18th International Conference on Space Operations, Montreal, Canada, 26 - 30 May 2025.

A Digital Twin Solution for Solar Arrays Degradation Assessment and Power Production Prediction: Application to ESA Cluster Mission

Federico Antonello[a]*, Daniele Segneri[b], James Eggleston[c], Klara Widegård[d], Carlo Sgorlon Gaiatto, Beatriz Abascal Palacios, Anna Schiavo, Bruno Sousa, Mauro Bartesaghi, Jan Maass, Aniris Inojosa

[a] *European Space Operations Centre, European Space Agency, Robert-Bosch-Str. 5, 64293, Darmstadt, Germany, Federico.antonello@esa.int*
[b] *European Space Operations Centre, European Space Agency, Robert-Bosch-Str. 5, 64293, Darmstadt, Germany, Daniele.segneri@esa.int*
[c] *European Space Operations Centre, European Space Agency, Robert-Bosch-Str. 5, 64293, Darmstadt, Germany, James.eggleston@esa.int*
[d] *European Space Operations Centre, European Space Agency, Robert-Bosch-Str. 5, 64293, Darmstadt, Germany, Klara.widegardd@esa.int*
* Corresponding Author

Abstract

Precise modeling and simulation (M&S) of the degradation of spacecraft solar array power is crucial for mission planning, assessing remaining useful life, and extending operational lifespan. A relevant case is the Cluster spacecraft fleet, launched in and managed at the European Space Operation Centre (ESOC). The fleet's solar arrays have undergone significant degradation due to space radiation, posing challenges to regular operations and mission planning. However, the current models have shown limitations in effectively representing the substantial decrease in power generation over the spacecraft's extended operational life.

To address these challenges, this study presents a Digital Twin (DT) based strategy to model the degradation of solar arrays and offer reliable predictions of their power output. The proposed DT solution leverages simulation models, monitoring data, and computational tools. It includes i) a simplified physics-based model, ii) a Bayesian calibration framework that accommodates various uncertainty sources and utilizes domain-specific knowledge and monitoring data, and iii) machine learning algorithms in order to provide robust model parameters calibration and precise power production forecasts. The results demonstrate the efficacy of the proposed approach in providing accurate projections of the power evolution of the Cluster solar array.

Keywords: Digital Twins, Solar Arrays Degradation, Spacecraft Operations, Advanced Simulations, European Space Agency

1. Introduction

In the space industry, modeling and simulation (M&S) tools are essential throughout the lifecycle of a spacecraft, supporting specification, design, verification, and operations while reducing risks and costs [1]. High-fidelity M&S tools are crucial for mission planning, anomaly detection, and remaining useful life assessment, paving the way for Digital Twin Spacecraft (DTSC) solutions [2]. A relevant example is the precise M&S of spacecraft solar array power degradation, which is crucial for mission planning, evaluating remaining operational life, and extending mission duration. A notable case is the European Space Agency's (ESA) Cluster spacecraft fleet, launched in 2000 and managed by the European Space Operations Centre (ESOC) [3]. Over time, exposure to space radiation has significantly degraded its solar arrays, posing challenges for routine operations and mission planning [4]. However, existing physics-based and data driven models have struggled to accurately capture the substantial decline in power output over the spacecraft's extended lifespan [2].
In this light, at the European Space Agency (ESA), particularly at the European Space Operations Centre (ESOC), DTSCs are gaining attention for their potential to enable high fidelity simulation capabilities, enhanced mission situational awareness, procedure validation, autonomous operations, and predictive maintenance. A key aspect of a DTSC is the presence of physics-based or data-driven simulation models with configurable parameters that must be calibrated to closely characterize the behavior of the real system [1]. Model calibration is the process of estimating model parameters to improve the agreement between model predictions and experimental observations. Approaches

for model calibration can be classified as manual or automated. Automated calibration allows continuous, and potentially real-time, updating of the virtual replica with respect to its physical counterpart. Optimization-based methods are common for automated model calibration, relying on algorithms to minimize a cost function that quantifies the difference between observed data and model outputs [2]. Examples include population-based metaheuristic optimization algorithms, widely used in the space industry for their ability to handle high dimension and highly non-linear optimization problems. However, optimization-based calibration methods produce only a single estimate, can become trapped in local minima, be influenced by noise in the data, do not quantify the uncertainty associated with the calibrated model, impacting the reliability of model predictions [5].

