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Telemetry Data Assimilation into Operational Simulators to Enhance In-Flight Fidelity and Representativeness

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Abstract

Modeling and Simulation (M&S) serve as vital instruments in the product lifecycle within the space industry, especially at the European Space Operations Centre (ESOC), where M&S are extensively employed across the entire lifespan of a spacecraft. Despite its importance for pre-launch scenarios (e.g., assembly, integration and testing, training of personnel, and validation of operational procedures), the fidelity of M&S in operations and the consequent usage is limited due to *i*) challenging environmental conditions, *ii*) different conditions with respect to the testing environment, *iii*) presence of epistemic and aleatoric uncertainty, and *iv*) varying fidelity of simulated systems. To overcome these limitations, the authors propose a methodology and guidelines for assimilating telemetry data to calibrate operational simulators. The effectiveness of this approach is demonstrated through its application to real-world data from Earth observation spacecraft and simulation models.

Keywords: Data Assimilation, Digital Twins, Spacecraft Operations, Advanced Simulations, European Space Agency

1. Introduction

Modeling and Simulation (M&S) tools play a crucial role in the design, operation, and maintenance of products across various engineering fields. Their importance is particularly evident in the space industry, where organizations such as the European Space Agency (ESA) integrate M&S throughout a spacecraft's entire lifecycle [1]. The European Space Operations Centre (ESOC), which serves as ESA's primary mission control center, utilizes these tools for multiple functions, including system monitoring, control, training, maintenance, procedure validation, planning, and scenario analysis [1]. To ensure accuracy, M&S tools must be calibrated using real measurement data to determine unknown configurable parameters of the mathematical model, aligning it with the actual system's behavior [2]. However, the reliability of these tools and their calibration process can be affected by model simplifications, assumptions, missing physical phenomena, and gaps in knowledge [3]. This challenge is particularly significant in spacecraft simulations, as they struggle to precisely capture the unpredictable and extreme environmental conditions that evolve throughout a spacecraft's operational life. Consequently, three main types of uncertainties arise: (i) parameter uncertainty, stemming from an incomplete understanding of the physical system's properties; (ii) aleatoric uncertainty, caused by random environmental fluctuations; and (iii) model discrepancy uncertainty, which results from inherent errors, approximations, and simplifications in numerical modeling [4].

Here, we focus on modeling the sources of uncertainty (i) and (ii) mentioned earlier and, accordingly, explore different methods for calibrating simulation models: optimization-based calibration (OBC) and stochastic model updating, also known as direct Bayesian calibration (DBC) [5]. OBC involves using optimization algorithms, such as evolutionary techniques like genetic algorithms or differential evolution, to determine the optimal set of model parameters that minimize the discrepancy between simulated and experimental data. However, while OBC methods effectively measure the alignment between numerical simulations and experimental results, they do not incorporate uncertainty and have limited capacity to address model discrepancies.

Conversely, stochastic model updating methods utilize Bayesian theory to calibrate model parameters by incorporating prior knowledge. Instead of identifying a single optimal parameter set, this approach enhances calibration robustness by representing aleatory uncertainty and mitigating epistemic uncertainty.

In this context, we introduce a Bayesian framework that integrates surrogate models and employs a Markov Chain Monte Carlo (MCMC)-based calibration method for the stochastic updating of operational simulation models, using data from orbiting spacecraft. Additionally, we analyze and compare how model discrepancies impact different calibration techniques. The key contribution of this work lies in its pioneering attempt to apply stochastic calibration using real spacecraft data and operational simulators.

1.1. Mathematical formulation of the problem

In this study, we examine the thermal behavior at a critical location on a spacecraft in flight. The input variables for the simulation models ($\overline{X}$) include controllable factors such as the spacecraft's position relative to the Earth and the Sun, operational modes, and solar aspect angles, among others. Meanwhile, the configurable model parameters ($\overline{\vartheta}$) represent underlying thermal properties.

Figure 1 illustrates an example of a simulation using an uncalibrated model, compared against real monitoring data. The simulation depicts the temperature of a specific thermistor over two orbital periods, while the actual values are obtained from spacecraft telemetry during the same timeframe. Accurately predicting temperature variations is crucial for mission planning and optimizing resource utilization throughout the spacecraft's operational lifespan. However, the significant discrepancy between the simulated and actual thermal behavior indicates that the current simulator cannot be reliably used for such critical tasks.

