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Bayesian Framework For In-Flight Calibration Of Spacecraft Operational Simulation Models

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Abstract

Modeling and Simulation (M&S) is an indispensable tool during the lifecycle of products in the space industry, particularly at the European Space Agency (ESA), which relies heavily on M&S throughout the entire lifetime of a spacecraft. However, when used in operational settings, i) the scarcity of data available for testing and validating models in flying conditions, and ii) the presence of epistemic and aleatoric uncertainty results in inaccuracies and challenges. This limits their use for delicate operational tasks. In addressing those challenges, we present a Bayesian framework leveraging a Markov Chain Monte Carlo-based calibration approach and surrogate models to achieve stochastic updates in spacecraft simulation models. The approach's effectiveness is shown by its application to real flying Earth observation spacecraft data and operational simulation models.

Keywords: spacecraft, modeling and simulation, bayesian update, calibration, european space agency

1. Introduction

Modeling and Simulation (M&S) tools have become indispensable for the comprehensive design, operations, and maintenance of products across various engineering disciplines. This is exemplified in the space industry, particularly at the European Space Agency (ESA), which relies heavily on M&S throughout the entire lifecycle of a spacecraft (Crues et al., 2022). In particular, the European Space Operations Centre (ESOC), the primary ESA mission control and operation center, employs M&S tools for various tasks, including monitoring and control, procedure validations, training, maintenance, planning, and scenario investigations (Pantoquilho et al., 2017). This requires using measurement data to accurately calibrate M&S tools by learning the unknown configurable parameters of the mathematical model to match the real-world system's behavior (Ward et al., 2021). However, the validity of M&S tools and the effectiveness of their calibration may be biased by model simplification, assumptions, missing physics, and lack of knowledge (Lee et al., 2019a). This is particularly relevant for spacecraft simulation models, which can hardly accurately represent the harsh, uncontrollable, and often unforeseen environmental conditions that may also dramatically change throughout a spacecraft's lifespan. This results in:

- model parameter uncertainty, related to the inherent properties of the physical system which are imprecisely determined due to the lack of knowledge;
- aleatoric uncertainty resulting from environmental noise;
- model discrepancy uncertainty, accounting for the errors and inaccuracies due to the numerical inevitable simplifications and approximations (Bi et al., 2023).

We here focus on modeling the uncertainty sources *i*) and *ii*) above and, therefore, consider the following methods for simulation models calibration:

- optimization-based calibration (OBC) (Lee et al., 2019b);
- stochastic model update (Bi et al., 2023) or direct Bayesian calibration (DBC) (Hu et al., 2018).

OBC consists of the use of optimization algorithms, e.g., evolutionary algorithms such as genetic algorithms (Antonello et al., 2024) or differential evolution (Huang and Li, 2023), to identify the optimal set of model parameters, which minimizes the difference between simulated and experimental data. However, despite the capability of OBC methods to assess the agreement between the numerical simulations and experimental data, they do not account for any form of uncertainty, and their ability to correct model discrepancies is limited (Jiang et al., 2020). On the other hand, methods based on stochastic model update, leverage Bayesian theory for model parameter calibration based on prior knowledge (Bi et al., 2023). This approach surpasses the objective of identifying a single optimal set of parameters by seeking to guarantee the robustness of the calibration via representing aleatory uncertainty and reducing the epistemic uncertainty (Bi et al., 2023).

In this light, we present a Bayesian framework embedding surrogate models, a Markov Chain Monte Carlo (MCMC)-based calibration approach for the stochastic update of operational simulation models leveraging data from flying earth-orbiting spacecraft. Furthermore, we investigate and compare the effect of model discrepancy on calibration approaches. The novel contribution of the work is represented by the first attempt to perform stochastic calibration with real spacecraft data and operational simulators.

