Detecting Satellite Laser Ranging Station Data and Operational Anomalies with Machine Learning Isolation Forests at NASA's CDDIS

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ABSTRACT

The International Laser Ranging Service (ILRS) is currently composed of 45 active satellite laser ranging (SLR) stations with several more set to join the network over the next several years. Station changes and histories are logged to files, but not always in real time. Sometimes these details are not added until long after changes have been made to the station – on occasion, years later. This in addition to unexpected hardware errors and other system issues that are not immediately detected impact the products generated by analysts. The ILRS Central Bureau (CB) and NASA's Crustal Dynamics Data Information System (CDDIS) have worked to provide tools for station engineers to use. This includes the creation of station plots which contain temperature and pressure information along with LAser GEOdynamic Satellite (LAGEOS) and LAser RElativity Satellite (LARES) tracking information that enable the monitoring of station performance and to determine whether the station has undergone any changes. The CDDIS is working to enhance these station performance monitoring tools through machine learning. Isolation forest is an unsupervised machine learning algorithm commonly applied to anomaly detection. In this poster, the CDDIS details the steps taken to track anomalies within SLR station performance using isolation forest with LAGEOS and LARES satellite data.

PROJECT OBJECTIVE

Build a machine learning model to determine if active SLR stations in the ILRS network are sending an automatic alert when a potential change to the station is detected in the data (anomaly), providing a reminder for station engineers to review existing station performance monitoring plots and update the station site history logs.

CURRENT STATION MONITORING TOOLS

Currently, plots for each active SLR station in the ILRS network are available on the ILRS website (1, 2). Metrics for station monitoring include the following:

- Meteorological data – used to calculate tropospheric correction, changes in these values may indicate an issue with hardware/software but is prone to false positives due with exceptionally good/bad weather
- LAGEOS plots to detect hardware and software changes or issues (Figure 1 shows a subset)
- 7-Day tracking – provide statistics on weekly performance including the duration and number of NPT collected per pass to visually show where improvements in tracking habits can be changed
- Satellite Data Information – gage the overall precision of the system and to inform better tracking habits

ALGORITHM & TRAINING DATA

Isolation forest models were built using data from Yarragadee (YARL) and acted as a starting point to determine if this type of analysis is possible. YARL's data doesn't have a lot of scatter and the station is the highest performer (obtains the most passes) making it easy to work with. LAGEOS and LARES were chosen due to their consistent orbits.

Reviewing historical data (2012/05/01 to 2022/07/19), the Isolation Forest algorithm makes predictions based on data from the past 90-days for the following 7-days. For each of the detections, the calculated RMS, calibration RMS, and system delay plots are created with the data considered anomalous highlighted. An example prediction is shown below under Sample Prediction.