Model uncertainty is classified into two types: aleatory (inherent randomness) and epistemic (lack of knowledge) [6]. Inverse uncertainty quantification (UQ) characterizes and quantifies the uncertainty of simulation models based on observations [7]. This work proposes a Bayesian calibration framework validated using a physics-based model describing solar array degradation and power generation of ESA's Cluster spacecraft. The DBC method accounts for model parameter and observation uncertainty, while the KOH method includes a bias term modeled using a GP to account for model form uncertainty [8]. This work introduces a systematic framework for robust calibration and UQ of a predictive physics-based model for solar array power under degradation, improves the robustness of results compared to previous optimization-based calibration, and validates the framework using real data from a flying spacecraft.

2. Case Study: ESA Cluster Mission

The proposed Bayesian calibration framework is utilized for the European Space Agency's (ESA) Cluster mission to refine a predictive physics-based model for solar array power degradation [2]. The Cluster mission comprises four spacecraft (CLU1, CLU2, CLU3, and CLU4), whose solar arrays have experienced significant deterioration due to exposure to space radiation [3]. This degradation resulted from intense solar particle events between 2000 and 2004, as well as crossings of the inner Van Allen belt from 2008 to 2013, creating challenges for routine operations and mission planning. By mid-2023, as the spacecraft re-entered the inner Van Allen belt, their power generation capacity declined even further.
In previous research [2], an evolutionary algorithm was employed to calibrate the physics-based model, yielding promising results. However, discrepancies remained between the model's predictions and observed data due to simplifications in the model and noise in the measurements. Additionally, the approach did not provide credible intervals for predictions—an essential component for robust mission planning. As a result, a calibration framework incorporating uncertainty quantification (UQ) is necessary to enhance the reliability of solar array degradation forecasts, enabling accurate assessments of the spacecraft's remaining operational life.

3. Monitoring data

The characteristics and units of the monitoring data are summarized in Table 1. The data consist of time-series measurements, with the exception of radiation fluence, which have been processed by averaging two-hour monitoring samples centered around apogee crossings. This approach helps mitigate the albedo effect observed at perigee. The dataset spans a 23-year period, from 2001 to the end of 2023. Further details regarding data characteristics and processing are available in [2]. However, due to confidentiality constraints, the monitoring data used in this study cannot be disclosed.

Table 1. Monitoring data types and their units.

Data type	Unit of measurement
Distance Sun-spacecraft (DSS)	Astronomical unit [AU]
Solar array temperature (SAT)	Degree Celsius [°C]
Solar aspect angle (SAA)	Degree [°]
Solar array power (SAP)	Watt [W]
Radiation fluence	1 MeV electron equivalent fluence [count/cm^2]

Figure 1 illustrates the solar array power generation trends for CLU2 from 2001 to 2023. The monitoring data exhibit seasonal oscillations, influenced by the spacecraft's varying distance from the Sun, as well as long-term degradation trends resulting from cumulative radiation damage to the solar cells. The primary goal of the simulation model is to forecast the future evolution of solar array power generation.

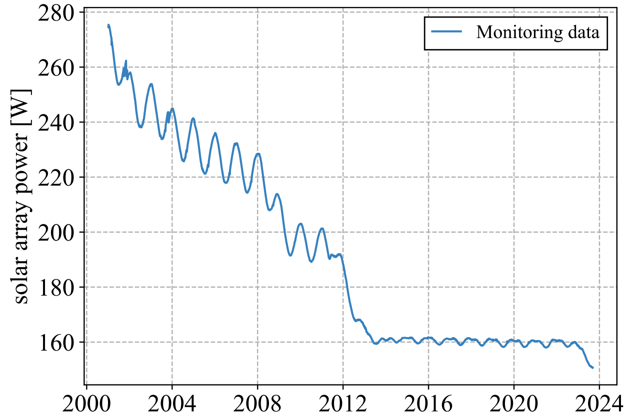


Fig. 1. Evolution of the power generation by CLU2 solar arrays at apogee.