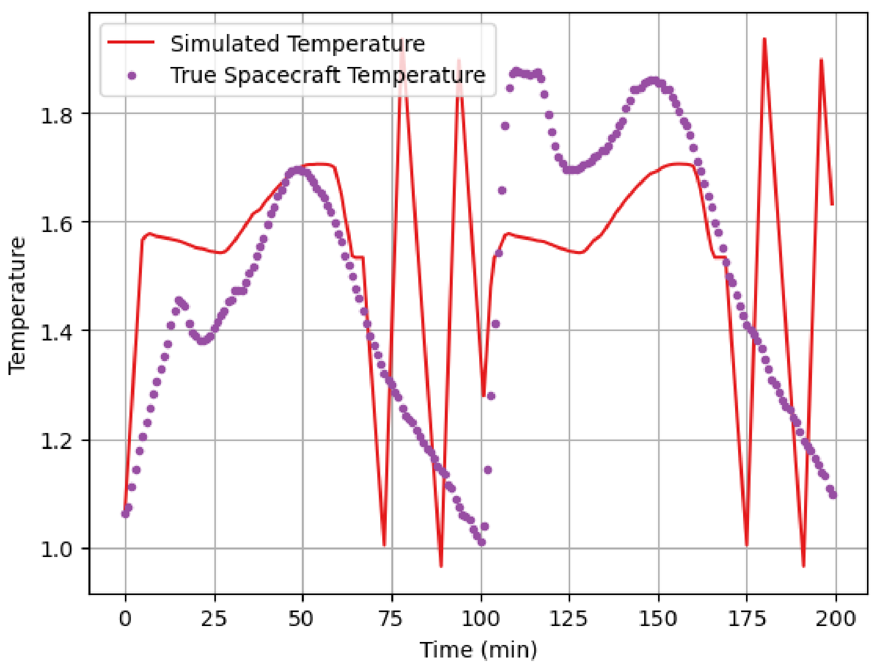

Fig. 1. Comparison of thermal node simulation predictions and real data when the model is not calibrated.

Figure 2 presents a comparison using a poorly calibrated simulator. Although the results show some improvement, significant systematic model discrepancies remain, underscoring the need for a more robust calibration framework.