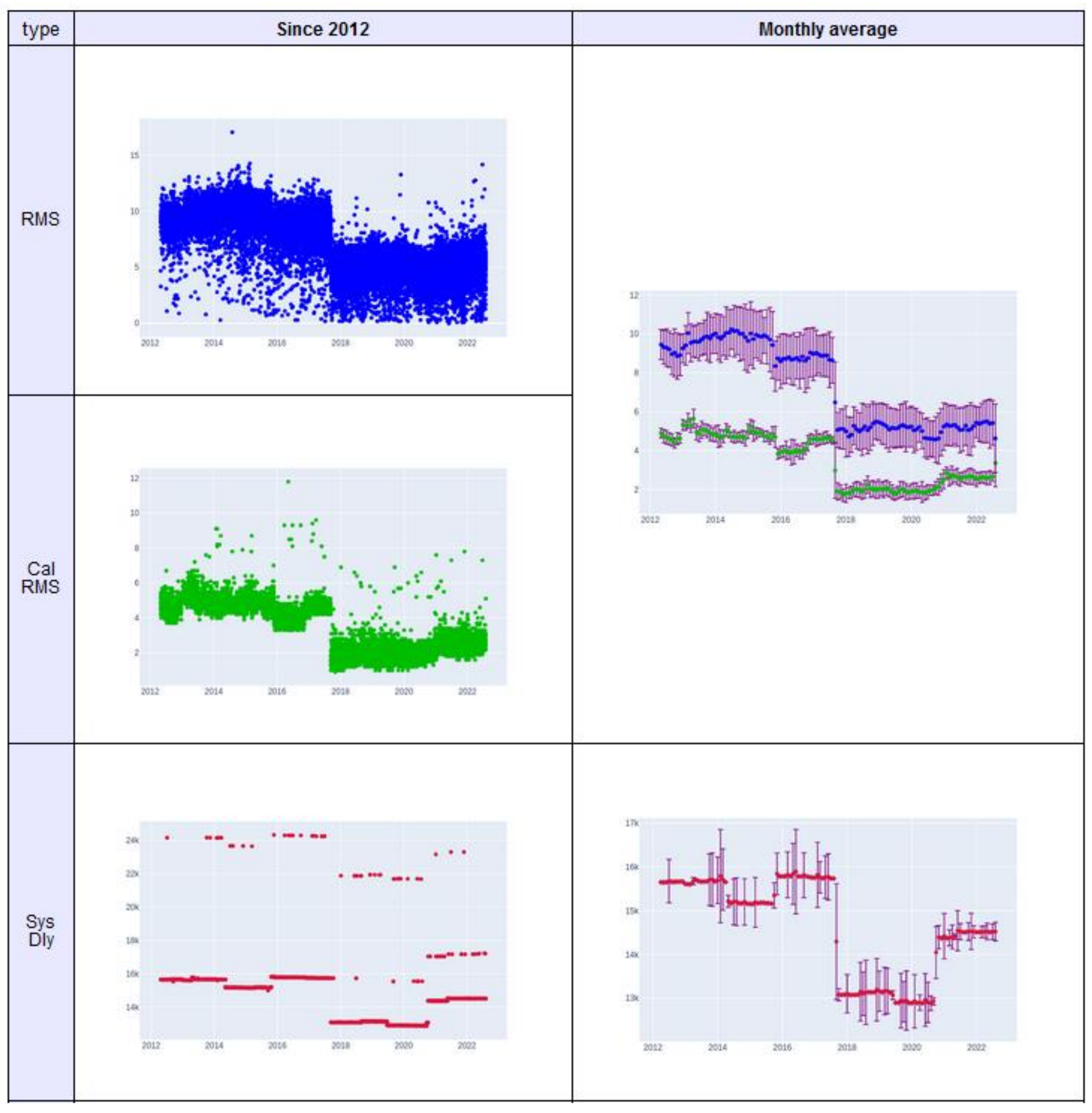

Figure 1: LAGEOS plots for YARL displaying the session RMS, calibration RMS, and the system delay; currently available on the ILRS website.

FEATURE SELECTION

The following features were selected in collaboration with SLR station engineers for anomaly detection:

- rms40 [ps] = calibration root-mean-square (RMS) of raw system delay
- medianRms40 = median of the calibration RMS
- rmsCalc [ps] = average bin RMS calculated from the range records (11) bin RMS from the mean of raw accepted time-of-flight values minus the trend function
- medianRmsCalc = median of the rmsCalc over the course of a day
- sysDelay [ps] = system delay peak (mean value) of the calibration
- satelliteSIC = satellite identifier

FEATURE JUSTIFICATION & FINDINGS

- The rms40 and the medianRms40 are used in an attempt to balance accuracy with expediency of the alert
- The rms40 rapidly predicts anomalies but has lower accuracy
- The medianRms40 was added to increase accuracy and helps provide a stronger pattern - however, using the median itself led to a delay in days for an anomaly to be detected!
- The medianRmsCalc used instead of the rmsCalc which was subject to too much natural deviation or noise
- The system delay proved to be the strongest indicator of when a change was made to the system for a majority of the correct detections
- The satelliteSIC was selected as an unimportant feature but can be used to determine if 3 or 4 satellites can be detected by the model

