3. Methodology

In this chapter we will discuss about the dataset that was used, how they were processed in order to be fit to use for training the models. Afterwards the process flow of how the models were built and assessed will be demonstrated.

3.1 Dataset

The data that were used were provided by Hellas-Sat and collected through their telemetry system for Hellas-Sat 3. The rates of all four reaction wheels were provided for a timespan of one year, from 1-1-2022 01:00 UTC to 31-12-2023 23:00 UTC. The measurements that were provided were the hourly average rpm of each wheel, which was calculated by taking the mean of the minimum and the maximum value in a 60 minute window. For each wheel the dataset that was use contained 8749 measurements.

! Figures of the wheel rates before and after the processing to be added.

! Description of plots and any patterns identified, in accordance with the operations schedule that is used by Hellas-Sat.

Additionally, all data were scanned for any missing or corrupted values and an additional step that had to be taken is that we took the absolute values of the measurements. This is related to the fact that the reaction wheels have the ability to rotate both clockwise and counter-clockwise and at all times two of the wheels are spinning CW and two CCW. For purposes of maintenance, once per year the satellite operators make each wheel spin in the opposite direction and therefore we had to filter out of the dataset this transition, in order to avoid confusing the model during the training, because this is not a normal behavior of the wheel that the model needs to be able to predict.

Moreover, during the process of training, experimenting and building the models we came to the conclusion that all values needed to be normalized with respect to the maximum value that the rate of the wheel is allowed to reach, as advised by the constructor and Hellas-Sat. In this way better performance of the models was achieved.

Finally, before the data was fed to the models they had to be split into three subsets: Training, Validation and Testing. For training purposes 70% of the original dataset was used, for validation 20% and for testing 10%. The resulting subsets contained 6124 datapoints for training, 1750 for validation and 802 for testing.

3.2 Model Building

To create a model for timeseries forecasting, there are several parameters that need to be taken into account and combined result into many different architectures that have to be explored.

Those parameters are the number of layers within the model, as well as the type of layers and the number of neurons in each layer. For our case, Long Short Term Memory layers were used. They are a type of Recurrent Neural Network layer and they are widely used for speech recognition, text predictions and more importantly for timeseries forecasting. They offer the ability to recognize both long term and short term dependencies in the dataset and to remember them, because of their internal structure. Another type of layer that was used is the Dense layer, which is the basic time of layer in machine learning.

! Picture of lstm structure to be added.

Other parameters that affect the performance of the model are the learning rate and the optimizer that is used and the input window.

! Explanation of the input window.

For a more complete exploration of the possible architectures, a tool for hyperparameter optimization was created, so that our research would be more extensive and would include as many candidate architectures as possible. This tool was utilizing hyperband search, which means that it combines different values for the parameters that are given and creates multiple models that then trains and compares with each other. Every time it compares two models it keeps the most efficient one and then compares it to a new model. In this way the resulting model is the one that had the best performance compared to all the combinations that it made.

Although the reaction wheels are similar to their characteristics a model for each one had to be created, because they are positioned in different spots within the spacecraft and therefore they experience and are affected by the perturbations in a unique manner each.

! Table of the parameters that were explored to be added.

! Table of hyperparameter optimization for each reaction wheel to be added. I should include the results of the optimization for different architectures.

3.3 Ticket Creation

Once the models for each reaction wheel are built and trained, we can make predictions for each one to detect if their rate is going to exceed a specific threshold.

If none of the wheels exceed the set limit, then no action needs to be taken and operations can proceed nominally. However, if the predictions indicate that one of the wheels will surpass the limit at a specific time, a ticket needs to be created in the operation’s center workbench, so that the operators can be notified that a manual wheel unloading will need to take place.

To achieve that a process of scanning the prediction results was created, which identifies which wheel will exceed the limit and when and then creates a ticket with the appropriate information on the workbench, by creating an entry in the right tables in its database. The information that is input is the date of the procedure, which is the date that the rate will pass the threshold, which wheel will it be and the steps of the procedure that will need to be followed.

The ticket shall be marked as unverified, so that the flight dynamics team can process the information that is given and decide in what direction the unloading will be performed and if there is a more efficient time to execute the procedure than the one that is predicted.

! Screenshots of the tables, or ticket to be added.