SET3125

Machine Learning Workflows for Digital Energy Systems

Project: Electrical System

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Introduction

The aim of this project is to develop a supervised learning regression model to predict the results of a DC Optimal Power Flow for a 14-bus power system, in order to create a fast and reliable model that can be used in real-time operations. The answers to the questions for each task of the project are listed, as below.

Basic Workflow with Fully Connected Neural Network (FNN)

Task 1

- After checking the distributions of the load demands and generator supplies, it is clear from the graphs that most of the diagrams in the *load-demand* dataset have a shape similar to a Gaussian curve with no clear outliers. Whereas, in the *generator-supply* dataset, the histograms suggest there could be some outliers — for example, in *Column 2*, it is over a range where some values are between 0.55 and 0.6. One good way to handle outliers would be to use standardization, a scaling technique in which the values are centered around the mean with a unit standard deviation. Although this technique does not remove outliers directly, it attenuates their impact on most of the algorithms.

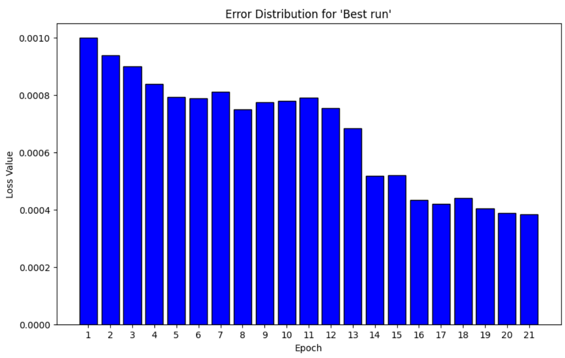
- Looking at the total demand for each data sample, it can be observed that the total load and the total demand for each observation are consistently equal, with a very small difference of the order of 10^{-16}. For computational efficiency, this is demonstrated using the first 50 observations; however, it can be assumed to hold for all rows. This suggests that *generator-supply* is meeting *load-demand*.

Task 5

- Model hyperparameters significantly influence the model accuracy as they control the training process and affect how well the model learns patterns in the data. For instance, a small learning late can lead to prolonged training, while a large one might cause the model to oscillate or diverge. The batch size is crucial too, because large batch sizes lead to smoother gradients but may result in poor generalization, whereas small ones can introduce noise but could improve generalization. Another example is the number of epochs: too many epochs may result in overfitting; not enough epochs can cause underfitting. The same goes for the number of hidden layers and neurons. Some optimizers, like Adam, adapt the learning rate dynamically and improve convergence.

Task 6

- Plotting an histogram of the prediction errors, it can be stated that errors decrease with an hyperbolic trend which seems to stabilize after epoch 13, as shown here:

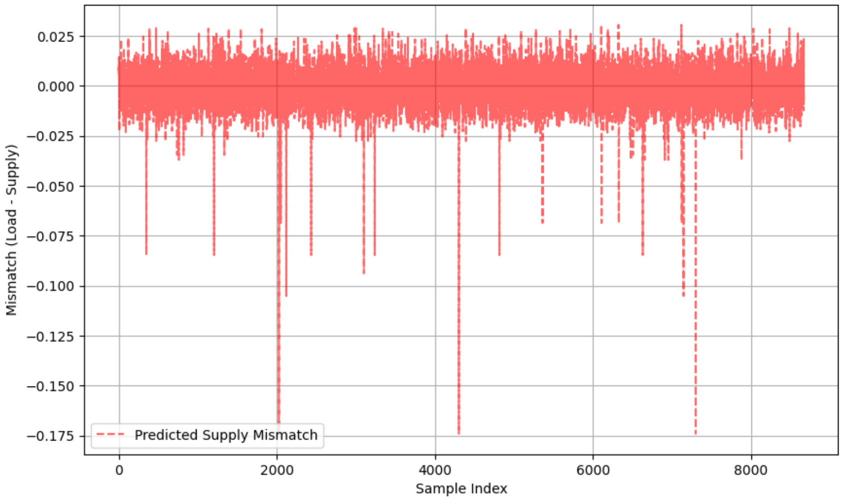


- For the test data, after plotting the mismatch between the sum of demands and sum of predicted generator supply, it is observed that the maximum mismatch is 0.1977 and the mean mismatch is 0.0181.

Physics-Informed Training

Task 4

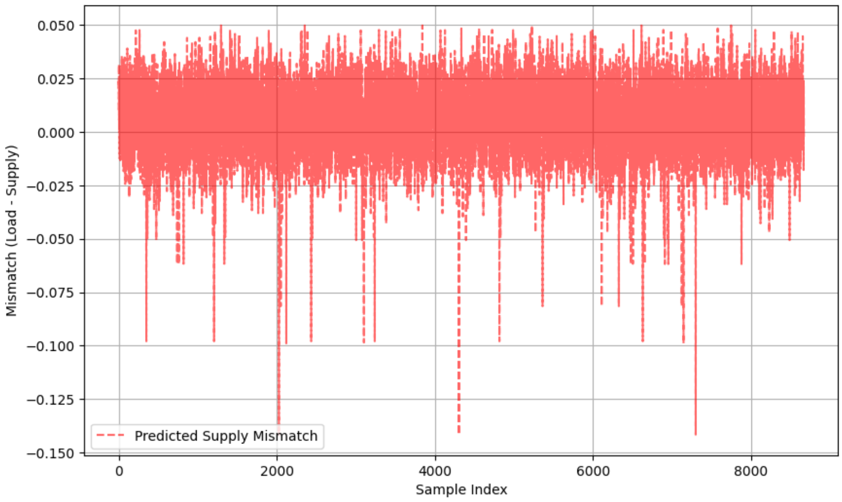
- In order to check how well the power balance constraint is satisfied with the physics loss included, the maximum and mean power balance mismatches are computed, which are 0.1741 and 0.0079, respectively.
- The error distribution is shown in the following figure:



GNN Training

Task 5

- For the GNN model, the maximum and mean power balance mismatches are 0.1416 and 0.0141, respectively.
- The error distribution is shown in the following diagram:



Task 6

- Comparing the total number of parameters between the two models, the FNN model turns out to be more parameter efficient: while GNNs are good with graph-structured data and focus on situations where the relationships between nodes matter (like power grids), FNNs are simpler and better at dealing with tabular data or simple inputs in general.