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Digital Twinning for Onboard Health Monitoring of Solar Panels for Space Exploration Missions

Sachin SOLANKI[1,a *], Francesco DI FIORE[1,2,b] and Laura MAININI[1,2,c]

[1]Department of Aeronautics, Imperial College London, London, United Kingdom, SW7 2AZ

[2]Brahmal Institute for Sustainable Aviation, Imperial College London, UK, SW7 2AZ

[a]sachinksolanki02@gmail.com, [b]f.difiore@imperial.ac.uk, [c]l.mainini@imperial.ac.uk

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Abstract. Spacecraft solar panels are among the most failure-prone subsystems, requiring onboard health monitoring to ensure reliable operation in harsh space environments. This work demonstrates and validates the FREEDOM digital twin for onboard near real-time health management of spacecraft solar arrays under limited computational resources. The twin is trained offline through a two-stage data-assimilation process, and operates online to predict degradation via inverse Bayesian optimization. Validation performed on a solar panel integrating AZUR SPACE 3C44 cells under incipient damages across a ten-year geostationary-orbit mission scenario yielded a mean damage-prediction error of 5.2 % with a computational time of 62 s.

Introduction

Spacecraft solar panels represent the dominant source of unrecoverable faults within the electrical power system (EPS) [1]. Fault detection and isolation (FDI) for these systems remains particularly challenging due to their coupled electrothermal dynamics, limited sensing capability, and continuous exposure to the harsh space environment [2]. Solar panels are subjected throughout their operational life to radiation, micrometeoroid and debris impacts, and ultraviolet (UV) darkening, which induce gradual and often coupled degradation in the photovoltaic materials and interfaces [3]. These effects alter the current–voltage response in subtle ways, producing variations in telemetry that remain within nominal limits until significant power loss occurs [2]. The detection of such incipient degradations is further complicated by the need for near real-time monitoring in geostationary and deep-space missions, where long communication delays prevent continuous ground supervision [4].

State-of-the-art FDI methods for spacecraft solar panels are not yet capable of meeting these requirements. Hardware redundancy and threshold-based limit checking [5] lack sensitivity to progressive incipient degradation, while analytical model-based approaches [6] rely on high-fidelity physics models whose computational cost exceeds the capabilities of flight-qualified processors. Moreover, the scarcity of in-orbit fault data limits the applicability of purely data-driven methods, which typically depend on extensive labeled datasets to generalize effectively [7]. These constraints highlight the need for data-efficient FDI frameworks able to operate autonomously onboard, extract fault-relevant information from sparse telemetry, and detect early degradation before functional losses become critical.

In recent years, digital twin technologies have emerged as a promising alternative for health monitoring of complex engineering systems [8]. By maintaining a dynamic virtual counterpart of the physical asset that evolves in parallel with flight operations, digital twins enable continuous synchronization between measured and simulated responses to infer system health and predict degradation trends [9]. To address the challenges of fault diagnosis in spacecraft solar panels, this work demonstrates the FREEDOM digital twin - Fast Reliability Estimate and incipient fault

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Detection Of Multiphysics aerospace systems-, a computational framework tailored for onboard near real-time health monitoring of complex multiphysics systems subject to incipient damages [10]. The FREEDOM digital twin combines offline data assimilation and online inference in a unified, computationally efficient architecture. Offline, it employs Dynamic Mode Decomposition and Self-Organizing Maps to compress high-dimensional telemetry into a fault-informative representation; online, it assimilates new data and predicts evolving degradation states via inverse Bayesian optimization, continuously updating the virtual counterpart of the physical system. The twin is validated for a spacecraft solar panel composed of AZUR SPACE 3C44 triple-junction cells operating in a 10-year geostationary-orbit mission scenario, and considering multiple concurrent incipient damages.

Digital Twins Requirements for FDI of Spacecraft Solar Panels

Extending the digital twin concept to spacecraft solar panels presents unique challenges arising from the panels' coupled electrothermal behavior and limited sensing capability. Their electrical response depends on complex interactions between environmental and material effects, yet only a few low-rate telemetry channels - typically voltage, current, and temperature - are available for monitoring. At the same time, onboard processors impose strict computational limits, and the scarcity of in-orbit fault data restricts the use of supervised learning approaches. To operate effectively under these conditions, a digital twin for spacecraft solar arrays must meet three key requirements:

1. *Efficient data assimilation and compression*: extract and compress fault-relevant features from sparse low-rate telemetry while retaining sensitivity to early degradation signatures.

2. *Incipient fault prediction*: accurately predict multiple co-occurring early-stage degradation mechanisms whose effects are weakly observable in the measured signals.

3. *Computational tractability*: ensure near real-time operation within the strict processing and memory constraints of flight-qualified onboard hardware.

Methodology

The FREEDOM digital twin enables near real-time onboard health monitoring of spacecraft solar arrays by maintaining a continuously updated virtual representation of the physical subsystem. The framework is organized into two complementary phases: an offline efficient data assimilation and compression stage, and an online prediction stage, in which the twin operates onboard assimilating telemetry to predict the evolving degradation state. The division between offline and online stages ensures that the computationally demanding tasks are performed on the ground, while the flight implementation remains lightweight and data-efficient. Fig. 1 illustrates the conceptual interaction of the FREEDOM digital twin with the real solar panel. In the following, we outline the mathematical foundations of the FREEDOM framework. A complete description of the digital twin is provided in [10].

