Recurrent Neural Networks for Energy Forecasting

Nikil Pancha[1], Richard Povinelli[2]

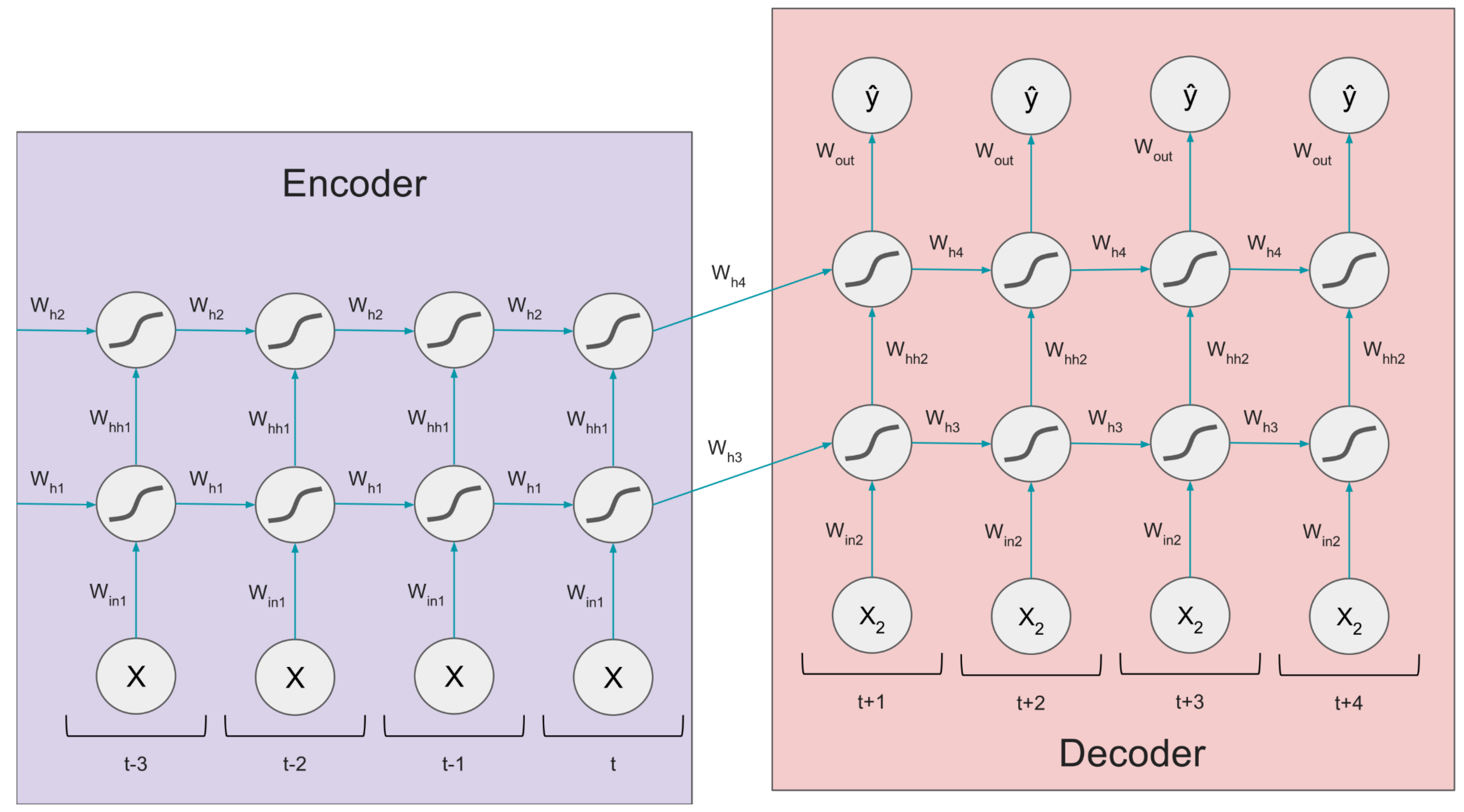
Case Western Reserve University[1], Marquette EECE[2]

Problem Statement

- Improve hourly gas and electricity demand predictions using deep learning

Why Deep Learning?