SAMPLE PREDICTION

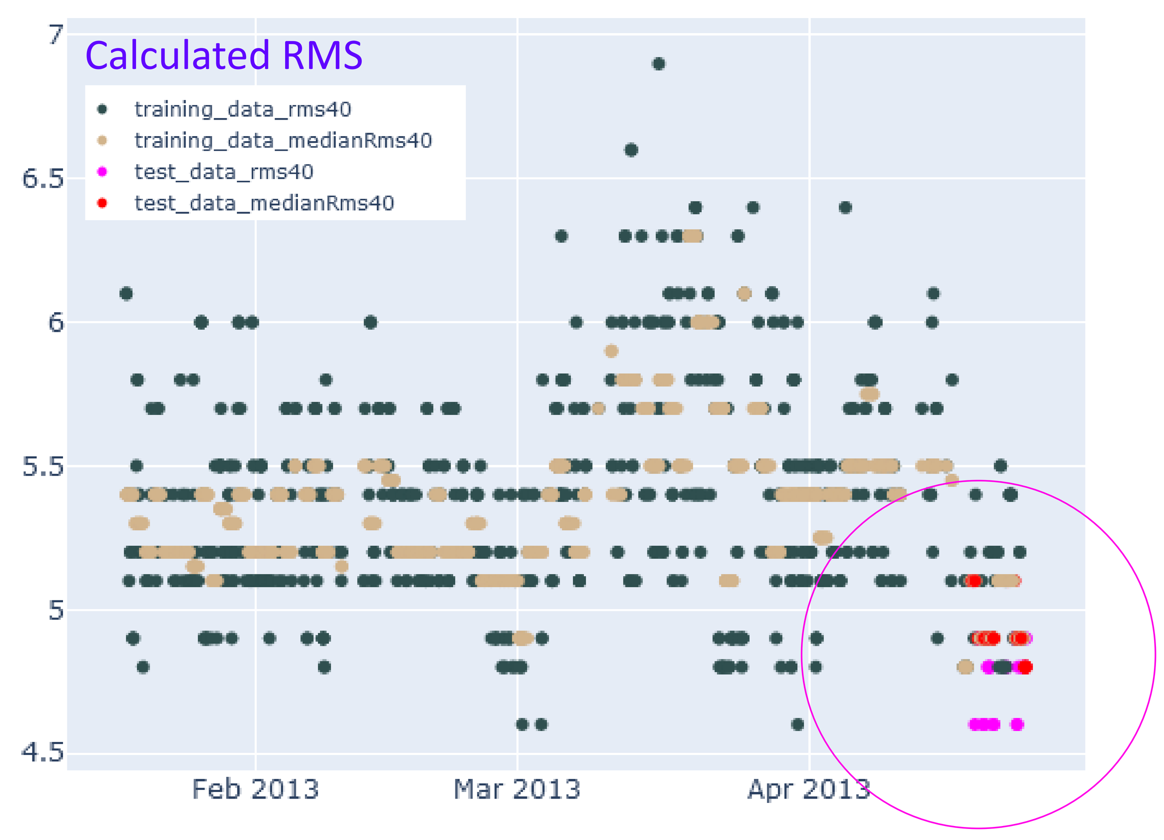

Figure 2: Plot of the Calculated RMS training and test data where an anomaly was detected (circled).

