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Prediction of Power Outages using LSTM

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Abstract: *Prediction of power outages is very useful today when grid related issues could result in an outage as in Spain April 2025. Assuming a model being trained on one type of power outage, it should be possible to predict a power outage of that particular type. For example, in daylight, sunny weather, rather warm outside temperature, not windy and between 8 AM and 5 PM. At a known point in the grid, data collection is performed retrieving phase voltages, frequency, active, and reactive power. Today's hybrid inverters, used for Photo Voltaic (PV) and Battery, provide that data every five minutes. Assuming that an outage is possible to detect by a model, a sequence of data for 30 minutes is used to make a prediction if an outage is likely to appear next. A Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) is trained on sequences without and with a power outage. The results in terms of training error are promising, despite the bad balance in the data..*

Keywords: LSTM, Power Outage, Prediction, Sequential Data

1. Introduction

Power outages are inevitable, but still very unpractical. It would be beneficial to know ahead that a power outage is likely to occur in the next 5 minutes. At the Transmission System Operator (TSO) or Distribution System Operator (DSO) level of the grid, there are several methods to prevent a coming power outage. Some of these methods are instant or at least fast enough, but other methods are not particularly fast. At an ordinary customer, after the Point of Common Coupling (PCC), there are few if any methods to prevent a power outage, but the information of a coming power outage would be very practical. However, a PV-site that is connected to the DSO could be ordered to stop generating power. This paper proposes the use of an LSTM model to predict power outages based on measured electrical variables.

Power outages could be caused by many reasons, but in this paper it is narrowed down to one typical situation, during daylight, not in the winter, sunny weather. Furthermore, there is a high penetration of PV-sites in the area. At the location of the experiment, the majority of power outages occur during the above situation. To be consistent, collection of training data and test data are performed at this situation but at two different power outages.

Under the assumption that it is possible to predict a future power outage by feeding a LSTM model with a sequence of measured electrical data preceding the possible power outage, the question is how far back in time is it reasonable to look? In [1] it was stated that the last 30 minutes before the grid failure contained many measured deviations. Another question is how fast the sample rate must be in order to capture the underlying patterns. As suggested in [2] every 0.1 seconds is sufficient to measure most common frequency oscillations. The experiment setup could deliver all electrical data but is limited to one sample every 5 minutes. The experiment setup is located at the PCC and for this experiment the following variables are collected; frequency, reactive power, active power, and all three phase to neutral voltages. Currents are deliberately excluded to avoid variables that depend on one or two others, since voltages and active power are collected already. All three phase to neutral voltages are used in order to ensure detection of any unsymmetrical problem.

In [3] a LSTM based model is proposed to predict power outages but is applied to a 110 kV grid with several measure points. Here, the currents are included, but the frequency is excluded, and the sample time is 15 minutes. However, the results are very good. The purpose of [3] is the same as this paper but there are some differences in the approach such as selection of variables and measuring at several physical locations but the obvious difference is the amount of data used in [3].

In [4] a LSTM based model is proposed to predict power grid loss with good results. Several other electrical applications with LSTM are referenced by [4].

In this paper, we show, through low training loss, that LSTM can be used to predict power outages. The remainder of the paper is organized as follows. Data and data preparation are presented in Section II. Proposed model with hyper parameters is presented in Section III. The results are presented in Section IV and conclusion of the experiment in Section V.

2. Data

The data is collected at the PCC as shown in Fig. 1.

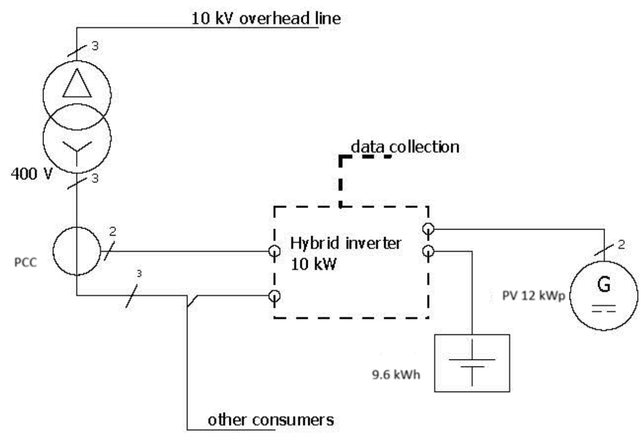

Fig. 1. Experiment setup.

The data collection starts early in the day and ends with the power outage. Data after the power outage is deleted. The measured electrical properties with units and typical values are shown in Table I.

The model including data preparations is implemented in Python by Jupyter Notebook from Anaconda Navigator which is fully sufficient to do this experiment. Libraries used are pandas, numpy, sklearn, and pytorch.

In this experiment, the training data consist of 213 entries and the test data consist of 233 entries. After checking for missing data and outliers the data is standardized to zero mean and unit variance using StandardScaler from sklearn.preprocessing. As stated in Section I, the training data and the test data represent two different power outages, but the underlying situation is supposed to be equal or similar.