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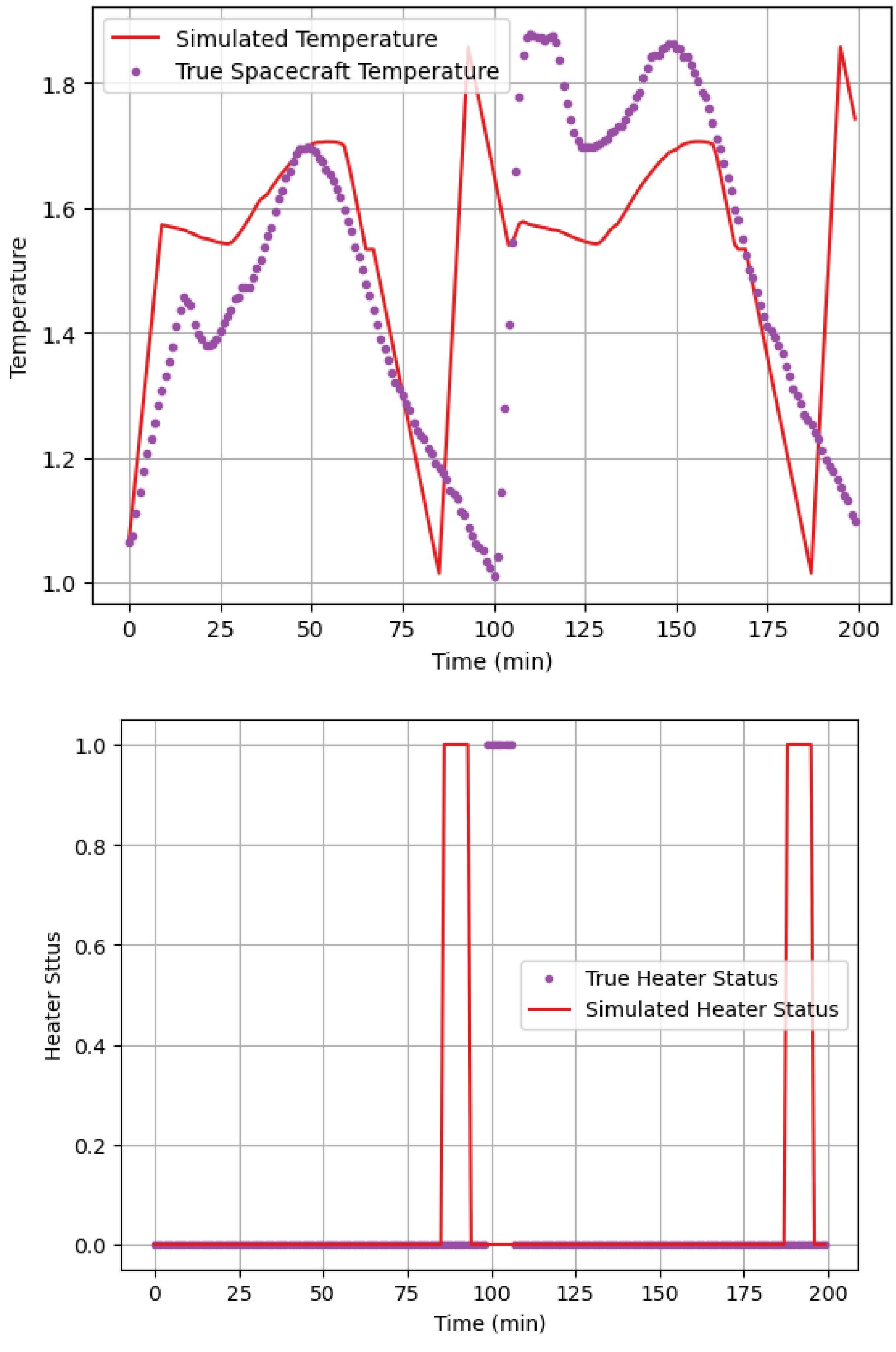

Fig. 2. Comparison of model simulation and acquired data for thermal node temperature (a) and heater status (b) when the model is poorly calibrated.

3. Simulation model calibration

3.1. Optimization-Based Calibration

In this study, we utilize a Genetic Algorithm (GA) as the optimization-based calibration (OBC) approach. GA is a meta-heuristic evolutionary method inspired by the principles of biological evolution, employing operators such as recombination, crossover, and mutation to iteratively refine a population of candidate solutions with the goal of optimizing a given metric. Here, we use the root mean squared error (RMSE) between the observed and simulated telemetry data as the optimization criterion [1]. To enhance robustness and mitigate the risk of converging to local minima, we conduct ten independent GA runs and use the average of the resulting parameter set ($\mathfrak{I}$) for calibration.

3.2. Stochastic model update

Stochastic model updating naturally accounts for model uncertainties by treating configurable parameters as random variables, each characterized by a probability distribution. Initially, prior distributions reflecting incomplete knowledge (i.e., epistemic uncertainty) are assigned. These distributions are then refined using monitoring data, reducing epistemic uncertainty and allowing for the assessment of the posterior distribution of the parameters [6]. This updating process is grounded in Bayes' Theorem.

In this study, we assume that the observations are independently and identically distributed (i.i.d.) and employ a Markov Chain Monte Carlo (MCMC) method to sample from the posterior distribution. Specifically, we utilize the No-U-Turn Sampler (NUTS), an advanced variant of the Hamiltonian Monte Carlo (HMC) algorithm [3]. The MCMC approach generates a Markov chain over multiple iterations to approximate the posterior distribution effectively.

4. Results

4.1. GA

The Genetic Algorithm (GA) was trained using telemetry data collected over two consecutive orbits and tested on a separate two-orbit dataset. Figure 3 illustrates the results obtained from the calibrated simulation model on the test dataset. While the calibration improves the alignment between the true and simulated heater activations, the simulated temperature still exhibits significant systematic errors, leading to a substantial overall model discrepancy.

