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FAULT ISOLATION OF REACTION WHEELS ONBOARD 3-AXIS CONTROLLED IN-ORBIT SATELLITE USING MACHINE LEARNING TECHNIQUES

Abstract

As systems become more complex, due to the advances in technology, the cost of maintenance for such systems follows. Satellites are an example of costly complex systems where downsizing individual satellites to smaller interconnected constellations has been explored as a viable solution to avoid high costs. However, the transition from larger systems to smaller interconnected units imposes less available space on each for hardware redundancy and calls for alternative solutions. Projections indicate as many as 2,600 nano/microsatellites will require launch over the next five years. Furthermore, annual nano/microsatellite launches have grown by over 200% in the last five years. This growth requires advanced monitoring systems that can compensate for the lack of redundancy in hardware due to smaller designs. It is evident that advances in analytical redundancy along with diagnosis, prognosis, and health monitoring frameworks can help adopt emerging technology and safeguard its progression. Hence, the primary objective of this study is to explore novel applications of data-driven machine learning methods for fault detection, isolation, and identification of nonlinear systems with a case-study for an in-orbit closed-loop controlled satellite with reaction wheels as actuators. High-fidelity models of the 3-axis controlled satellite are developed to provide an abundance of data for both healthy and various faulty conditions of the satellite. This data is then used as input for the proposed data-driven fault isolation method. Once a fault is detected, the fault isolation module is activated, where it employs a machine learning technique that incorporates ensemble methods involving decision trees, random forest, and various gradient boosting implementations. Results of the classified faulty condition are then cross-validated using k-folding. A comprehensive comparison of the performance of different combinations for the ensemble architecture, as well as sensitivity analysis for the hyperparameters of each model is provided. Results show promising outcomes for fault isolation of the nonlinear systems using ensemble methods.