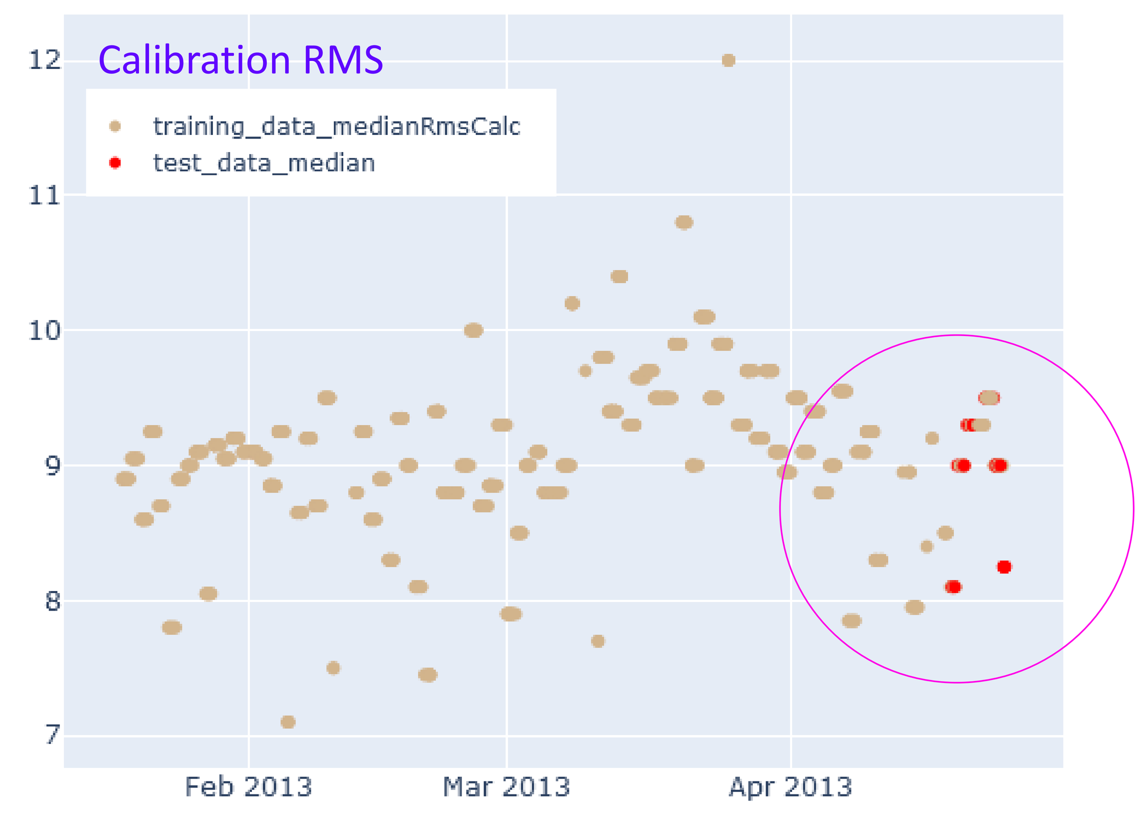

Figure 3: Plot of the Calibration RMS training and test data where an anomaly was detected (circled).

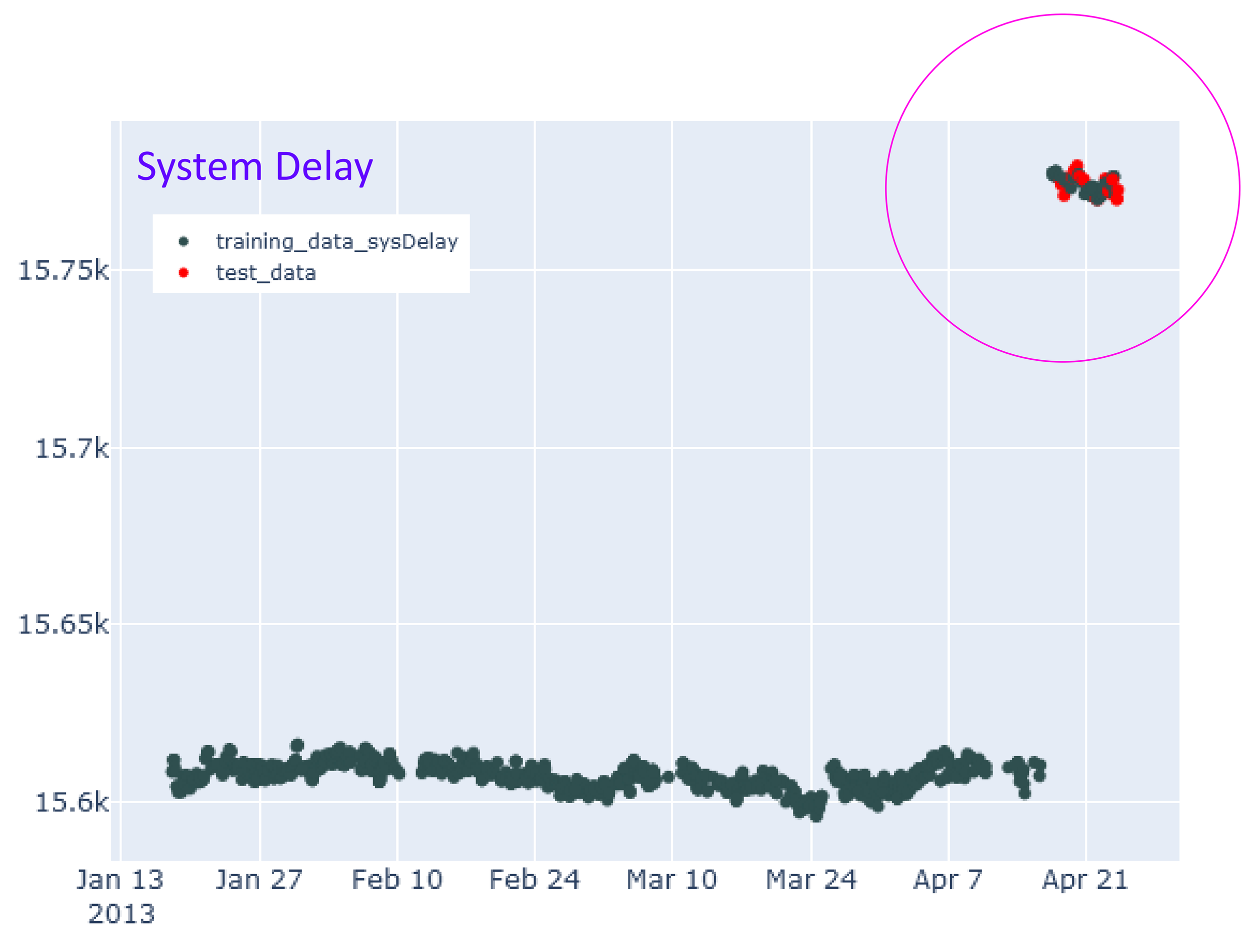

Figure 4: Plot of the System Delay training and test data where an anomaly was detected (circled).