- No feature engineering
- High model capacities
- Effective at a variety of tasks (computer vision, robotics, etc.)
- Highly nonlinear

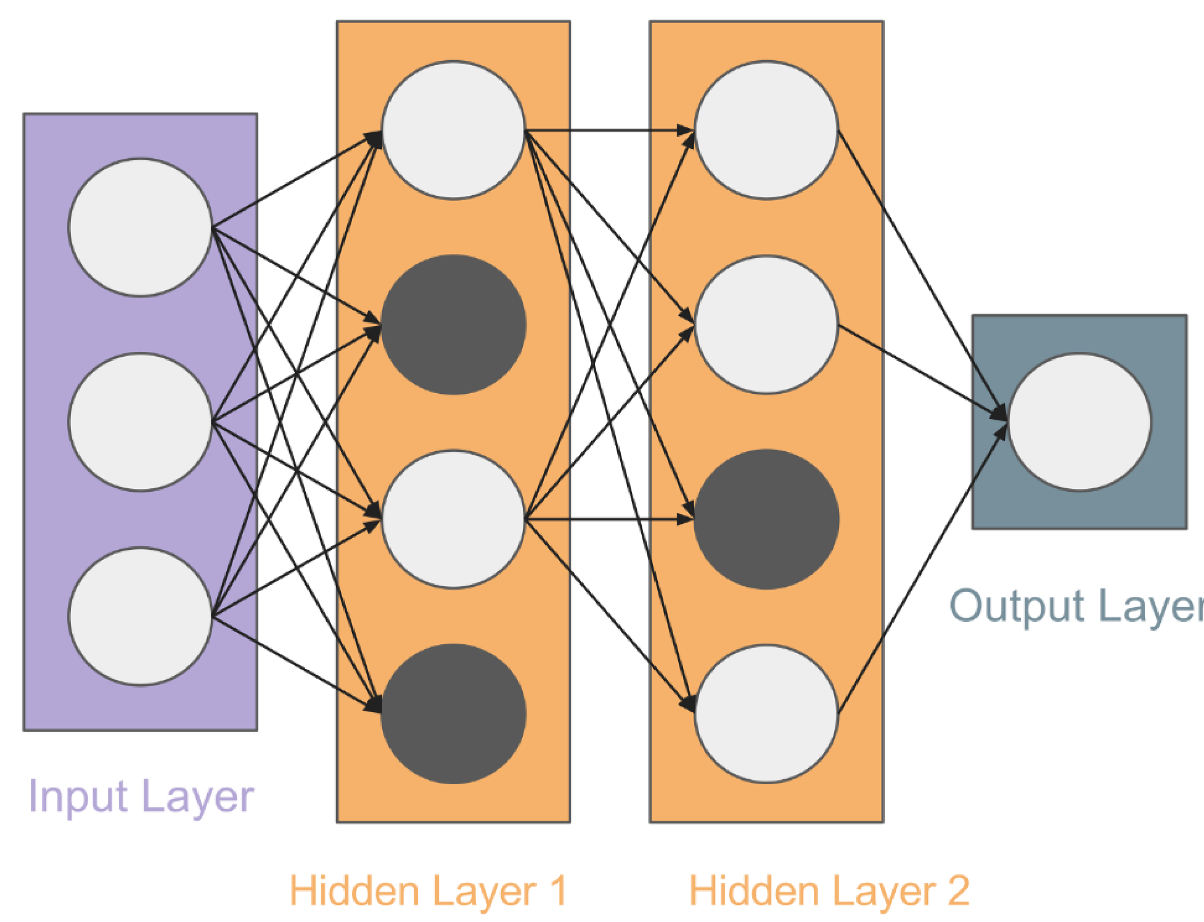


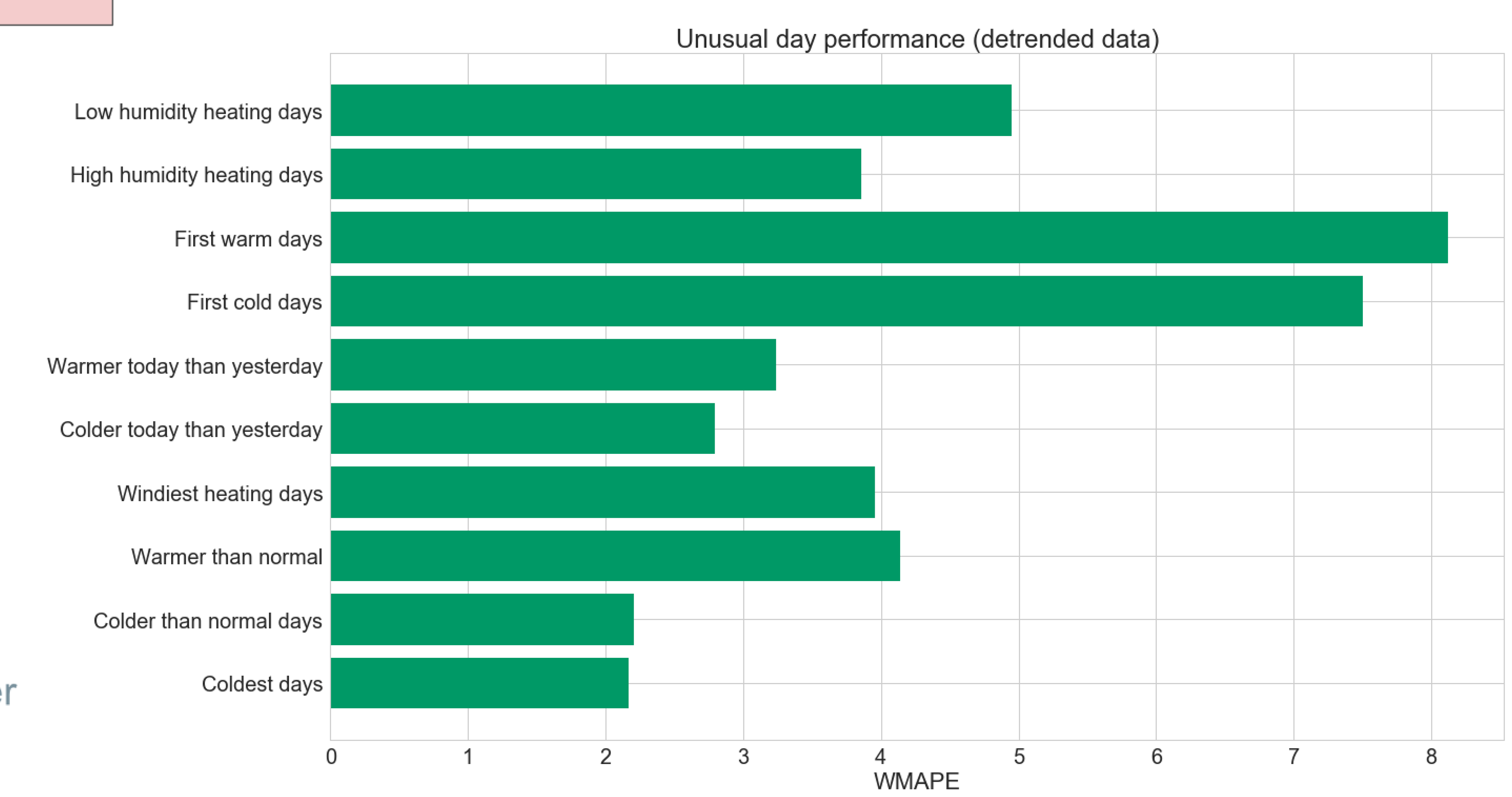
Sequence to Sequence

- Two separate LSTMs: Encoder and Decoder
- Encoder determines a dense representation of past flow and weather
- Decoder translates encoder output and future weather information to predicted flow
- Most common architecture for machine translation models

Long Short-term Memory (LSTM)

- Used to process sequences
- Use previous output, previous state, and current input to predict current output
- Commonly used in natural language processing tasks
- Operated either autoregressively (AR) or sequence to sequence (seq2seq)





Results

- Seq2seq performs better than AR at most horizons
- AR prediction accuracy quickly declines as prediction horizon increases
- Adding an encoder on daily data improves the basic seq2seq model on short horizons
- Regularization is necessary, but some forms are too expensive to apply.

