Project Proposal

Karel Križnar, Anton Križnar, Vid Kališnik, Tomo Testen

November 16, 2023

1 Aplication domain

Nowadays operators of electrical distribution networks are faced with new challenges of supplying voltage inside legal bounds with an increasing number of photovoltaics, electrical vehicles and heat pumps. We are going to tackle the problem of short term voltage forecasting 30 and 60 minutes ahead. Our predictions should minimize mean square error compared to the real value of voltages on our network at that time stamp. This data set was used because we were able to get access to it and it presents a great chance to work on some current problems the industry faces.

Our data set provides us with anonymized data for several low voltage distribution networks from Elektro Gorenjska, d. d. for 2 years. For one network our data set consists of:

- topological data of the network such as meter points, cables, junctions and transformers locations (example topology can be seen in figure 1)
- technical data such as transformers nominal power, cables length, diameter, resistance, capacitance. . . , meter point's connected power and connected photovoltaics power
- measurements data from meter points for energy aggregate every 15 minutes, voltage aggregated every 10 minutes and from transformer aggregate every 5 minutes such as voltage, current, active power and reactive power
- hourly temperature and irradiance data for the networks area

2 Graph ML techniques

Voltage prediction is a similar problem to traffic forecasting. Both problems deal with temporal and spatial information. Methods that were shown to work well for this problem, of traffic prediction and we will use are Graph Convolutional Recurrent Networks (GConvLSTM) [4], Attention Temporal Graph Convolutional Network (A3T_GCN) [7] and Spatial Temporal Graph Convolutional Networks (STGCN) [6].

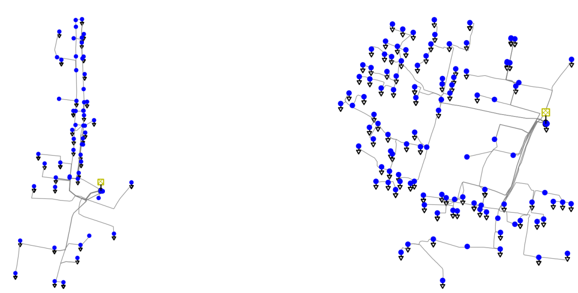
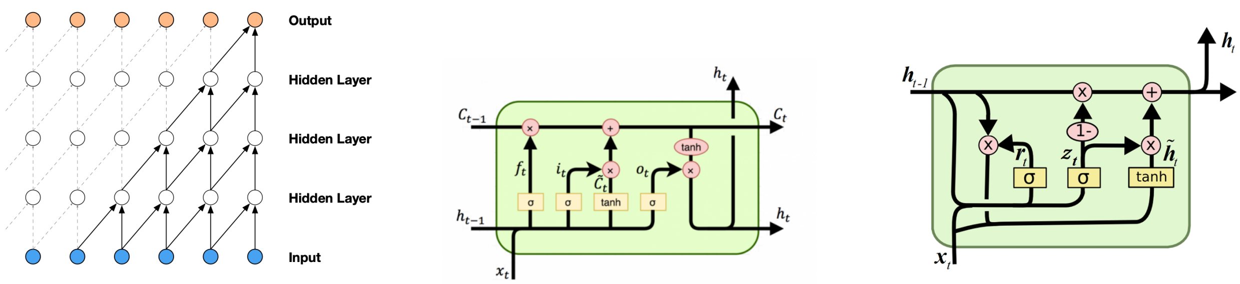


Figure 1: Two examples of electrical networks.



(a) Causal convolution (b) LSTM cell. (c) GRU cell.

Figure 2: Different components for temporal features.

2.1 Some components

2.1.1 Long Short-Term Memory

Long Short-Term Memory (LSTM) [3] is a type of Recurrent Neural Network (RNN) architecture that was designed to overcome some of the limitations of traditional RNNs, its biggest advantages are their superior ability to handle long-term dependencies, prevent gradient-related issues, and maintain a dedicated memory cell for extended sequence context, making them more effective for a wide range of sequential data tasks. Its structure can be seen in figure 2b.