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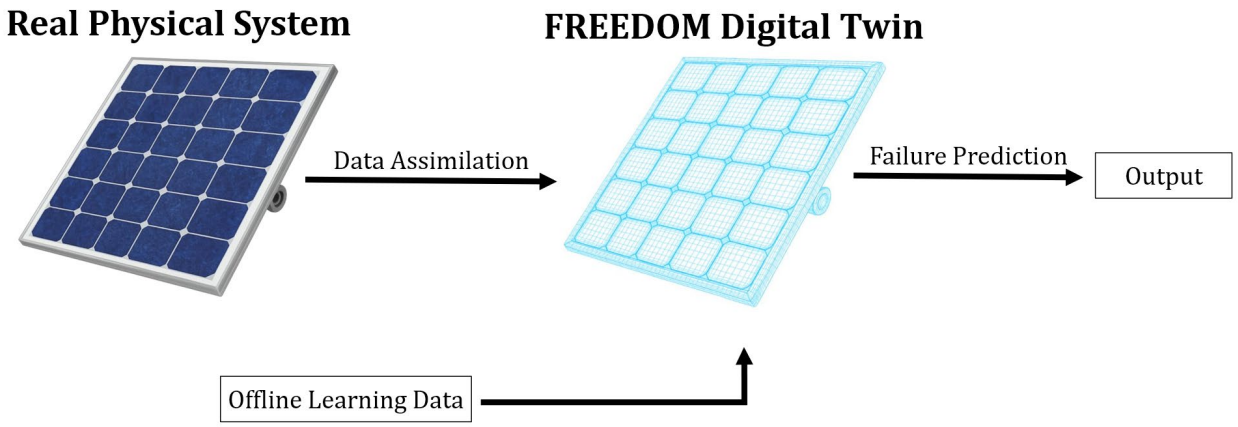

Figure 1: FREEDOM digital twin conceptual interaction with the real physical system

Offline Learning. In the offline phase, FREEDOM learns a reduced-order representation of the system encoding the essential system dynamics and fault sensitivity in a compressed form that minimizes onboard computational requirements. Time-series voltage signals $v(t,k)$ are generated from a high-fidelity model of the solar array under varying degradation parameters k. The first stage applies Dynamic Mode Decomposition (DMD) to extract the dominant temporal modes of the system response: $v(t+\Delta t) \approx A\, v(t)$, where A is the best-fit linear operator capturing the system's coherent dynamics. The DMD decomposition yields modal structures and eigenvalues (ϕ_i, λ_i) that form a reduced basis:

$$v(t) \approx \sum_{i=1}^{r} b_i\ \phi_i e^{\omega_i t}, \tag{1}$$

where r is the retained rank determined by the cumulative energy criterion, and $\omega_i = \ln(\lambda_i)/\Delta t$ represents the modal frequency content. The resulting modal amplitudes are processed using a Self-Organizing Map (SOM) to cluster similar degradation signatures, and identifies the most informative temporal points $\hat{x}$ defining a compression mask that preserves diagnostic information. The outcome of this stage is a mapping function $\mathcal{C}: v(t) \rightarrow \hat{v}(\hat{x})$, where $\hat{v}$ is the low-dimensional fault-informative projection of the original signal. This compression significantly reduces the dimensionality of the inverse problem to be solved during onboard operation.

Online Prediction. During the mission, the FREEDOM digital twin operates continuously updating its internal state based on incoming telemetry. The objective is to predict the current health status k^* of the solar panel. The health estimation problem is formulated as an inverse optimization task:

$$k^* = \arg\min_{k} \delta\left(\hat{\boldsymbol{v}}_{meas}, \hat{\boldsymbol{v}}_{sim}(\boldsymbol{k})\right) \tag{2}$$

where $\hat{\boldsymbol{v}}_{meas}$ is the compressed voltage measurement obtained from telemetry, $\hat{\boldsymbol{v}}_{sim}(\boldsymbol{k})$ is the corresponding twin-predicted signal. Eq. (2) is addressed through Bayesian Optimization (BO) with a Gaussian Process (GP) surrogate model [11] to approximate the discrepancy function, $\delta(k) \sim \mathcal{GP}\left(\mu(k), \sigma^2(k)\right)$, where μ and σ^2 represent the mean and uncertainty of the GP model prediction. The next query point k_{n+1} is selected by maximizing a non-myopic acquisition function $k_{n+1} = \arg\max_{k} \alpha(\boldsymbol{k}; \mu, \sigma)$ [10]. This iterative process converges to the optimal degradation vector k^* while minimizing the number of model evaluations. The resulting k^* defines the twin's current health state, which is continuously updated as new telemetry becomes available.