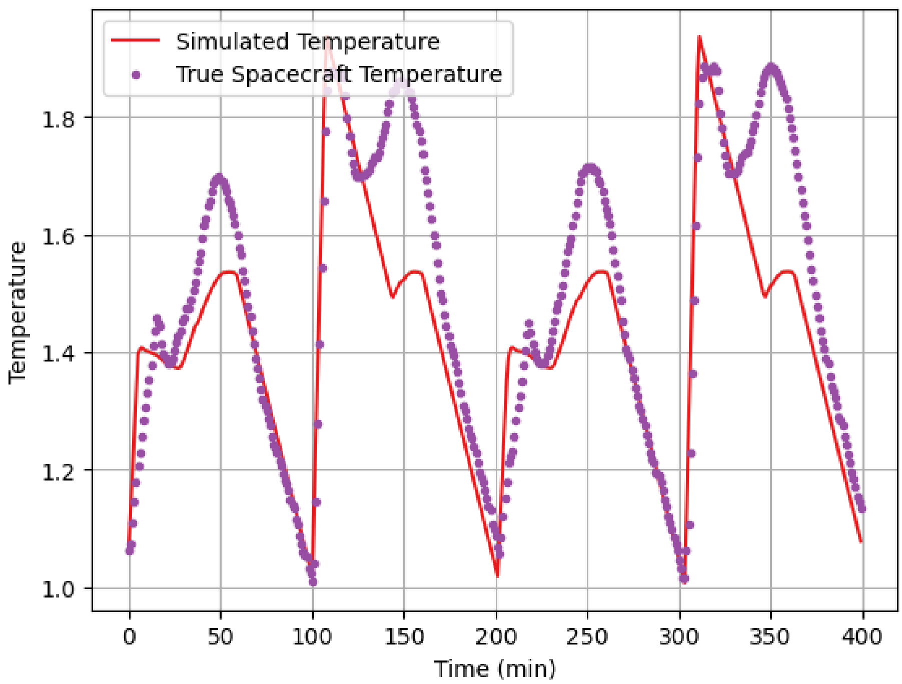

Fig.3. Comparison of simulator calibrated with a GA predictions and monitoring data for thermistor temperature.

4.2. Stochastic

This section presents the results obtained using the stochastic model update described in Section 3.2. The method was implemented with the same training dataset used in Section 4.2. Unlike optimization-based calibration, the stochastic approach estimates the posterior probability distribution of the input parameters, refining them based on monitoring data.

Figure 4 provides an example of the posterior probability distributions for three configurable parameters (denoted as a, b, and c). Notably, the four MCMC chains converge for all three parameters, and the resulting posterior distributions are concentrated around the optimal values, indicating a successful reduction in uncertainty.

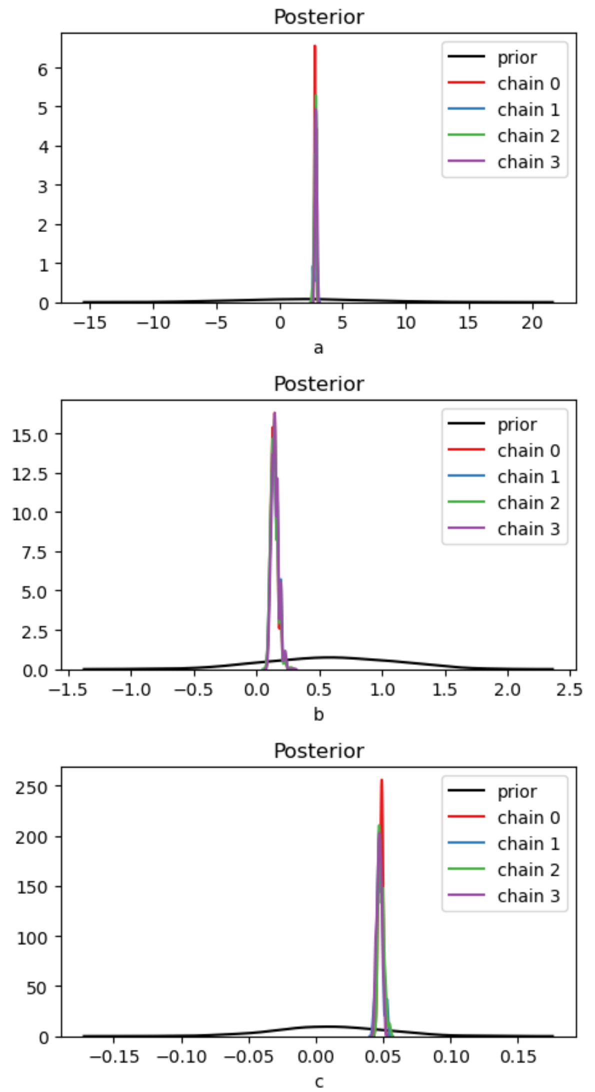

Fig. 4. Comparison prior and posterior probability distribution of the model parameters.