2. Earth-orbiting spacecraft thermal model

Monitoring and investigating Earth's environment, climate, and natural resources is imperative, and Earth observation satellites play a pivotal role in this endeavor. These satellites embed a variety of sensors and instruments that, while orbiting the Earth, collect data on various environmental factors, including temperature, humidity, vegetation cover, and ocean salinity (Melloni et al., 2018). Typically, Earth-orbiting spacecraft are equipped with critical components and payloads, which conditions have to be carefully monitored to ensure their safe operation. For instance, all spacecraft components must be kept to specified temperature ranges to meet survival and operational requirements throughout all mission phases (Yendler, 2021). For the satellites operated at ESOC, operational simulators represent the thermal behavior by modeling

- the physical thermal properties;
- the numerical equation describing systems heat exchange;
- the onboard computer and OBSW.

Thus, the simulators also mimic the response of the OBSW to critical thermal transients and the consequent activation of the thermal control systems. Notice that a significant computational burden characterizes such complex operational simulators, mainly associated with the complexity of the OBSW. They usually run in real-time (e.g., simulating one minute of satellite operations requires one minute of computations) to six times real-time (e.g., simulating one minute of satellite operations requires ten seconds of computations). Thus, in this work, we make use of Reduced Order Models (ROM) surrogate, which is a code-intrusive method to alleviate the computational burden by reducing the original physical models' complexity and accuracy. Notice finally that, for confidential and proprietary reasons, further details on the mathematical models and numerical equations of the operational simulators cannot be provided. Also, details on the specific satellite under analysis are not given and the data and results provided in this paper are manipulated and masked.

2.1. Mathematical formulation of the problem

Let $\overline{y_t}^* = [y^*_{t,1}, y^*_{t,2}, \dots, y^*_{t,N}] \in R^N$ be the set of N telemetry variables measured at time *t*, where $y_{t,i}$ is the telemetry observation of the *i*-th variable y_i, (e.g., temperature of a specific thermistors) and $Y^* = [\overline{y_1}^*, \overline{y_2}^*, \dots, \overline{y_T}^*] \in R^{TxN}$ is the matrix describing their time evolution during the period *T*. We then consider a simulation model representing the evolution of the same set of variables for a predefined period of time *T*. let $\bar{X} = [x_1, x_2, \dots, x_d] \in R^d$ be the set of model inputs and $\overline{\vartheta} = [x_1, x_2, \dots, x_p] \in R^p$ the set of configurable parameters of the simulation model, $M(\bar{X}, \overline{\vartheta}) = Y^X = [\overline{y_1^X}, \overline{y_2^X}, \dots, \overline{y_T^X}] \in R^{TxN}$ the model output, and $\overline{y_t^X} = [y^X{}_{t,1}, y^X_{t,2}, \dots, y^X_{t,N}] \in R^N$ the set of simulated variables at a time *t*. $\bar{X}$ are variables which are controllable during measurement, while are $\overline{\vartheta}$ are epistemic random variables affected by missing of knowledge (Jiang et al., 2020). Notice that, given the computational burden required to simulate Y^X with complex simulation models of Earth-orbiting spacecraft, which operate at 6x real-time, the aim of this work is to perform model calibration by substituting Y^X with a computationally cheaper surrogate model.

In this work, we consider the thermal behavior in a critical location of a flying spacecraft. The input vector of the simulators $\bar{X}$ includes controllable variables such as, spacecraft position with respect to earth and sun, operational modes and solar aspect angles, to mention a few; while the configurable model parameters $\overline{\vartheta}$ include the underling thermal properties. Figure 1 give an example of a simulation of a not calibrated model and its comparison with real monitoring data. The simulation represents the temperature of the considered thermistor for a period of 2 orbits, while the true values are the telemetries collected from the spacecraft at the same period of time. It is worth mentioning that the accurate predictions of temperatures are fundamental for planning and assessing the resources usage during the mission lifetime. Notice, however, the large difference between the thermal behavior of the simulator and the real spacecraft, which do not allow the use of the simulator for such critical tasks.