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Experimental Setup

We simulate a representative mission scenario to validate FREEDOM using a detailed solar cell model subjected to multiple evolving degradation mechanisms. The model employs the AZUR SPACE 3C44 triple-junction GaAs solar cell, widely used in geostationary and deep-space missions [12]. Implemented in the Simulink/Simscape Electrical environment, it reproduces the electrical behavior of a solar panel element through an equivalent-circuit (EC) representation. We estimate the EC parameters - photocurrent, series resistance, shunt resistance, diode saturation current, and ideality factor - from manufacturer datasheet values, defining the nominal healthy condition of the system. We model three primary degradation mechanisms: micrometeoroid and debris impacts (k_1), radiation damage (k_2), and ultraviolet (UV) darkening (k_3). We simulate (i) radiation-induced effects using ESA's SPENVIS toolkit [13], (ii) micrometeoroid and debris impacts using empirical relations from NASA's Handbook for Designing MMOD Protection [14], and (iii) UV darkening with an empirical factor that reduces photocurrent over time [15]. These effects combine into a time-dependent parameter set that captures realistic in-orbit degradation over a ten-year GEO mission. In particular, we focus on modeling and predicting incipient damages define as $k_i < 0.1$ for the k normalized damage variable. Within this range, damages generate subtle and hardly detectable variations in the current–voltage curve, providing a challenging test of FREEDOM's sensitivity to early fault signatures. We generate the input measurement set for the FREEDOM offline learning phase by running 10000 high-fidelity simulations, each corresponding to a unique degradation vector $k = [k_1, k_2, k_3]^T$ determined using a scaled Latin hypercube design with a scaling exponent of 1.5.

Results and Discussion

Fig. 2(a) shows thirty informative temporal points identified for data assimilation by the offline learning phase over a representative voltage signal. The density of informative points increases toward the end of the simulated mission, where the dominant dynamic modes extracted by DMD exhibit greater divergence between health states, indicating that FREEDOM allocates computational resources to the temporal regions carrying the highest degradation informative content. Fig. 2(b) reports the evolution of the mean Relative Parameter Error (RPE) over twenty runs for each degradation mechanism during online inference. The FREEDOM digital twin accurately tracks the evolution of incipient degradations across all modes. Radiation-induced damage (k_2) is estimated with negligible error, while micrometeoroid and debris impacts (k_1) and ultraviolet (UV) darkening (k_3) show consistently low RPE values. The overall mean estimation error of 5.2% demonstrates the accurate prediction of multimodal failures under realistic mission conditions. All evaluated cases fall within the incipient degradation regime targeted for prediction by FREEDOM during operation. The high accuracy achieved in this range demonstrates the framework's ability to capture the subtle electrical signatures of early-stage damage, well before measurable power loss occurs. In addition, FREEDOM completes the entire prediction phase in 62s, confirming its computational efficiency.

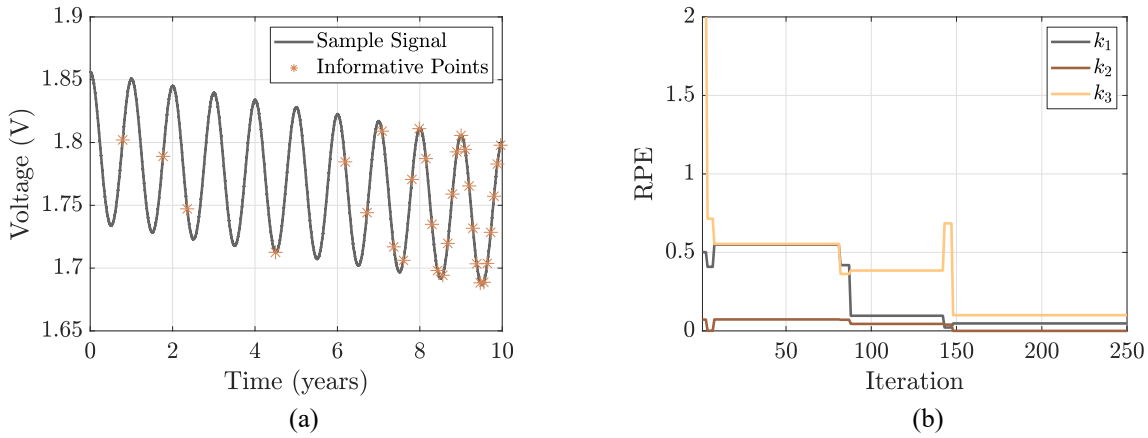

Figure 2: (a) Offline learning output showing the informative temporal points extracted by the DMD-SOM compression. (b) Online predictive performance showing the mean Relative Parameter Error of the damage prediction.

Concluding Remarks

This work demonstrated the FREEDOM digital twin for autonomous health monitoring of spacecraft solar arrays, addressing the challenges of data efficiency, incipient fault prediction, and onboard computational limits. FREEDOM combines offline data assimilation through Dynamic Mode Decomposition and Self-Organizing Maps with online Bayesian inference to identify multiple degradation mechanisms in near real-time. Validation on a solar panel composed of AZUR SPACE 3C44 cells over a ten-year geostationary-orbit scenario achieved a mean relative parameter error of 5.2% with a runtime of 62s, confirming its capability for accurate, data-efficient, and computationally tractable onboard degradation diagnosis.

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