RESULTS

Prediction accuracies was estimated by checking against station history logs. The results are reported below:

- All records for '05' and '06' subsystems where the impact factor is >1 were detected as anomalies
- 271 total anomalies detected (Figure 5)
- 99% of correctly detected anomalies were detected the same day as recorded in the station log
- 55% of detected anomalies were recorded in station logs
- Of the 45% of detected anomalies that were not present in station logs, only 17% would realistically generate an email to alert stations engineers (21 over 10 years). It is possible that station changes were not recorded to the station log. However, of these cases reviewed, this only occurred once.

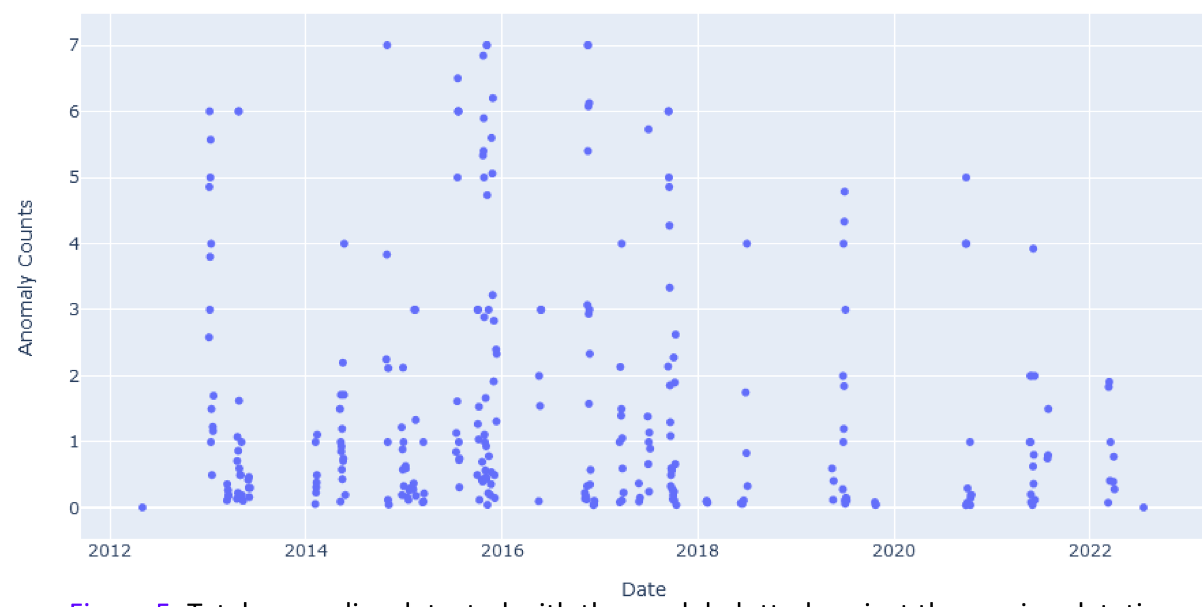

Figure 5: Total anomalies detected with the model plotted against the session datetime.

SHAPLEY VALUES

For all the predictions where an anomaly is detected but a corresponding record is not found in the station log, the CDDIS references the Shapley (SHAP) values to check how the different features are weighed by the model. SHAP values are the average expected marginal contribution of each feature after all possible combinations have been considered. It is a widely used approach from cooperative game theory for machine learning explainability. In this example (Figure 6), we see that the primary indicator that a station has changed (anomaly) is the system delay (Figure 4). This feature was added to provide clarity on the way the model is making a prediction because it is not always visually clear how items are weighted. As a sanity check, the satellite identifier is included because this should not impact the data.