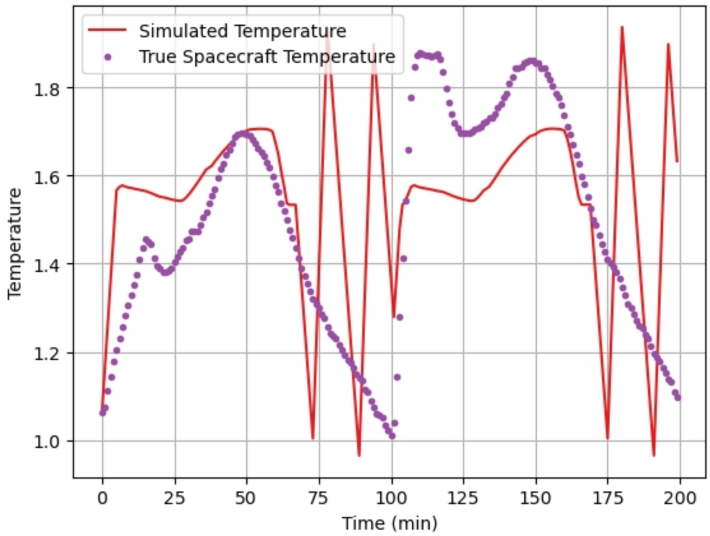

Fig. 1. Comparison of simulation predictions and real data for thermistor temperature when the simulator is not calibrated.

Figures 2 and 3 show the same comparison with a poorly calibrated simulator. It should be noticed that, despite the better results, the simulation present large systematic model discrepancies, highlighting the necessity for a robust calibration framework.

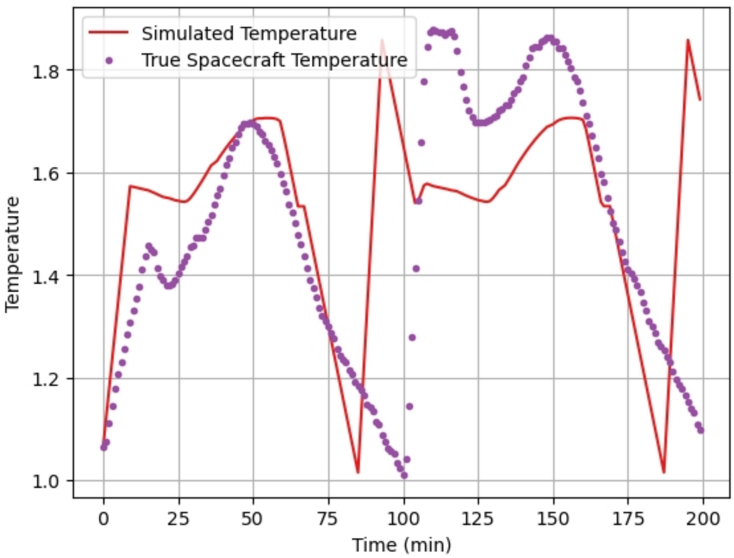

Fig. 2. Comparison of simulation predictions and real data for thermistor temperature and heater status.

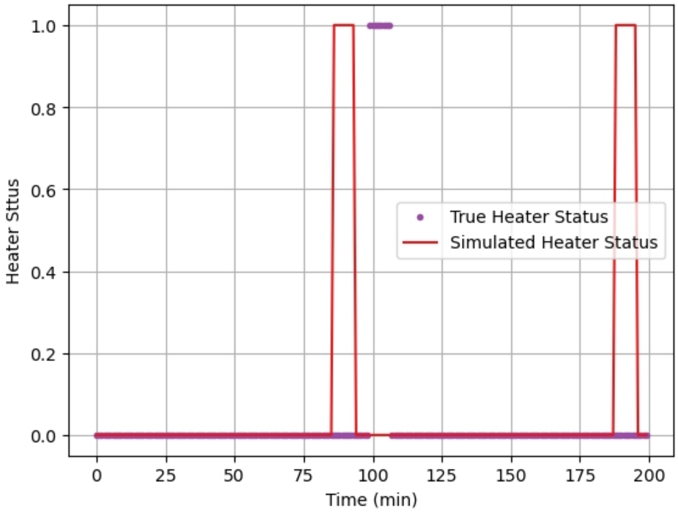

Fig. 3. Comparison of simulation predictions and real data for thermistor temperature when the simulator is poorly calibrated.

