Deep Recurrent Neural Networks for Building Energy Prediction

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Objective

Develop a deep recurrent neural network (RNN) model using long-short-term memory (LSTM) cells to predict energy consumption in buildings at one-hour time resolution over medium-to-long term time horizons ($\geq$ 1 week).

Background

Building energy consumption behavior often exhibits transient and sequential patterns. Recurrent neural networks (RNN's) can model temporal dependencies from observed data, and so can be used for longer term energy prediction when explicit knowledge of such transient variables are inaccessible.

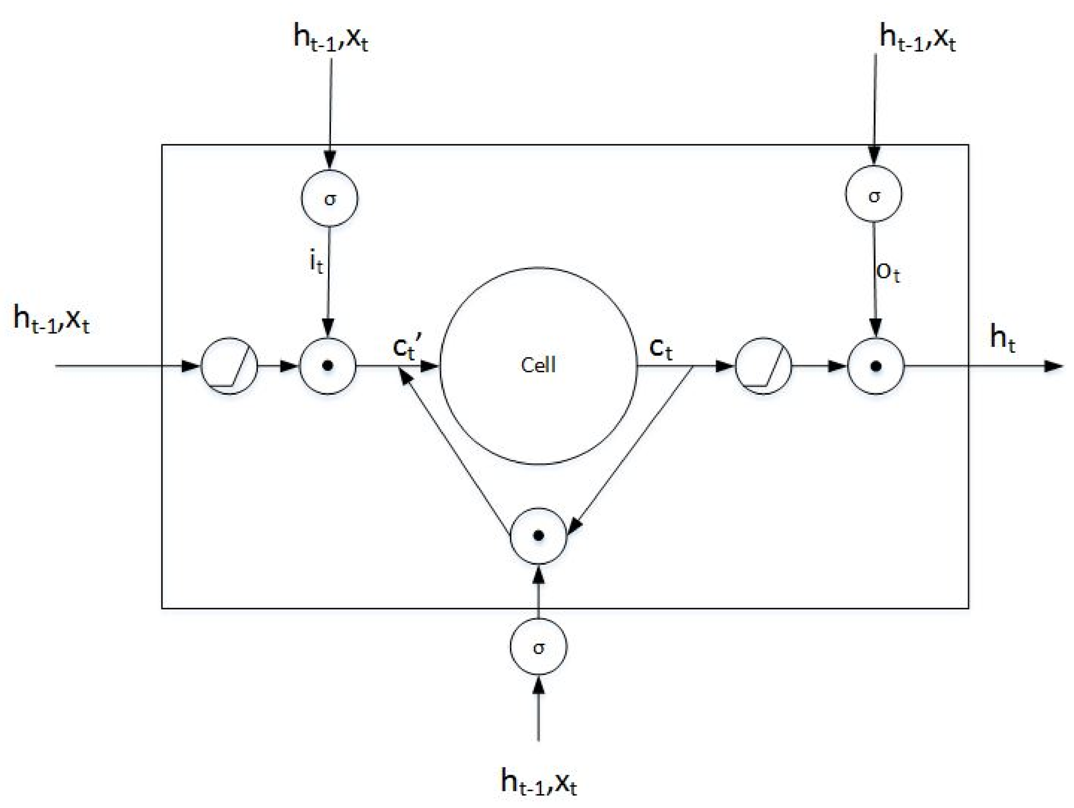

Figure 3: Schematic diagram of long short-term memory activation function

Figure 3 shows the schematic of LSTM activation function. The LSTM avoids the vanishing gradient problems in conventional RNN's. Using multiple gating functions, the LSTM function adaptively scales the input, remembers or forgets the transient state value, and scales the output.