The identified posterior distributions of the configurable parameters are then propagated through the model, incorporating the estimated aleatoric uncertainty (ε). This process yields a probability distribution for the simulation model's output.

Figure 5a illustrates the mean temperature along with the 95% confidence interval (CI), compared against real data. Due to the significant model discrepancy, the 95th percentile range appears broad and imprecise. It is important to note that this approach assumes model discrepancies to be mean-zero, independently, and identically distributed, thereby accounting for systematic errors.

To further evaluate the results in relation to the simulated heater status, 1,000 simulations were generated from the posterior distribution and compared with the observed monitoring data. The comparison is shown in Figure 5.

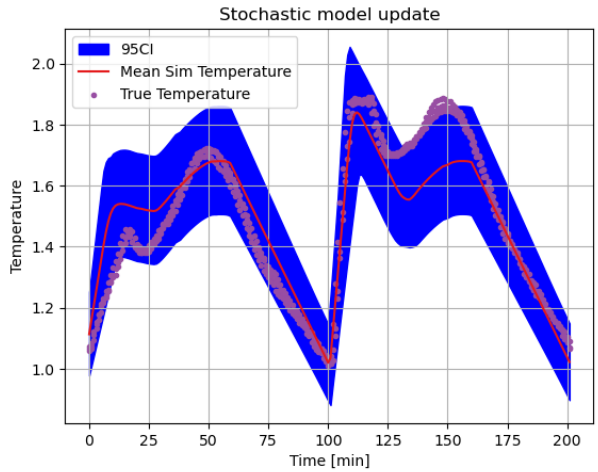

Fig. 5. Comparison of simulation predictions and real data for thermistor temperature for the stochastic model update.

5. Conclusions

This paper explores advanced techniques for calibrating operational simulation models of flying spacecraft. It compares optimization-based calibration with stochastic model updating and examines how model discrepancies impact these approaches.

The effectiveness of the proposed methodology is demonstrated through its application to a real Earth observation satellite. The results indicate that: (i) both optimization-based and stochastic update methods struggle to address significant model discrepancies, and (ii) the stochastic approach effectively generates credible confidence intervals, enabling a more accurate representation of uncertainty in predictions.

Future research will focus on integrating stochastic model updating with methods designed to account for simulation errors and discrepancies.

References

[1] Antonello, F., Segneri D., Reggestad V., "Surrogate model-based calibration of a flying Earth observation satellite, Advances in Space Research", Volume 73, Issue 3, 2024, Pages 1925-1935, ISSN 0273-1177.

[2] Gaiatto S. C., Antonello F., Segneri D., Sousa B., Abascal Palacios B., Schiavo A., Bartesaghi, M. Maass J., Inojosa A. A novel physics-based computational framework to model spacecraft solar array power under degradation: Application to European Space Agency (ESA) Cluster mission, Acta Astronautica, Volume 226, Part 1, 2025

[3] Antonello, F., Segneri, D., Eggleston, J., A Bayesian framework for in-flight calibration and discrepancy reduction of spacecraft operational simulation models, Advances in Space Research, Volume 74, Issue 11, 2024

[4] Lee, G., Kim, W., Oh, H., Youn, B. D., & Kim, N. H. (2019a). Review of statistical model calibration and validation—from the perspective of uncertainty structures. Structural and Multidisciplinary Optimization, 60(4), 1619–1644.

[5] Ward, R., Choudhary, R., Gregory, A., Jans-Singh, M., & Girolami, M. (2021). Continuous calibration of a digital twin: Comparison of particle filter and Bayesian calibration approaches. Data-Centric Engineering, 2(3).

[6] Bi, S., Beer, M., Cogan, S., & Mottershead, J. (2023). Stochastic Model Updating with Uncertainty Quantification: An Overview and Tutorial. Mechanical Systems and Signal Processing, 204, 110784.