TABLE I: DATA OVERVIEW

Measured variable	Unit	Typical values	Nominal
Frequency	Hz	49.89 – 50.10	50
Reactive Power	kVAr	- 0.043 – 0.067	-
Phase C	V	227.1 – 233.2	230
Phase B	V	228.2 – 234.5	230
Phase A	V	227.2 – 233.8	230
Active Power	kW	-10.00 – 10.00	-

3. Model

In [5] further steps are described in order to arrange the data before training and evaluation. The first step is to add a variable Y that indicates if the grid is operating in the next sample. Since the last sample is the one before the power outage, Y will be 0 in the last sample, indicating the power outage in the next sample, but 1 for every other one. So, for the training data, Y will be a vector of size 213. The 6 measured variables will form a matrix X of size (213, 6).

The second step is to prepare sequences and in Section I we decided to look 30 minutes back and since our sample time is 5 minutes, we should use a sequence length of 6. So, for example, the first 6 samples are used to predict the next one, and the evaluation is done by comparing the output of the LSTM model to the corresponding value of Y for that sequence.

The third step is to convert the sequence data from X to a tensor using PyTorch, resulting in the tensor size of (213, 6, 6) now meaning that we have 213 different sequences with a length of 6 containing 6 variables. Y is also converted to a tensor.

The fourth step is to create an instance of the LSTM model in PyTorch with hyperparameters according to Table II.

TABLE II: MODEL HYPERPARAMETERS

Hyperparameter	Chosen value	Comment
Input size (for X)	6	Equal to number of variables
Number of layers	6	Equal to sequence length
Hidden size	128	
Output size (for Y)	1	Equal to number of variables
Dropout	0.4	
Loss function	MSELoss	
Optimizer	Adam	
Learning rate	0.001	
Batch size	6	
Number of epochs	200	

The fifth and last step is to train the model, evaluate the model using test data, and calculate the training and test loss. With the hyperparameters in Table II the computation time is around 20 seconds.

4. Result

We evaluate the performance of the LSTM model by calculating the average loss for the training data and the test data separately. The average loss is the difference between the predictions from the LSTM model and the variable Y.

The result in Table III indicates convergence for both the training data and the test data. Training losses are low and demonstrate that the LSTM model can capture useful patterns in the X variables.

The test losses are too high, and a detailed inspection of the prediction value of the power outage shows that it is wrong at one sample. The predictions for all the rest of Y seem reasonable, which explains the test loss close to 0.005 which equals 1 error out of 200 which is close to the number of samples in the test data.

Some experimentation with the hyperparameters has been done and if the sequence length was shortened to 3 both the training losses and the test losses increased to 0.15 making the model useless.

TABLE III: MODEL AVERAGE LOSS

Epoch iteration	Training loss	Test loss
Epoch [10/200]	0.0125	0.0169
Epoch [20/200]	0.0103	0.0127
Epoch [30/200]	0.0087	0.0117
Epoch [40/200]	0.0106	0.0059
Epoch [50/200]	0.0101	0.0056
Epoch [60/200]	0.0001	0.0053
Epoch [70/200]	0.0001	0.0052
Epoch [80/200]	0.0000	0.0052
Epoch [90/200]	0.0000	0.0052
Epoch [100/200]	0.0001	0.0051
Epoch [110/200]	0.0000	0.0051
Epoch [120/200]	0.0000	0.0051
Epoch [130/200]	0.0001	0.0051
Epoch [140/200]	0.0000	0.0051
Epoch [150/200]	0.0000	0.0051
Epoch [160/200]	0.0000	0.0051
Epoch [170/200]	0.0000	0.0051
Epoch [180/200]	0.0000	0.0051
Epoch [190/200]	0.0000	0.0051
Epoch [200/200]	0.0000	0.0051

5. Conclusion

The proposed LSTM model performs well in training data with low average loss indicating good predictions regardless of whether Y, grid status, is 1 or 0. The model shows poor performance on the test data when predicting the power outage when Y, the status of the grid, is 0. When Y is 1 the model performs close to the training data.

The experimentation with the sequence length demonstrates that the length of 6 is reasonable as a minimum. An overall shorter training data reduce the performance as well. The model should benefit from more training data.

The poor performance of the test data could be a result of overfitting. This experiment used one data set for training and another for testing, each of which contained one power outage. Training data should be extended with more power outages. In addition, a higher sample rate should improve model performance.

With an increase in the number of training data, the balance between data sequences with and without power outages will not be affected unless the data is heavily truncated in order to reduce the number of sequences without power outages. However, the total number of power outages at the experiment site are less than 15 occurrences per year. In that perspective, it is more likely that increasing the size of the training data is better than aiming for a balance between data with and without power outages

5. References

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He has worked with telecom, heavy industry, military aviation, medical instrument and process industry in roles from Test Engineer, Software Engineer, Crash Team Leader, Electrical Design Engineer, Electrical Inspector to Project Manager. Currently, he works as an Electrical Design Engineer at SSAB in Oxelösund, Sweden. His previous research included a decrease in the frequency of the transmission lines grid, and current research includes combinations between electrical power and machine learning.

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