2.1.2 Gated Recurrent Unit

Gated Recurrent Unit (GRU) [1] is a simpler version of LSTM that get rid of the memory matrix C_t. GRUs are faster to train and less complicated than LSTM. Its structure can be seen in figure 2c.

2.1.3 Gated Linear Unit (GLU)

Gated Linear Unit (GLU) [2] is a type of activation function that combines elements from the input tensor using a gating mechanism. It helps control which input elements are relevant for discovering compositional structure and dynamic variances in time series, enabling the network to capture important features and patterns in the data efficiently.

2.1.4 Causal convolution

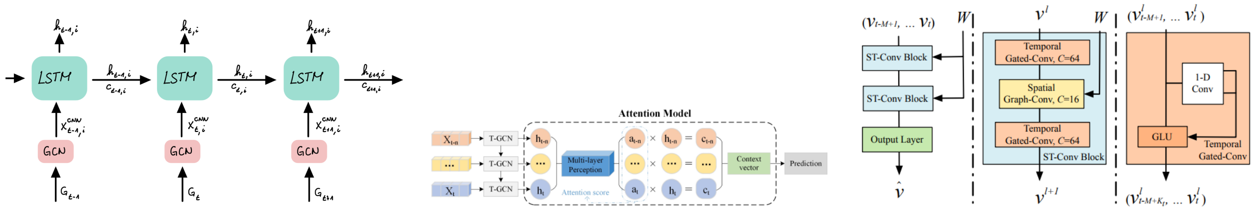
Causal convolution [5] is a specific type of convolutional operation that unlike regular convolutions, which consider both past and future values of the input data, only incorporates past or present values but not future one. Its computation is represented in figure 2a.

2.2 Graph Convolutional Recurrent Networks (GConvLSTM)

Gated Convolutional Long Short-Term Memory (GConvLSTM) is a neural network architecture that combines the capabilities of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. It can be seen in figure 3a. At time stamp t, the graph G_t is input into a Graph Convolutional Network (GCN), which generates $x_{t,i}^{CNN}$ for each node i in the graph G. Subsequently, each output is fed into a Long Short-Term Memory (LSTM) model, producing $h_{t,i}$, which is then utilized in future LSTM computations.

2.3 Attention Temporal Graph Convolutional Network (A3T_GCN)

This model processes spatial data at each point with a graph convolution network model, that produces node embeddings, and passes them to gated recurrent units model, where temporal data is processed in a similar way to a GConvLSTM. It then expand that idea with attention model that produces context vector at each time stamp based on earlier embeddings (after LSTM) of a node by assigning them some learned attention weights. Its structure can be seen in figure 3b.



(a) GConvLSTM (b) A3T_GCN (c) STGCN

Figure 3: Different graph convolutional networks to capture spatial and temporal dependencies.

2.4 Spatial Temporal Graph Convolutional Networks (STGCN)

Spatial Temporal Graph Convolutional Networks (STGCN) can be effectively utilized in broader spatio-temporal sequence learning tasks. The spatio-temporal block within STGCN integrates graph convolutions and gated temporal convolutions. This combination enables the extraction of valuable spatial features and the coherent capture of essential temporal features. Its structure can be seen in figure 3c.

References

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

[2] Y. N. Dauphin, A. Fan, M. Auli, and D. Grangier. Language modeling with gated convolutional networks, 2017.

[3] S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[4] Y. Seo, M. Defferrard, P. Vandergheynst, and X. Bresson. Structured sequence modeling with graph convolutional recurrent networks, 2016.

[5] A. van den Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu. Wavenet: A generative model for raw audio, 2016.

[6] B. Yu, H. Yin, and Z. Zhu. Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence*. International Joint Conferences on Artificial Intelligence Organization, jul 2018.

[7] J. Zhu, Y. Song, L. Zhao, and H. Li. A3t-gcn: Attention temporal graph convolutional network for traffic forecasting, 2020.