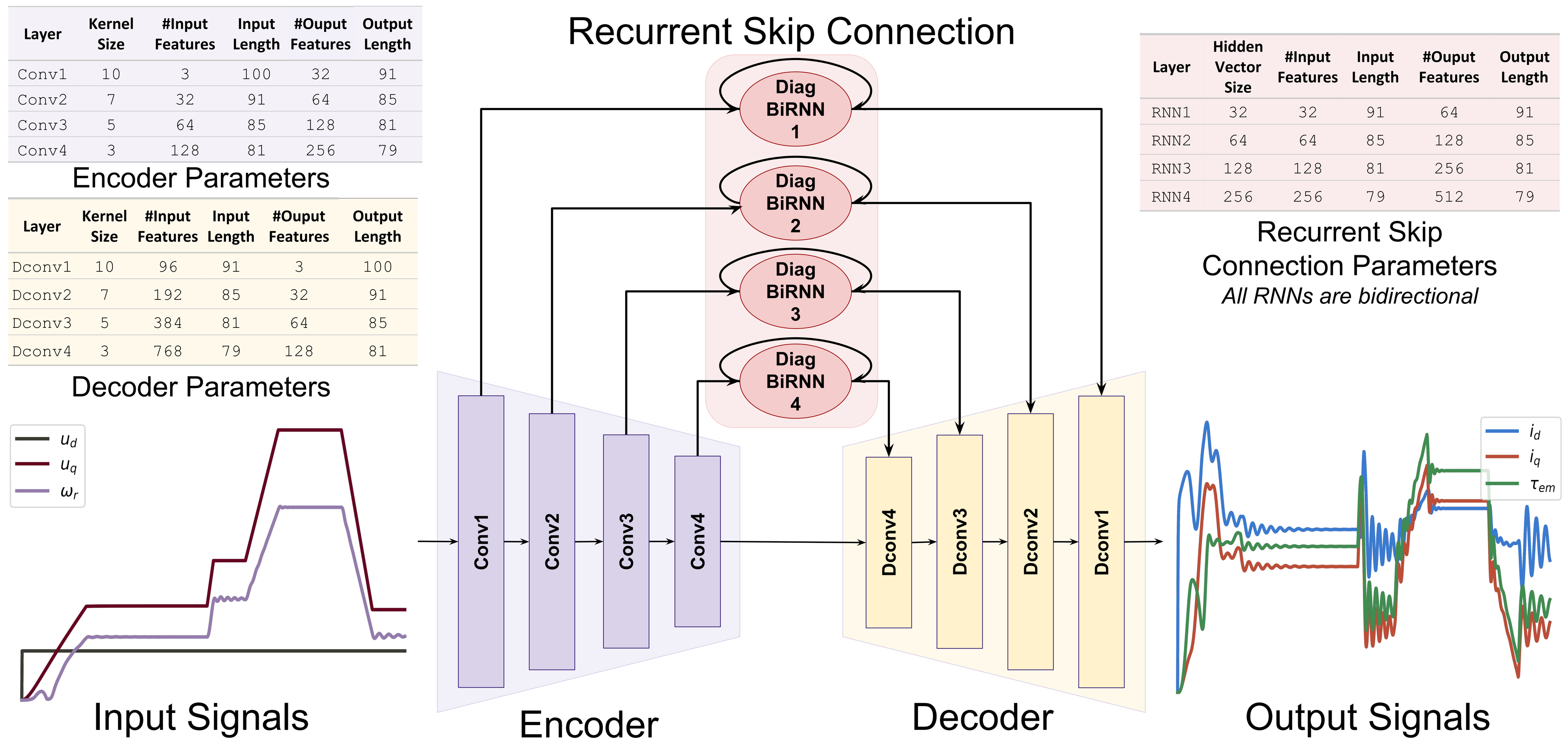
Related Work

- Physics of electrical motors and controller design [1, 2].
- State space model of an induction motor [3].
- Electrical motor dynamics modeling using analytical mechanics [4].
- Competetive performance of CNNs on sequential tasks [5].
- Independent Recurrent Neural Network [6].