3. Simulation model calibration

This section describes the considered methods for model calibration. In the more classical terms, calibration consists in the identification of the optimal set of configurable parameters $\overline{\vartheta}$ which minimizes the difference between the simulation model and the experimental results (Antonello et al., 2024). However, this definition does not include the uncertainty and model discrepancy. In this respect, the relationship between the simulations and the monitoring values can be express as follows:

$$Y^* = M(\bar{X}, \overline{\vartheta}) + \delta(\bar{X}) + \varepsilon, \varepsilon \sim N(0, \sigma^2), \tag{1}$$

where $\delta(\bar{X})$ is the model discrepancy and ε is the aleatoric uncertainty or the process noise, represented as a zero mean Gaussian white noise.

3.1. Optimization-based calibration

OBC is widely use in engineering applications thanks to its straightforward implementation and the reduced computational burden with respect to stochastic update or KOH. The main idea is to define a metric representing the difference or the distance between the simulated and the real data and, then, to employ an optimization algorithm to identify optimal $\overline{\vartheta}$ which minimizes such metric (Lee et al., 2019b). in this work, we employ a Genetic Algorithm, which is a meta-heuristic evolutionary approach inspired by the laws of biological evolution (Katoch et al., 2021). They make use of evolutionary operators, such as recombination, crossover and mutation, to evolve a population of possible solutions objective of maximizing the optimization metric (Yoshimura et al., 2019). We here consider the root mean squared error (Singla et al., 2022), among the monitored and the simulated telemetries. In order to avoid the local minima and to check the robustness of the results, ten runs of the GA are performed and the mean of the resulting $\overline{\vartheta}$ is considered.

3.2. Stochastic model update

Stochastics model update inherently addresses model uncertainties by threating the configurable parameters as random variables, each with an associate probability distribution. Initially, prior distribution with incomplete knowledge (i.e. epistemic uncertainty) are considered; then, monitoring data are used to update and reduce the epistemic uncertainty and assessing the posterior distribution of the parameters. The Bayesian updating is based on the Bayes' Theorem:

$$P(\overline{\vartheta}|Y^*) = \frac{P_L(Y^*| \overline{\vartheta}) * P(\overline{\vartheta})}{P(Y^*)}, \tag{2}$$

where $P(\overline{\vartheta})$ is the prior distribution of the calibrating quantity $\overline{\vartheta}$, $P(\overline{\vartheta}|Y^{*})$ is its posterior distribution, $P_L(Y^{*}|\ \overline{\vartheta})$ of is the likelihood function, i.e., the probability of the monitoring values, given the configural parameters; and $P(Y^{*})$ is normalization factor, which guarantees the integration of the posterior distribution equal to one. The significance of the likelihood function is twofold. Firstly, it serves as the criterion for sample selection in each Markov chain within the MCMC algorithm. Secondly, it incorporates information pertaining to both the current measurements and the parameters slated for calibration. The diverse formulations of the likelihood, accounting for different levels of uncertainty information, play a pivotal role in determining whether the overarching model updating process is stochastic or deterministic. In this work we assumed the observations to be identically and independently distributed (i.i.d.), following a Gaussian distribution with mean given by the computer model and standard deviation σ. We, therefore, use the following log-likelihhod:

$$P_L(Y^{*}|\ \overline{\vartheta}) = \log\ (\prod N(y_i^{\overline{\vartheta}}, \sigma^2)). \quad (3)$$

We use a Markov Chain Monte Carlo (MCMC) method to sample from the posterior distribution. Specifically, we adopt the No U-turn sampler (NUTS) algorithm, an extension of the Hamiltonian Monte Carlo (HMC) algorithm. The MCMC method is a sample approach that approximates the posterior distribution through a Markov chain over iteration.

4. Results

This Section summarizes the obtained results and provides a comparison among the various calibration methods.

