A New State-of-the-Art Transformers-Based Load Forecaster on the Smart Grid Domain

André Luiz Farias Novaes, Student Member, IEEE, Rui Alexandre de Matos Araújo, Senior Member, IEEE, José Figueiredo, and Lucas Aguiar Pavanelli, Student Member, IEEE

Abstract—Meter-level load forecasting is crucial for efficient energy management and power system planning for Smart Grids (SGs), in tasks associated with regulation, dispatching, scheduling, and unit commitment of power grids. Although a variety of algorithms have been proposed and applied on the field, more accurate and robust models are still required: the overall utility cost of operations in SGs increases 10 million currency units if the load forecasting error increases 1%, and the mean absolute percentage error (MAPE) in forecasting is still much higher than 1%. Transformers have become the new state-of-the-art in a variety of tasks, including the ones in computer vision, natural language processing and time series forecasting, surpassing alternative neural models such as convolutional and recurrent neural networks. In this letter, we present a new state-of-the-art Transformer-based algorithm for the meter-level load forecasting task, which has surpassed the former state-of-the-art, LSTM, and the traditional benchmark, vanilla RNN, in all experiments by a margin of at least 13% in MAPE.

Index Terms—Transformers, deep learning, long-short term memory, meter-level load forecasting, short-term load forecasting.

I. INTRODUCTION

ELECTRICAL load forecasting plays a crucial role on the Smart Grid (SG) domain, particularly on efficient energy management and power system planning [1], [2], [3]. Consequently, high-accuracy forecasts are required in multiple time horizons for tasks associated with regulation, dispatching, scheduling, and unit commitment of power grids [2], [7].

The meter-level load forecasting has become an active research topic, with a variety of algorithms applied on it: [2], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], and others. However, more accurate and robust models are still required in meter-level load forecasting [2], mainly due to the following reasons: external factors influencing forecasts, e.g., climate, calendar events, occupancy patterns, social conventions; the stochastic and non-linear behavior of consumers; the sensitive decision making process and operation of the SG. There is a 10 million currency units increase in the overall utility cost if the load forecasting error increases in 1%.

II. THE METHOD

Our Transformer-based forecaster follows the one developed in [2], which is in turn based on the original architecture of [14], minutely described in Figure 1.

The Transformer is a encoder-decoder architecture. On a high level, the encoder maps an input sequence, e.g., a time series sequence, into an abstract continuous representation that holds all information learned from the input. The decoder takes that continuous representation and, step-by-step, generates a single output while also feeding the previous output.

The encoder, the left block of Figure 1, is composed of a stack of \( N = 6 \) identical layers, with two sub-layers each: the first layer is a multi-head self-attention mechanism; and the second layer is a fully connected feed-forward network. Residual connections [15] and normalization operations [16] are applied on each sub-layer.

The decoder, the right block of Figure 1, is similar to the encoder. The main difference, not the only one, is an extra sub-layer on the stack, Masked Multi-Head Attention.

The Transformer architecture mainly differentiates itself from other deep networks created before by self-attention, a
mechanism that balances long-range dependencies modeling and computational efficiency [2]. The full self-attention module calculates response at a position as a weighted sum of the features at all positions. Unlike the RNN-based methods, Transformers allow access to any part of the time series history regardless of distance, potentially grasping recurring patterns with long-term dependencies [2].

### III. Experiments and Results

**The Smart Meters in London Dataset** is composed of 5567 London Households energy consumption readings between November/2011 and February/2014, with a 30 minutes frequency. For this letter, we have selected for forecasting the same eight houses as in [2], each of them with its own number of samples.

The dataset is split into training and test sets, with a 80%-20% ratio. The inputs to the prediction model are the measurements of the consumption on the last \( n \) time intervals (TI), from the current TI \( k \) to the past, i.e. the inputs are the consumption measurements on intervals \( k - n + 1, \ldots, k \); and the output of the model is the consumption forecast for the next TI, \( k + 1 \), in kWh.

Experiments were conducted on the Amazon Web Services (AWS) ml.p2.xlarge instance, 4 vCPUs, 1xK80 GPU, 61 GB of memory, and 12 GB of GPU memory, totaling approximately 310 hours of GPU-time. The proposed transformer-based algorithm is compared against the former state-of-the-art in residual load forecasting [2], LSTM, and the vanilla RNN, traditionally used as a benchmark in the TSF domain. Since all the models rely on random initialization of network weights, five experiments were performed for each of the three models, for all eight houses, training using four distinct values for the number \( n \) of TIs, specifically for \( n = 2, 3, 6, 12 \). Therefore, the total number or runs is 480.

Overall results are shown in Table I, where MAPE Avg. is the average of the mean absolute percentage error (MAPE) over all the 40 experiments performed in the test sets for the configuration (type of model, and number of TIs) detailed in the corresponding line of Table I, and Total Train. Time [sec] is the total training time, in seconds, for the same 40 experiments for each line. The results show that the Transformer-based algorithm outperforms LSTM and RNN in all experiments by a margin of at least 13% in MAPE.

![Transformer Architecture](image)

Fig. 1. The Transformer Model Architecture [7].

| Algorithm       | MAPE Avg. | Total Train. Time [sec] |
|-----------------|-----------|-------------------------|
| Transformer-2TI | 64.87%    | 11.53668                |
| LSTM-2TI        | 82.62%    | 3.04872                 |
| RNN-2TI         | 78.50%    | 2.08464                 |
| Transformer-3TI | 62.75%    | 10.68004                |
| LSTM-3TI        | 75.38%    | 3.09136                 |
| RNN-3TI         | 79.62%    | 2.11384                 |
| Transformer-6TI | 62.87%    | 7.84844                 |
| LSTM-6TI        | 80.50%    | 3.08364                 |
| RNN-6TI         | 81.25%    | 2.10912                 |
| Transformer-12TI| 64.87%    | 8.42956                 |
| LSTM-12TI       | 81.88%    | 3.09936                 |
| RNN-12T         | 76.25%    | 2.11384                 |

Note: all the time values have been multiplied by \( 10^{-4} \) in the column Total Train. Time [sec].

![Energy Forecast](image)

Fig. 2. Forecasting energy for house MAC000002.

Figure 2 shows how each of the methods perform on house MAC000002 in a specific day. Qualitatively, it is possible to observe that Transformers better responds to volatile movements in the load series, identified by “Truth”.  

The selected houses are: MAC000002, MAC000033, MAC000092, MAC000156, MAC000246, MAC000450, MAC001074, and MAC003223.

**TABLE I**

LOAD FORECASTING SUMMARY.
IV. Conclusion

The relevance of a new state-of-the-art Transformer model in the meter-level load prediction is remarkable. The results indicate that the Transformer learning model achieves superior performance when compared to LSTM and RNN models for meter-level load prediction. Created in 2017, Transformers are allowing new possibilities for TSF in distinct areas, with pure and hybrid models. Presented to the load forecasting community in 2018 as a new state-of-the-art [?], LSTM networks are still valuable forecasters, with at least one advantage over Transformers: the smaller amount of training time. Next research directions will explore ways on developing less costly Transformers models in terms of training time.

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