Dataset

- 4-kilowatt induction motor
- Acquisition rate: 250 Hz
- Seven quantities $i_d, i_q, u_d, u_q, , \omega_r, \omega_s, \tau_{em}$
- Simulate 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



Layer	Kernel Size	#Input Features	Input Length	#Ouput Features	Output Length
Conv1	10	3	100	32	91
Conv2	7	32	91	64	85
Conv3	5	64	85	128	81
Conv4	3	128	81	256	79

Encoder Parameters

Layer	Kernel Size	#Input Features	Input Length	#Ouput Features	Output Length
Dconv1	10	96	91	3	100
Dconv2	7	192	85	32	91
Dconv3	5	384	81	64	85
Dconv4	3	768	79	128	81

Decoder Parameters

Layer	Hidden Vector Size	#Input Features	Input Length	#Ouput Features	Output Length
RNN1	32	32	91	64	91
RNN2	64	64	85	128	85
RNN3	128	128	81	256	81
RNN4	256	256	79	512	79

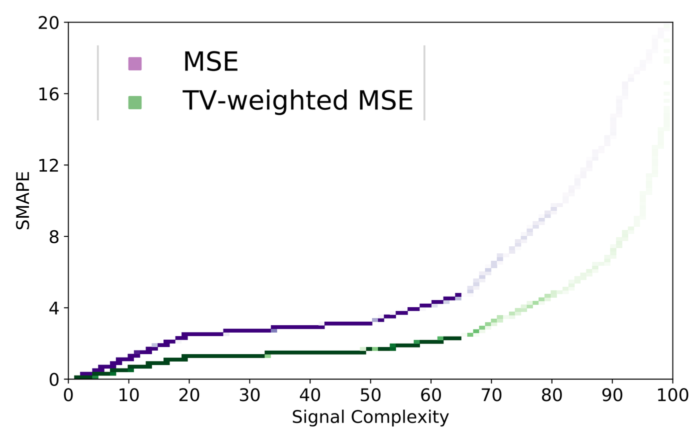
Recurrent Skip Connection Parameters

All RNNs are bidirectional

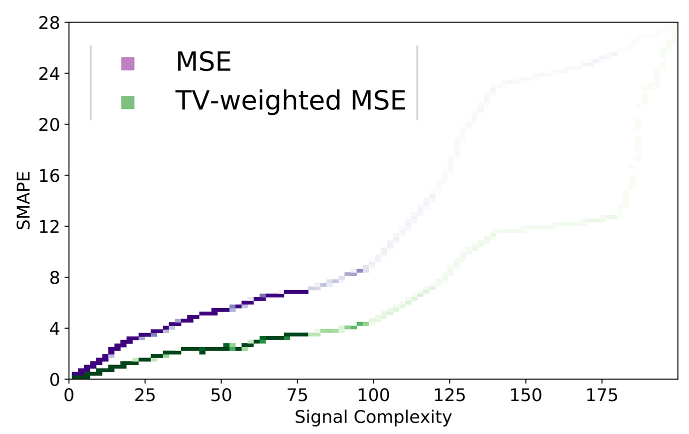
Results

Model	Window Size	Parameters	MAE	SMAPE	R^2
Feed-Forward	20	1118209	78.91	8.53%	-0.39
RNN	150	12001	78.26	7.76%	-0.35
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
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**	**1.09%**	**0.95**

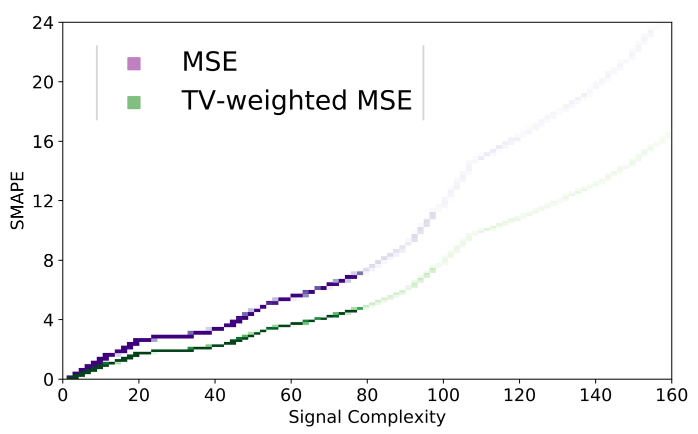
Results for the benchmark and the proposed model variants obtained on the simulated validation set.



