Encore Abstract: "Online learning of windmill time series using Long Short-term Cognitive Networks"

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Abstract. The amount of data generated by windmill farms makes online learning the most viable forecasting strategy. However, updating a forecasting model with a new batch of data is often very expensive when using recurrent neural network models. Long Short-term Cognitive Networks (LSTCNs) are a novel gated neural network consisting of chained Short-term Cognitive Network blocks, each processing a temporal data chunk. The learning algorithm of these blocks is based on a very fast, deterministic learning rule that makes LSTCNs suitable for online learning tasks. The simulations using a case study involving four windmills showed that our approach reported the lowest forecasting errors and training time with respect to traditional models.

Keywords: long short-term cognitive network · recurrent neural network · time series forecasting

1 Long Short-term Cognitive Network

Recently, [1] introduced a recurrent neural system termed *Long Short-term Cognitive Network* (LSTCN) that seems suitable for an online learning setting where data might be available for a short time. Moreover, the cognitive component of such a gated recurrent neural network allows for interpretability [2].

Let us assume that $X \in \mathbb{R}^{M \times T}$ is a multivariate time series of M variables observed T times. A time patch is a fragment of X that is temporarily available for analysis. An LSTCN model can be defined as a collection of Short-term Cognitive Network (STCN) blocks [1], each processing a specific time patch and transferring knowledge to the following STCN block in the form of weight matrices ($W_1^{(k)}$ and $B_1^{(k)}$). Therefore, a STCN block will receive the data available in a time patch and forecast the multivariate time series over a horizon. Figure 1 shows the recurrent pipeline of an LSTCN involving three STCN blocks to model a time series decomposed into three time patches. Learning happens

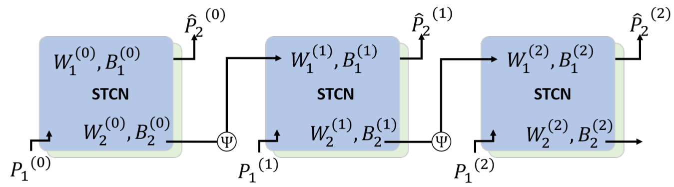

Fig. 1. LSTCN architecture of three STCN blocks

inside each STCN block to prevent the information flow from vanishing as the network processes more time patches. We refer the reader to [2,1] for a detailed analysis of the network architecture and neural reasoning of the LSTCN model.

2 Results and Conclusions

In our experiments, we used four public datasets from the ENGIE web page.[7] Each dataset corresponds to a windmill where eight variables were recorded every 10 minutes from 2013 to 2017. Our approach was compared against a simple RNN, a Long Short-term Memory (LSTM), a Gated Recurrent Unit (GRU), and a Hidden Markov Model (HMM). Table 1 shows the average training and test Mean Absolute Error (MAE), and the average training and test times (in seconds) for the third turbine (using one hour in the past (R) to forecast the next hour (L) in the multivariate times series).

Table 1. LSTCN outperforms other models in both in MAE and training time

	LSTCN	**RNN**	**LSTM**	**GRU**	**HMM**
Training error	0.0474	0.1221	0.1107	0.1219	0.0683
Training time	0.0103	0.6418	1.6932	1.6821	318.11
Test error	0.0564	0.1532	0.1455	0.1499	0.1768
Test time	0.037	1.3171	2.6672	2.3471	118.31

The numerical simulations conducted using four windmill datasets report that our approach outperforms other state-of-the-art recurrent neural networks in terms of forecasting errors. In addition, the LSTCN-based model is significantly faster than these recurrent models when it comes to both training and test times. Such a feature is of paramount relevance when designing forecasting models operating in online learning modes.

[7] https://opendata-renewables.engie.com/explore/index

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