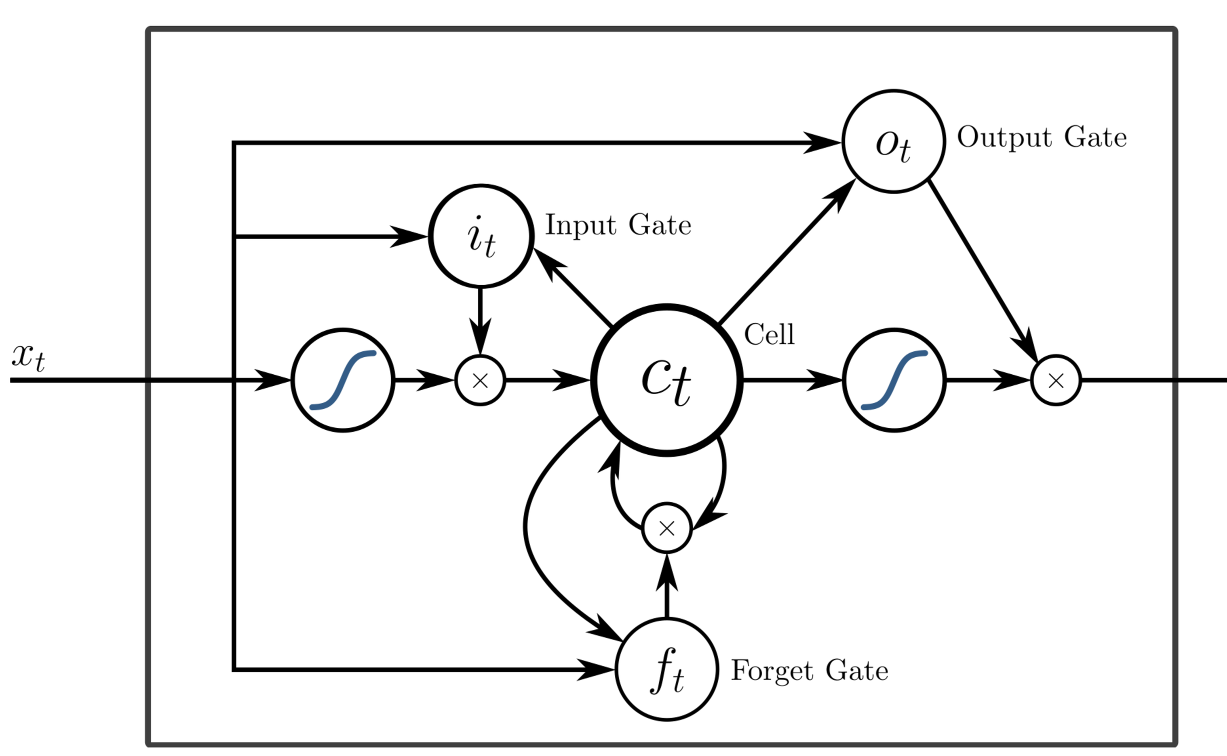
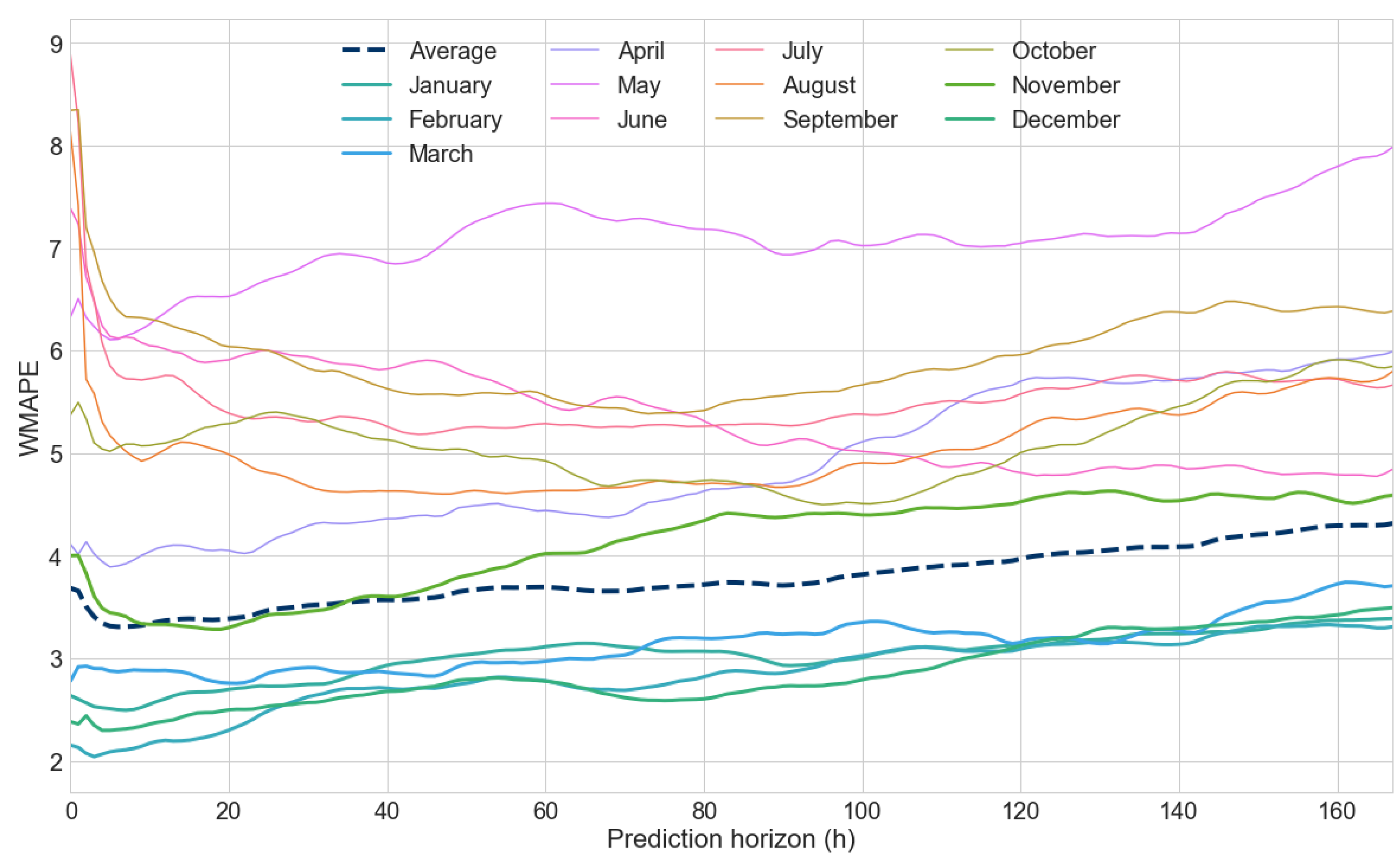