4.1. GA

The GA described in Section 3.1. has been trained on a dataset of telemetries acquired during two consecutive orbits and is tested on a different two-orbits dataset. Figure 4 shows the results obtained in the test dataset by the calibrated simulation model. The calibration provides a good correspondence among the true and the simulated heater activations. However, the simulated temperature presents large systematic errors which result in an overall large model discrepancy.

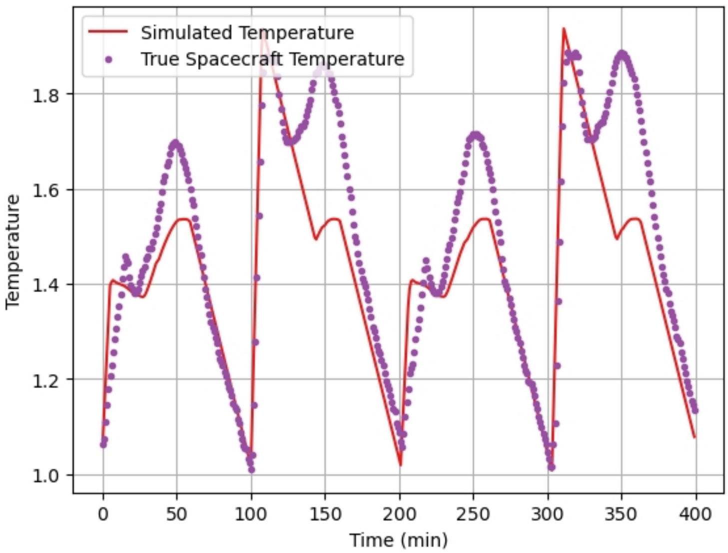

Fig.4. Comparison of simulation predictions and real data for thermistor temperature when the simulator is calibrated with a GA.

4.2. Stochastic

This section reports the results obtained using the stochastic model update described in Section 3.2. The method has been implemented considering the same training dataset used in Section 4.2. Differently from optimization-based calibration, the stochastic approach computes the posterior probability distribution of the input parameters, updated thanks to the monitoring data. Figure 5 shows, as example, the posterior probability distribution of 3 of the considered configurable parameters (named here a, b, and c). it is worth noticing that the 4 chains used in the MCMC converge for all the 3 parameters and the posterior distributions result are narrowed around the optimal value.

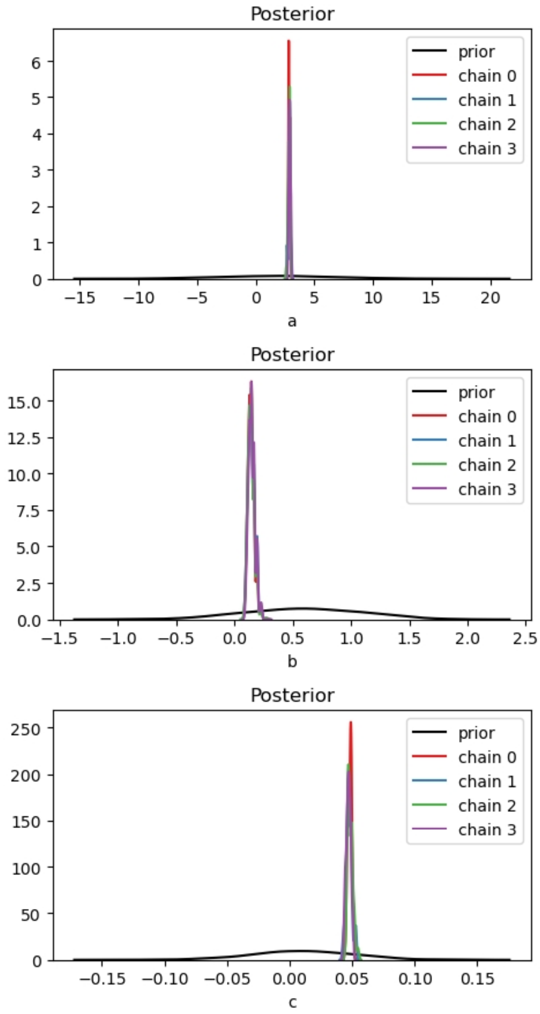

Fig. 5. Comparison prior and posterior probability distribution of 3 of the considered configurable parameters for the 4 chains used in the MCMC.