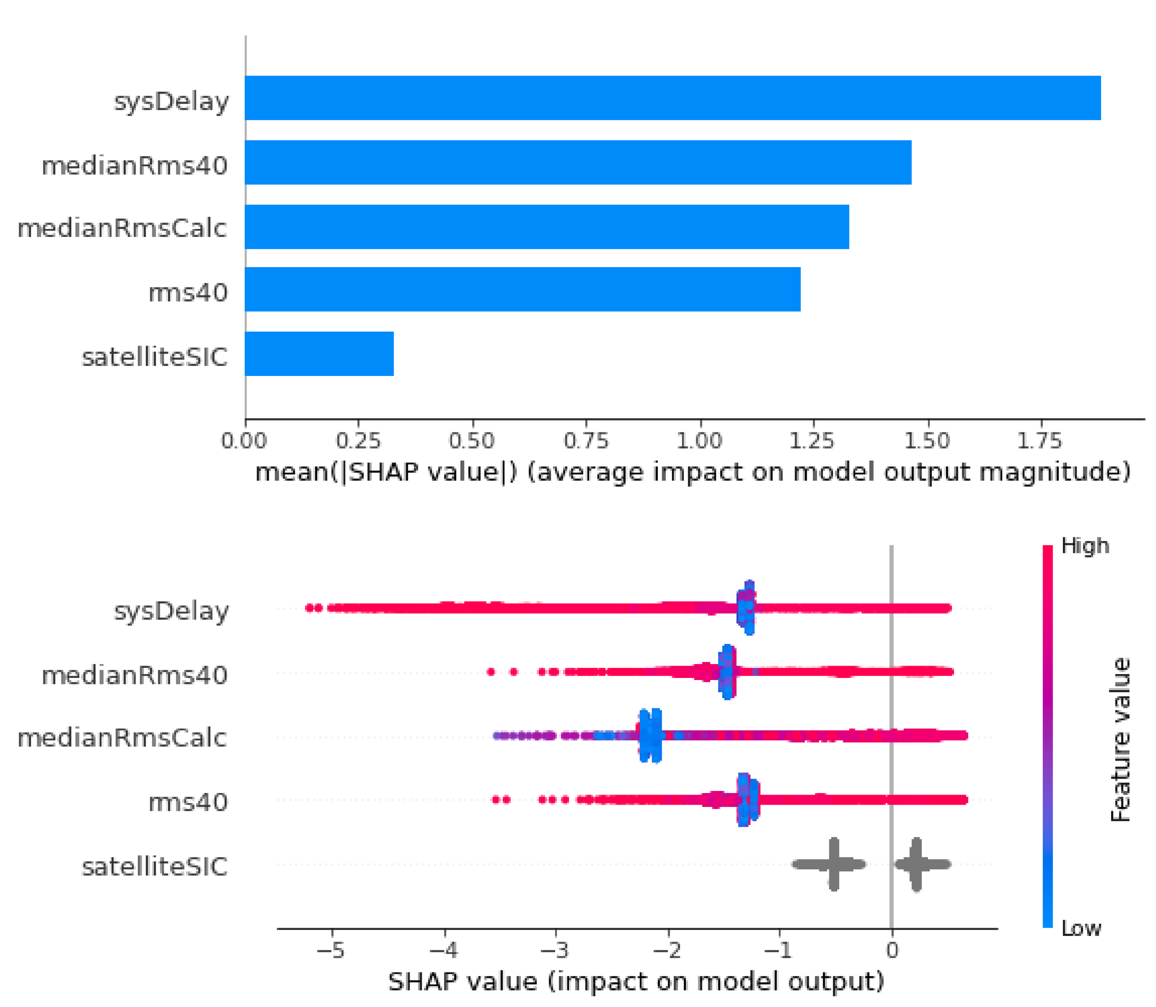

Figure 6: SHAP values from the sample prediction.

APPLICATION TO OTHER STATIONS

The CDDIS has begun applying these methods to other stations. The model and accuracy checks will vary for each unique station. The following are being considered:

- Session availability: predictions are currently made only when 500 sessions are available over a 90-day period and when detections are found in 3/7 of the test days. Lowering the number of sessions available, extending the period reviewed, or adding additional satellites to increase the number of sessions will result in a lower level of accuracy and delays in anomaly detection.
- The model is transferrable only if there are similar contamination levels; stations with more noise will need additional changes to the model.
- Adding more features: RMS50, skew kurtosis, peak-mean, and pressure

These changes must be investigated before an automated program, which generates models for each station, can be released. For automation, the model weights, durations, and features can be updated based on the percentage of correct detections, setting a maximum for the percentage of false-positive emails that are sent, and comparisons against the site history log where applicable.

ACKNOWLEDGEMENTS

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REFERENCES

(1) ILRS website: https://ilrs.gsfc.nasa.gov/
(2) ILRS overview of active station plots: https://ilrs.gsfc.nasa.gov/network/stations/active/overview_of_station_plots.html