Proposed Model

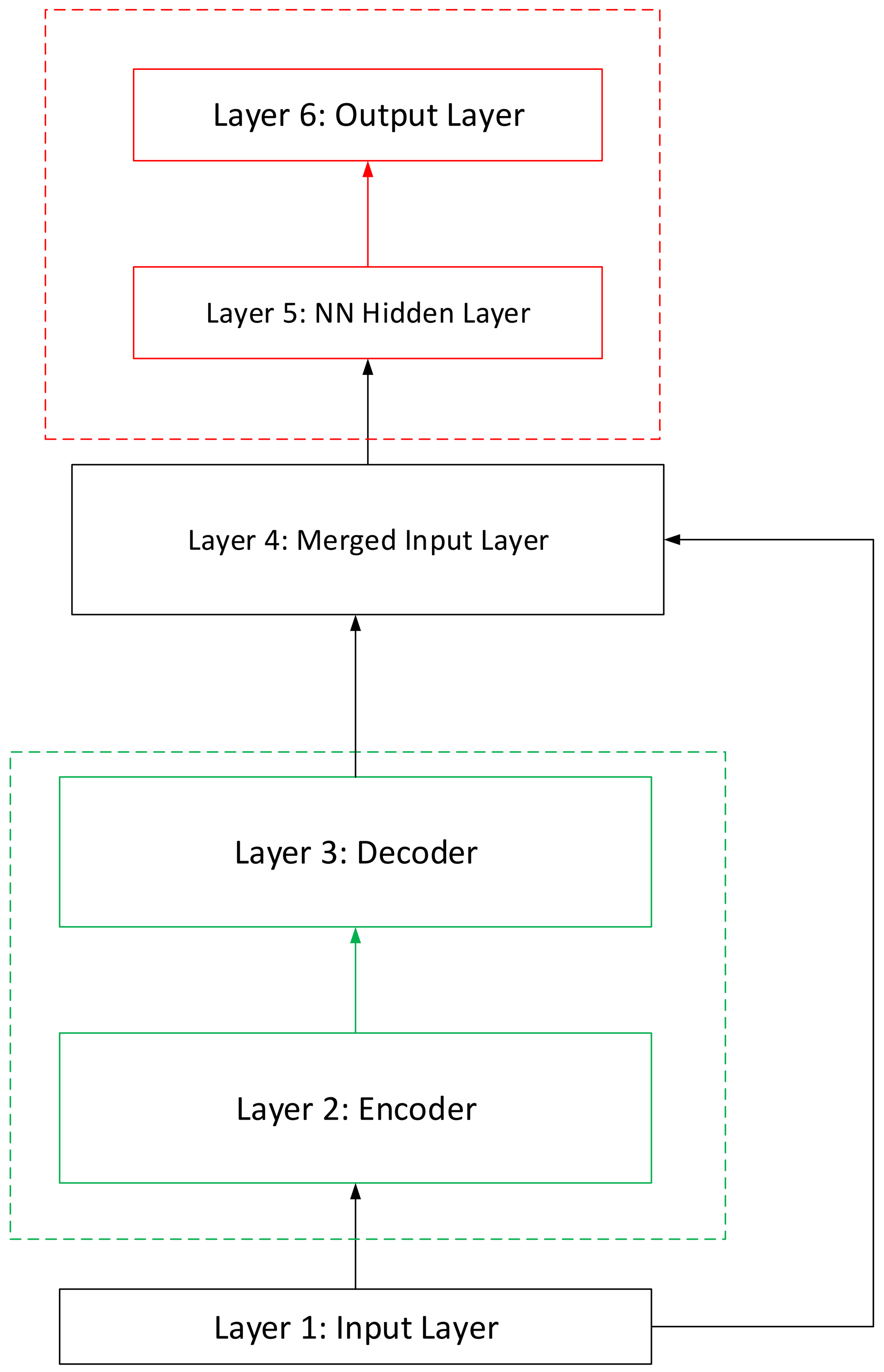

Figure 4: Schematic Diagram of Proposed Model

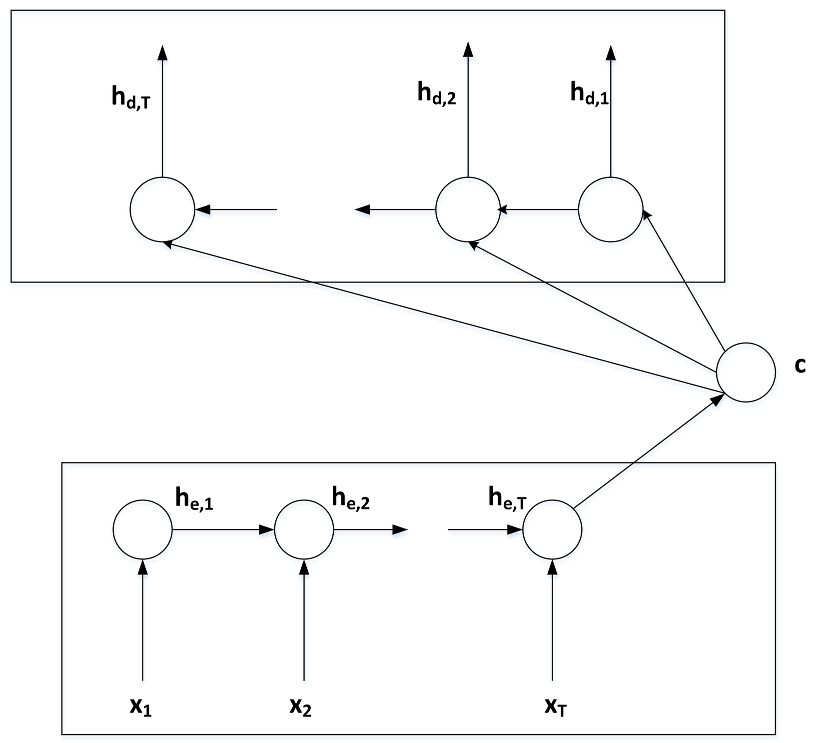

Figure 5: Schematic Diagram of Encoder Decoder model

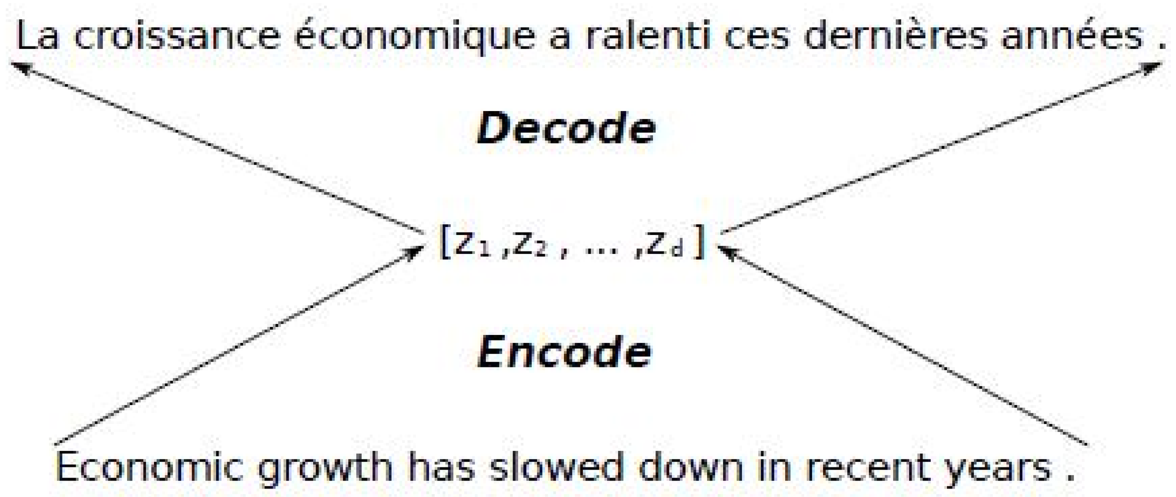

Figure 6: Example of encoder-decoder in machine translation

A deep RNN model with LSTM activation function can exploit the sequential behavior in energy consumption to make predictions over longer time horizons. The proposed model (figure 4) is a combination of the encoder-decoder model and a multi-layered perceptron neural network. The encoder-decoder architecture (figure 5), which is often used in machine translation context (figure 6), consists of an encoder that converts an input sequence to a fixed vector representation, and a decoder that converts the said vector representation to an output sequence.

