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DATA FRUGAL MACHINE LEARNING FOR SIMPLIFYING SPACECRAFT MISSION PLANNING

Abstract

When monitoring the state of a spacecraft orbiting around a planet in our solar system, data comes from different sources, and at a different pace. For instance, data relating to outer factors such as distance between the planet and the Sun, or the intensity of the solar radiation can be easily computed even prior to the spacecraft launch and are always accessible. On the other hand, measurements of the behaviour of the spacecraft's regulatory systems, which are often autonomous and hard to predict, are captured within spacecraft's logging files and only available after a certain time has passed.

Accessing historical data is done by carefully planned Earth-spacecraft communications. However, while it is desirable to monitor the spacecraft's state as frequently as possible, access to ground stations to receive the data is limited. Ground stations may suffer equipment failures, and atmospheric conditions may cause disturbances and interrupt such data transmissions, thus limiting the operators to work with incomplete information of the spacecraft's status. Despite such limiting factors, an accurate estimation of the status is crucial for a safe operation and control of a spacecraft.

In this work, we focus on the spacecraft Mars Express (MEX), operated by the European Space Agency (ESA). Launched in 2003, MEX is still performing its mission of gathering scientific data of the atmosphere, surface and subsurface of Mars. MEX is powered by electricity, generated by its solar arrays and stored in batteries to be used during the eclipses. The instruments and on-board equipment must be kept within their operating temperature ranges, therefore the spacecraft is equipped with an autonomous thermal control system composed of 33 heater lines. The system, together with the platform units, consumes a significant amount of the total available electric power, leaving a fraction to be used for science operations. After more than 16 years in space, MEX's components are slowly decaying, leading to reduced functionality and ever decreasing remaining lifetime, e.g. the batteries' capacity is now over 50% degraded, making accurate planning and use of the available power essential.

Most attempts at estimating the available power, have produced manually constructed models based on first-principles, expert knowledge and experience. These models, however, have limited predictive power and have been tedious to construct. Their shortcomings raised the need for more sophisticated machine

learning methods that will improve the precision on the power-consumption estimation by learning more accurate models.

In the context of MEX, such sophisticated machine learning approaches have proven to be a valuable asset. In particular, in our previous work, we have clearly demonstrated that machine learning models can be successfully employed for accurate estimation of the thermal power consumption, performing orders-of-magnitude better than manually constructed models. Using nothing but the spacecraft's operational data for constructing these models, we showed that such methods can be utilized to support decision making, improve adaptability to unforeseen circumstances, and ultimately prolong the operating life of a spacecraft. The operation data covers various aspects of MEX operation and status, consisting of streams of spacecraft telemetry data coupled with ground-control data. More specifically, the data pertaining to the status of MEX is comprised of five parts:

1. SAA (solar aspect angles) data that contain the angles between the Sun–MEX line relative to MEX's position.
2. DMOP (detailed mission operations plans) data that contain the information about the execution of different subsystems' commands at a specific time.
3. FTL (flight dynamics timeline events) data, containing the pointing and action commands
4. EVT (miscellaneous events) data, containing records during which MEX was in Mars' shadow as well as records when MEX is at apsis of its elliptical orbit.
5. LT (long-term) data that contain physical values computed in advance, such as the Sun–Mars distances and the solar constant at Mars.

The findings from our previous work indicate that one of the most important component for estimating the thermal power consumption is the DMOP data. However, employing these data for analysis can be performed only after a certain command is executed on the spacecraft and its effect measured subsequently. Therefore employing these data for accurate mission planning of the spacecraft's schedule is almost unfeasible.

In response, in this paper we show that estimating MEX's total thermal power consumption can be performed in absence of DMOP data without significant loss in performance. We investigate two approaches to constructing machine learning models. The first approach considers constructing a model without DMOP data. The second, and more sophisticated approach, considers constructing a two-stage model. More specifically, in the first stage, a model is constructed for estimating DMOP values. In the second stage, these estimated DMOP values are coupled with the rest of the data for constructing a model for estimating the thermal power consumption.

At input, both approaches take data that have been first cleaned and preprocessed. This includes data alignment, data interpolation and imputation of missing values in the descriptive features. Moreover, these data also includes new and informative features, constructed using feature engineering approaches that exploit the relationships present in the different parts of data. In particular, these include the energy influx features that represent the solar radiation upon the sides of the MEX's body. The final data set spans in a time-period from 22. 8. 2008 to 16. 5. 2017 and includes the preprocessed descriptive features, the newly constructed influx features as well as measurements of the consumption of 33 thermal power lines of the thermal control system.

To evaluate the two approaches, we first split the data set into a training and testing data sets. For constructing the two-staged model, we further divide the training data set into two parts to simulate a scenario when past DMOP data is available. Namely, the first part of the training data is used for constructing a model that estimates DMOP values. In turn, in the second stage, we use these DMOP estimates together with the second part of the training data to construct a model that predicts the consumption of each of the thermal power lines. In contrast, in the alternative approach, the DMOP data is completely removed from the training data set when learning the model. The performance of the obtained models in both approaches, is evaluated using the testing data set. For constructing the models, in both approaches we consider two state-of-the-art machine learning methods: random forests (RF) and extreme gradient boosting (XGB). Both of these machine learning methods have been successfully applied to various tasks of estimating MEX's thermal power consumption.

The empirical study reveals several important findings. First, in terms of models' dependence to the DMOP data: XGB models are more reliant on DMOP data than RF models. In particular, XGB models exhibit greater performance loss when DMOP data is absent from the training data set. Next, and more important, the constructed models are robust. Namely, the predictive performance loss of the models in the absence of DMOP data is not substantial. When expressed as power use, it amounts to only a couple of watts, which is within the acceptable error margins for practical use of the models. In sum, we show that in scenarios with limited DMOP data availability, machine learning models can be successfully employed for practically relevant estimations utilized for various tasks in spacecraft operations planing and scheduling.