(a) Current i_d

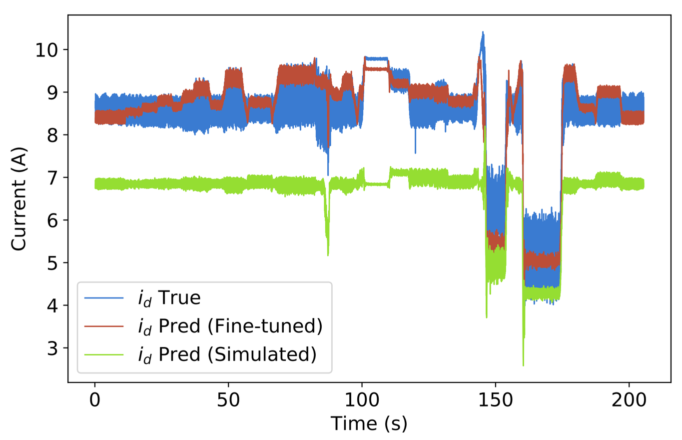


(b) Current i_q

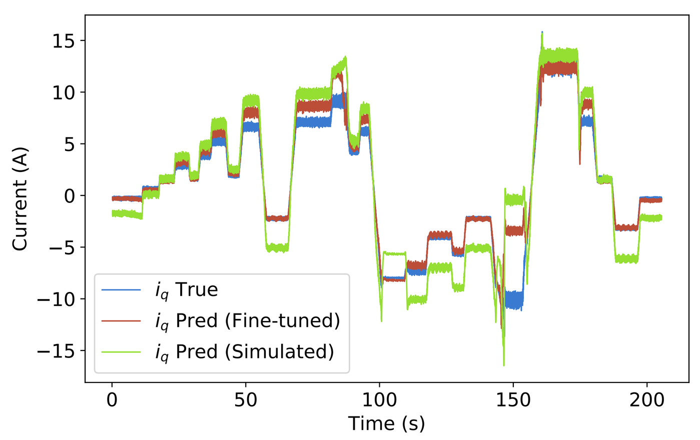


(c) Torque τ_{em}

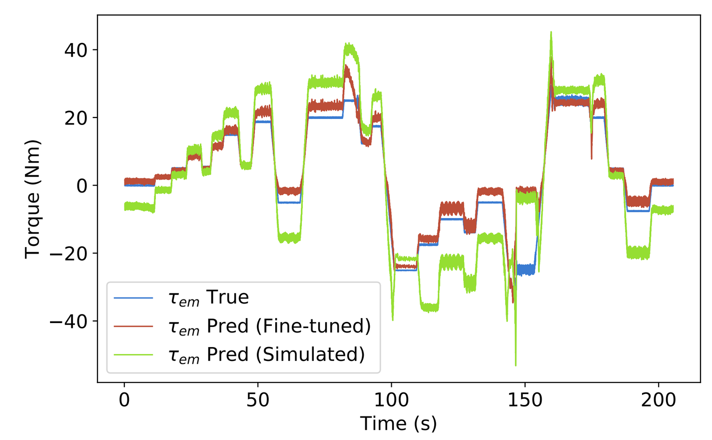
Comparison of simulated and fine-tuned model using SMAPE vs Signal Complexity graph.



(a) Current i_d



(b) Current i_q



(c) Torque τ_{em}

Predicted result of one of the experiments from test set.

DiagRNN and TV-Weight MSE

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

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

$$\mathcal{L}_{\text{TV-WeightMSE}} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T-1}|y_t^i - y_{t+1}^i|\frac{1}{T}\sum_{t=1}^{T}(y_t^i - \hat{y_t^i})^2 \quad (2)$$

where y_t^i and $\hat{y_t^i}$ 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.

Contributions

- This is one of the first works addressing the problem of learning nonlinear dynamics of electrical motors from recorded time-series data.
- We propose a new Encoder-Decoder architecture to learn time-series relationship between different electrical quantities.
- We validate our methodology on 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.
- We propose a novel loss function that uses fast variations present in the electrical motor signals to avoid model bias.
- We analyse the capability of the proposed method by using a new analysis technique and we demonstrate the transfer learning capability of our approach.

References

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