Results

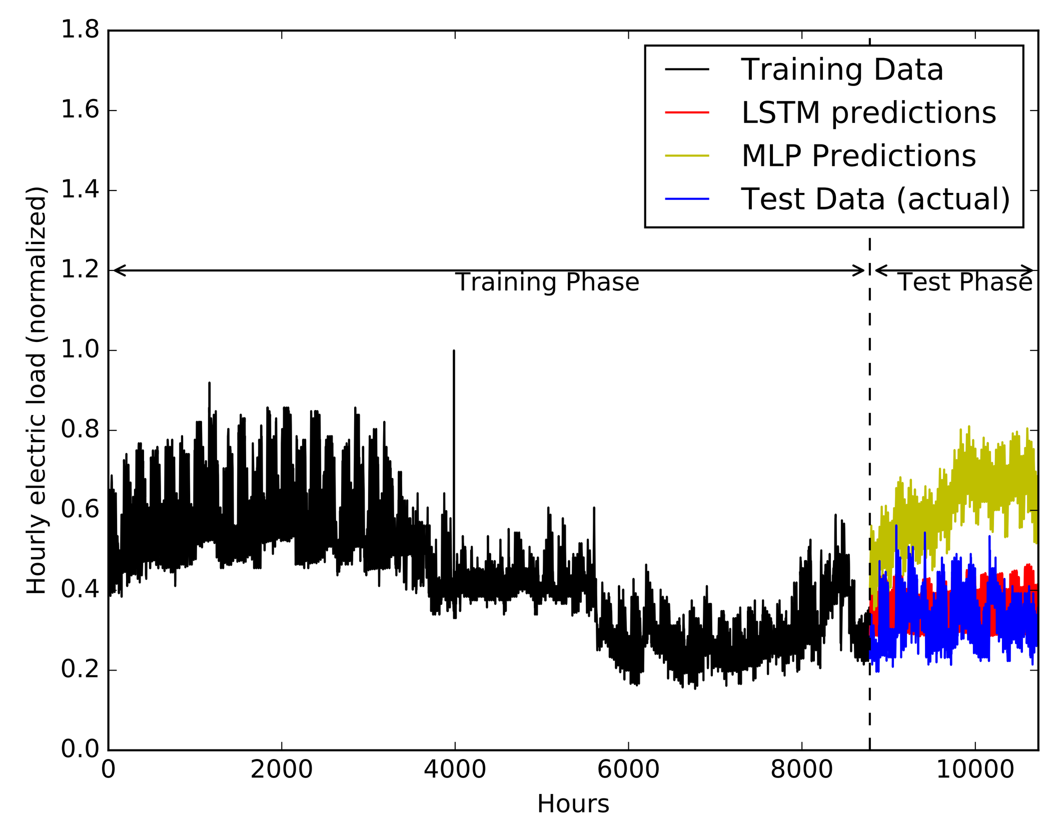

Figure 1: Results obtained using deep RNN predictions (RMS error $e = 11.2\%$) for HVAC Critical load profile, compared to MLP predictions ($e = 61.3\%$).

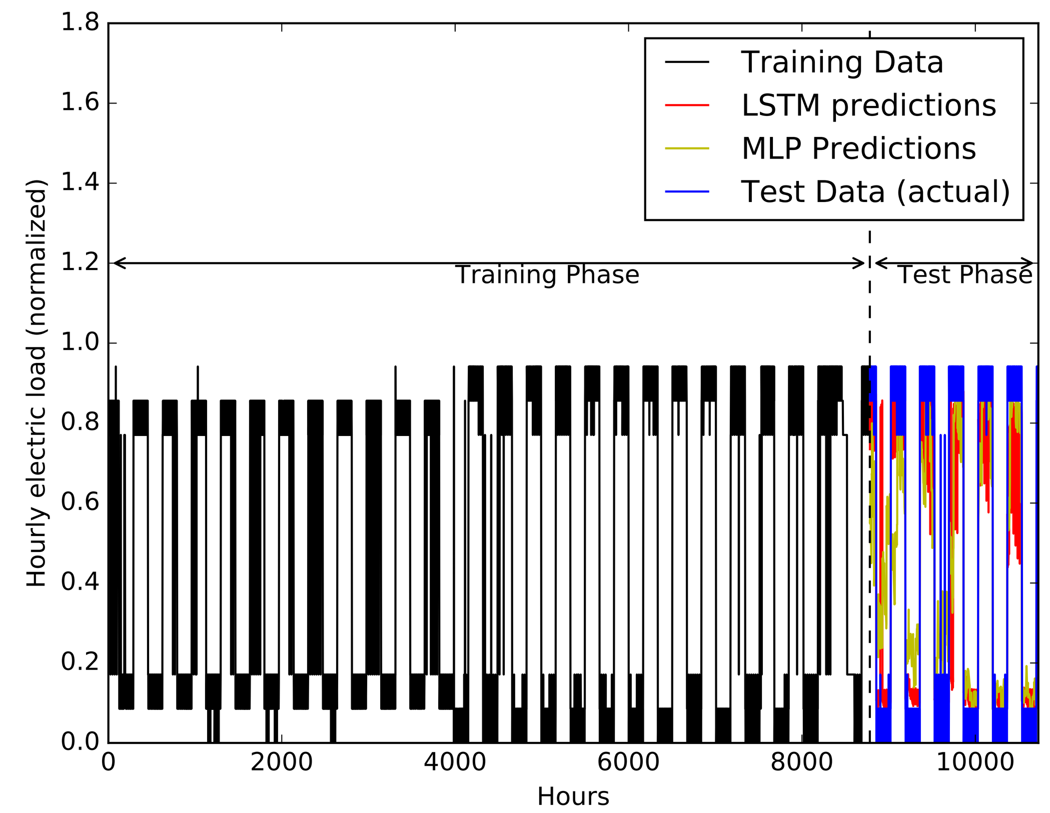

Figure 2: Results obtained using LSTM predictions ($e = 16.2\%$) for CRAC Critical load profile, compared to MLP predictions ($e = 22.3\%$).

References

[1] K. Cho, B. Van MerriÃńnboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, "Learning phrase representations using RNN encoder-decoder for statistical machine translation," 2014.

Future Research

Future work will focus on (i) Using the deep RNN model to perform interpolation where training data is missing (ii) Applying the deep RNN to capture sequential pattern over multiple characteristic timescales (iii) Using the deep RNN predictions to optimize design and operation of a building-scale thermal storage tank.

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