The identified posterior of the configurable parameters are, then, propagated through the model, along with the computed aleatoric uncertainty ε. This results in a probability distribution of the simulation model output. Figure 6 shows the mean temperature and the 95-confidence interval CI and their comparison with the real data. Notice that, given the large model discrepancy, the 95 percentile results broad and imprecise. Notice that the approach assumes the model discrepancies to be mean-zero and independent and identically distributed, and, therefore, the systematic errors are accounted for. Then, to assess the results with respect to the simulated heater status, 1000 simulations have been generated from the posterior distribution and compared with the monitoring data. The comparison is also displayed in Figure 6.

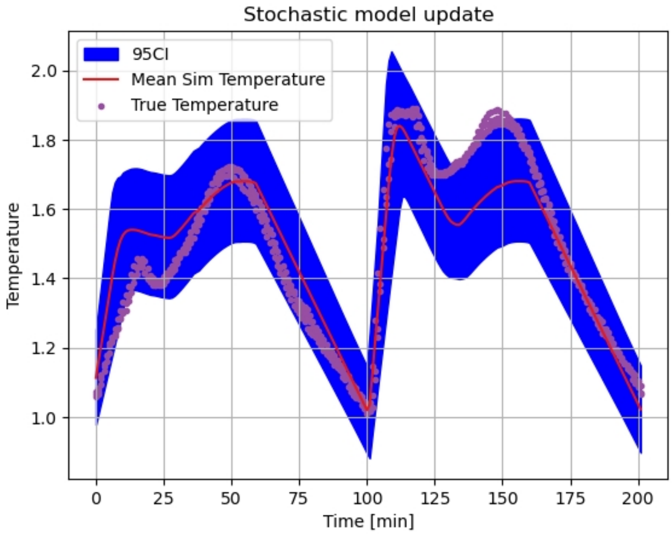

Fig. 6. Comparison of simulation predictions and real data for thermistor temperature for the stochastic model update.

5. Comments

This Section provides a quantitative comparison of the various calibration approaches presented in this work. More in details, the accuracy of the calibrated simulations is assessed by computing the *i*) Root mean squared error (RMSE) (Singla et al., 2022), which provides an indication of the overall error; *ii*) the Mean Absolute Percentage Error (MAPE) (de Myttenaere et al., 2016), which express the error as a variation from the actual value; and *iii*) the Prediction Interval Coverage Probability (PICP)(Wang, 2008) which assess the quality of the confidence intervals, and, therefore, the robustness of the computed uncertainty.

Table 1 reports the comparison of the metrics for each calibration approach. For the GA, the metrics are calculated considering the optimal configurable parameters, while the other approaches consider the mean value obtained by propagating the posterior distribution. It is worth noticing that the stochastic approach provides credible confidence intervals, which is expressed by the PICP close to 95. Moreover, it enhances the RMSE and the MAPE of the simulated temperature with respect to the GA.

However, the large confidence interval is due to the large systematic error or model discrepancy which cannot be modeled solely by the stochastic update approach. In this light, future work shall consider approaches for the modelling of the error along with the calibration of the parameters.

Table 1. methods results.

Method	Temperature RMSE	Temperature MAPE
GA	0.1346	0.061
Stochastic update	0.1014	0.054

6. Conclusions

This paper tackles the use of advanced methods for calibrating operational simulation models of flying spacecraft. The work compares optimization-based calibration and stochastic model update, and investigates the effect of model discrepancy on the different approaches.

The effectiveness of the approach is demonstrated by its application to a real flying Earth observation satellite. The results show *i*) the inability of the optimization based and stochastic update approaches in dealing with large model discrepancies; and *ii*) the capability of the stochastic and approach in providing credible confidence intervals, and, therefore, of representing the uncertainty in the predictions.

Future work lies on the implementation of approaches to combine stochastic model update and methods to model simulations errors and discrepancies.

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