Diagram by Eddieantonioooo, distributed under a CC BY-SA 4.0 license



Average Results over 48 hours

Model	WMAPE	MAPE	MSE
AR	3.926	5.196	3.144
Seq2seq, no daily	3.5886	4.974	2.385
Seq2seq, with daily	3.5404	5.087	2.262

$$WMAPE = \frac{\sum_1^N |y_i - \hat{y}_i|}{\sum_j y_j} \qquad MSE = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \qquad MAPE = \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i}$$

Acknowledgements

I would like to thank the NSF for funding this research (NSF Award ACI-1461264), Dr. Factor, Dr. Dennis Brylow, and Dr. Petra Brylow for running this REU, and the GasDay lab for their support

References

Marino, D. L., Amarasinghe, K., & Manic, M. (2016, October). Building energy load forecasting using deep neural networks. In Industrial Electronics Society, IECON 2016-42nd Annual Conference of the IEEE (pp. 7046-7051). IEEE.

Gers, F. A., Schmidhuber, J., & Cummins, F. (1999). Learning to forget: Continual prediction with LSTM.

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. In Advances in neural information processing systems (pp. 3104-3112).

Bianchi, F. M., Maiorino, E., Kampffmeyer, M. C., Rizzi, A., & Jenssen, R. (2017). An overview and comparative analysis of Recurrent Neural Networks for Short Term Load Forecasting. arXiv preprint arXiv:1705.04378.