# Experiment Setup

## Hardware

The tests were carried out on a PC with a Windows OS. The computer's features are described in the following:

* GPU: Intel Nvidia RTX 2070
* CPU: Intel Core i7 8th Generation
* RAM:
* Mother Board:

## Software

Python is the programming language utilised. The experiment is carried out in a virtual environment generated with Visual Studio Code and Python 3.9.0. The relevant packages are utilised in the experiment. A Jupyter Notebook was used to write and run the code. The network was trained using the Nvidia RTX 2070 GPU, which has 16 GB VRAM and CUDA version 11.0.

* TensorFlow
* Keras
* Scikit-learn
* Pandas
* Prophet
* Matplotlib
* NumPy
* Seaborn

## Settings

# Cases

# Data and Training

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Fold 1 | Train | Test | | | |
| Fold 2 | Train | | Test | | |
| Fold 3 | Train | | | Test | |
| Fold 4 | Train | | | | Test |

# Model Experiments

## Loss Functions

## Activation Functions

# Model Structure

## (How many layers)

# Output of the cases

# Experiments and Results

This chapter will go about performing ‘black-box’ testing to evaluate or created models and afterwards a visualization of the models will be shown ranking by the model with the best performance. All the models will be tested against a baseline prediction calculated using the simple persistence algorithm. The Zero Rule Algorithm is by far the most frequent baseline method for monitoring ML. In the instance of classifications, the algorithm correctly forecasts most classes. With regression cases, it predicts the expected average. This can be utilized with time-series data, but the sequence correlation architecture in the data set is not considered. The persistence algorithm is a similar technique for time series data sets. The persistence method predicts the expected outcome for the next time step (t + 1) based on the past time step (t-1). The following baseline forecast conditions must be fulfilled:

* **Simple**： A technique that does not need extensive training or understanding.
* **Fast**： Predicting in a quick and computationally simple manner.
* **Repeatable**： When given the same input, a deterministic technique gives the expected output.

## Queen’s Building

### Baseline

|  |  |
| --- | --- |
| Hourly Dataset | |
| Electricity | RMSE: 0.02661  MSE: 0.00071  MAE: 0.01548  : 0.94385 |
| Gas | RMSE: 0.0035  MSE: 0.000012  MAE: 0.000017  : -2.000004 |
| Water | RMSE: 0.01896  MSE: 0.00036  MAE: 0.01115  : 0.89510 |

From the table above we can see the gas dataset metrics could not accurately be measured which means a further investigation of the plot is needed.

Chart, line chart

Description automatically generated

The plot of Queen’s Building Gas Hourly Dataset

Based on the figure above we can see that the hourly dataset could not be plotted due to the fact we are dealing with data lower than the program can compute. The electric and water datasets produced very good metrics which could help in training the desired algorithm, but with the gas dataset producing such results, it could degrade the performance.

|  |  |
| --- | --- |
| Daily Dataset | |
| Electricity | RMSE: 0.12329  MSE: 0.01520  MAE: 0.07497  : 0.64504 |
| Gas | RMSE: 0.06667  MSE: 0.00445  MAE: 0.03305  : 0.54020 |
| Water | RMSE: 0.07459  MSE: 0.00556  MAE: 0.04598  : 0.74359 |

The daily baseline shows very good results and a perfect univariate baseline to try to beat for the chosen algorithms. These are all baseline metrics from a univariate model in hopes that adding regressors would improve it.

### LSTM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Layers** | **Neurons** | **Metrics** | **Output** | **Beaten?** |
| 2 | 50 | RMSE: 0.161  MSE: 0.026  MAE: 0.132  : 0.035 | Appendix A | No |
| 150 | RMSE: 0.162  MSE: 0.026  MAE: 0.133  : 0.019 | Appendix B | No |
| 6 | 50 | RMSE: 0.162  MSE: 0.026  MAE: 0.134  : 0.016 | Appendix C | No |
| 150 | RMSE: 0.164  MSE: 0.027  MAE: 0.134  : 0 | Appendix D | No |
| 8 | 32 | RMSE: 0.173  MSE: 0.03  MAE: 0.142  : -0.116 | Appendix E | No |
| 50 | RMSE: 0.169  MSE: 0.028  MAE: 0.139  : -0.064 | Appendix F | No |

From the table above, we can see that the simple LSTM achieved an RMSE score between 0.160 to 0.174 despite the amount the layers added. This shows the limit of the LSTM algorithm and failing to beat the set baseline.

