Lab 2 report: Utilizing Linear Multivariate Regression for Grid Loss Prediction in a 5-Bus "Kite" Network

Introduction

In the domain of power systems, accurately predicting grid losses is crucial for efficient energy management. Grid losses occur due to various factors including resistance in transmission lines, transformer inefficiencies, and other network-related losses. In this report, we focus on a 5-bus "kite" network and aim to discover a grid loss function using linear multivariate regression techniques.

Problem Description

Consider a grid comprising N buses where generators and loads are connected. The objective is to develop a grid loss function based on M per-bus power injection readings and the corresponding M total grid loss measurements. Despite the availability of analytical solutions, we opt to explore the effectiveness of linear multivariate regression in solving this problem.

Methodology

Synthetic data for the 5-bus network is generated including per-bus power injection readings and total grid loss measurements. Noise data is also introduced to simulate real-world scenarios. Various linear regression models are trained using the generated data. Different combinations of features are considered to capture the relationship between per-bus power injections and total grid losses.

Results

Looking at the results of the regression with the training data and no noise, we get a very small error rate of up to 1%. These are displayed in Figure 1.

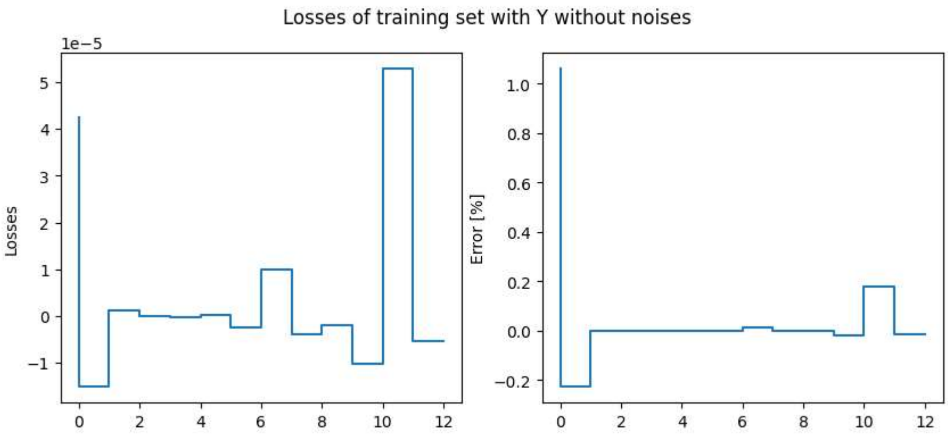

Figure 1: Losses of regression with training data and no noise.

The test data can be replicated in this case, with an average error of 0.049.

Furthermore, we introduce gaussian noise ($\mu = 0 \, and \, \sigma = 0.0025$) to our Y test set. Figure 2 shows the losses between Y and our prediction. Here, the error is much higher than without the introduction of noise, being more than 100%.

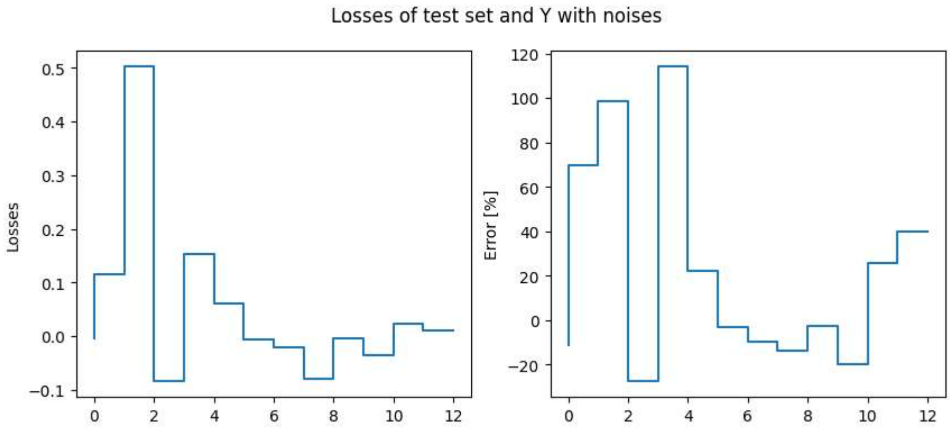

Figure 2: Losses of regression with noise in the test data.

Moreover, we used the training set to implement different approaches to this problem. First, the matrix X considering the network structure. Second approach, we reduced dimensionality considering only the squared injections. And lastly, reducing the dimensionality of X by summing electrically close bus injections before using them as explanatory variables of losses. Figure 3 shows the original data with noise and the predictions of all approaches. We can see, that the predictions have some similarities, like the peak at time step 7. However, they all differ and show significant differences to the original dataset.

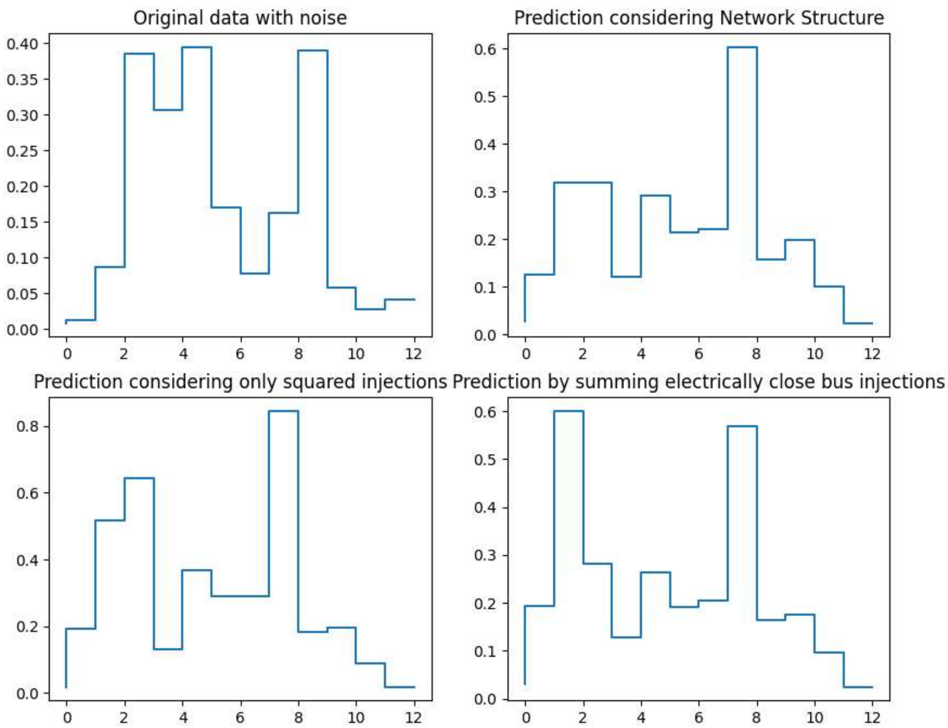

Figure 3: Data prediction considering different network structures.

Conclusion

When considering regression models trained on clean training data, we observed remarkably low error rates, with deviations of up to 1%. These findings underscore the robustness of the regression approach in accurately predicting grid losses when noise is absent. However, the introduction of Gaussian noise to the test data significantly impacted prediction accuracy, emphasizing the vulnerability of the model to noise.

Furthermore, we have explored the effects of considering the network structure in regression models. While all models did not deliver accurate results, similarities in the different predictions could be observed. This indicates, that it may not be necessary to use the most complex network structures and smaller, less complex structures can also deliver robust results, while being less computationally expensive.

More tests would need to be conducted to have precise results on the qualities of the models with reduced complexity.