### BLSTM

The testing is carried out using a timestep of 1 day to predict the next day.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Layers** | **Neurons** | **Metrics** | **Output** | **Beaten?** |
| 2 | 14 | RMSE: 0.153  MSE: 0.023  MAE: 0.127  : 0.114 | Appendix G | No |
| 50 | RMSE: 0.154  MSE: 0.024  MAE: 0.127  : 0.109 | Appendix H | No |
| 128 | RMSE: 0.154  MSE: 0.024  MAE: 0.127  : 0.109 | Appendix I | No |
| 6 | 14 | RMSE: 0.155  MSE: 0.024  MAE: 0.128  : 0.098 | Appendix J | No |
| 50 | RMSE: 0.154  MSE: 0.024  MAE: 0.128  : 0.105 | Appendix K | No |

From the table above, we can see that the simple BLSTM achieved an RMSE score between 0.153 to 0.155 despite the amount the layers added. This shows the limit of the BLSTM algorithm and failing to beat the set baseline. The next step is to test it in a timestep of 6 days.

### XGBoost

### LightGBM

#### Electricity

#### Gas

#### Water

#### All features

### Prophet

#### Electricity

#### Gas

#### Water

#### All features

## Hugh Aston

### Baseline

|  |  |
| --- | --- |
| Hourly Dataset | |
| Electricity | RMSE: 0.03744  MSE: 0.00140  MAE: 0.02256  : 0.91672 |
| Gas | RMSE: 0.04087  MSE: 0.00167  MAE: 0.01789  : 0.82682 |
| Water | RMSE: 0.02684  MSE: 0.00072  MAE: 0.01701  : 0.85265 |

|  |  |
| --- | --- |
| Daily Dataset | |
| Electricity | RMSE: 0.15479  MSE: 0.02396  MAE: 0.09641  : 0.35701 |
| Gas | RMSE: 0.08304  MSE: 0.00690  MAE: 0.04858  : 0.80535 |
| Water | RMSE: 0.16226  MSE: 0.02633  MAE: 0.10904  : 0.36028 |

### LSTM

#### Electricity

#### Gas

#### Water

#### All features

### BLSTM

#### Electricity

#### Gas

#### Water

#### All features

### XGBoost

#### Electricity

#### Gas

#### Water

#### All features

### LightGBM

#### Electricity

#### Gas

#### Water

#### All features

### Prophet

#### Electricity

#### Gas

#### Water

#### All features

## Gateway House

### Baseline

|  |  |
| --- | --- |
| Hourly Dataset | |
| Electricity | RMSE: 0.00352  MSE: 0.000012  MAE: 0.000018  : -1.99994 |
| Gas | RMSE: 0.06581  MSE: 0.00433  MAE: 0.02123  : 0.70234 |
| Water | RMSE: 0.00648  MSE: 0.000042  MAE: 0.00225  : 0.74066 |

|  |  |
| --- | --- |
| Daily Dataset | |
| Electricity | RMSE: 0.15049  MSE: 0.02265  MAE: 0.08710  : 0.54023 |
| Gas | RMSE: 0.14943  MSE: 0.02233  MAE: 0.07105  : 0.41088 |
| Water | RMSE: 0.13365  MSE: 0.01786  MAE: 0.07788  : 0.27141 |

### LSTM

#### Electricity

#### Gas

#### Water

#### All features

### BLSTM

#### Electricity

#### Gas

#### Water

#### All features

### XGBoost

#### Electricity

#### Gas

#### Water

#### All features

### LightGBM

#### Electricity

#### Gas

#### Water

#### All features

### Prophet

#### Electricity

#### Gas

#### Water

#### All features

# Appendix

Chart, histogram

Description automatically generated

A

Chart, histogram

Description automatically generated

B

Chart, histogram

Description automatically generated

C

Chart, histogram

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D

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E

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H

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I

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J

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K