4. Physics-based model

We consider the following explicit solar cell model depending only on the characteristic points of the I-V curve [2]:

$$I_{\text{cell}} = I_{\text{sc}}\left[1 - C_1\left(\exp\left(\frac{V_{\text{cell}}}{C_2 V_{\text{oc}}}\right) - 1\right)\right] \quad (1)$$

Here, V_{cell} represents the fixed cell driving voltage calculated as the main bus voltage (MBV) divided by the number of series-connected cells. The parameters C_1 and C_2 are defined in [2] as well as I_sc, I_mp, V_oc, V_mp correspond to the short-circuit current, maximum power current, open-circuit voltage, and maximum power voltage, respectively, at fixed environmental conditions. Additionally, he dependencies of the characteristic points to irradiance (G), temperature (T) and fluence (ϕ).

In this light, the SAP is calculated with the following model:

$$\text{SAP} = \text{MBV}\ I_{\text{cell}}(G_0, \text{SAT}, \phi)\ N_{\text{p}} \frac{G_{\text{s}}}{G_0}\left(\frac{1\ \text{AU}}{\text{DSS}}\right)^2 \sin(\text{SAA})\frac{1}{\pi} \quad (2)$$

where $I_{\text{cell}}(G_0, \text{SAT}, \phi)$ is assessed with the equations detailed in [2], N_{p} is the number of parallel-connected solar cells; G_{s} the solar constant [2]. The term $1/\pi$ represents the equivalent illuminated surface ratio, calculated by dividing the projection of the spacecraft's cylindrical surface onto a plane perpendicular to the incident Sun vector by the total area covered by the solar array.

5. Results

We present and analyze the results specifically for CLU2 as representative example, though the same observations apply to the other two spacecraft. The framework's performance is assessed using the root mean square error (RMSE) for both the training and test sets, calculated based on the mean of the posterior estimates of the model parameters.
Notably, discrepancies are observed between the DBC method's results and the solar array power (SAP) values recorded during the spacecraft's first crossing of the inner Van Allen belt, as illustrated in the figures below. To ensure a fair comparison with the KOH method, RMSE values for the training set are computed using only post-2013 data to exclude large residuals. These discrepancies likely stem from simplifications in the physical model and inaccuracies in fluence estimation during the initial crossing of the inner Van Allen belt—an issue specifically addressed by the

KOH method in this study. Additionally, the framework's performance is compared to previous work that utilized an optimization-based calibration approach, specifically the differential evolution (DE) algorithm [2].

Table 4 presents the mean and 95% confidence intervals (CI) for the posterior estimates of all calibrated parameters for both the DBC and KOH methods in the case of CLU2. Furthermore, Figure 2 compares the prior and posterior distributions of three key model parameters under the KOH method. For $\phi_{0,I_{sc}}$, the prior and posterior distributions closely align, indicating that the data is consistent with initial assumptions. However, for $\rho_{S_{\mathrm{inc}}}$ and σ the posterior distributions peak at different values than their priors, signifying updated parameter knowledge after incorporating the data.

Figure 3 illustrates SAP predictions based on the posterior predictive distribution, focusing on the period from 2008 to the end of 2023 for better visualization. Both the DBC and KOH methods yield calibrated models that align well with the monitoring data for both the training and test sets. The DBC method achieves an RMSE of 0.584 W in the training set and 0.752 W in the test set, while the KOH method outperforms it with RMSE values of 0.370 W and 0.696 W, respectively. The KOH method also demonstrates significant improvements over the DE approach, which produced results comparable to the DBC method but lacked uncertainty quantification for its predictions.

Another key finding is that the 95% CI width for SAP predictions is considerably narrower for the KOH method compared to the DBC method in both the training and test sets. Moreover, approximately 92% of the test data falls within the 95% CI for the KOH method, while the DBC method captures all test data within its intervals. This behavior can be attributed to two factors. First, the DBC method produces a posterior estimate for σ that is higher and has a larger CI than that of the KOH method. This is because the DBC method's noise term absorbs part of the model discrepancy that is not captured by the uncertain model parameters, particularly around 2012. Second, although the KOH method produces posterior estimates for model parameters similar to the DBC method, it effectively corrects model discrepancies through the incorporation of a Gaussian Process (GP). This allows for a more precise differentiation of uncertainty sources, leading to a lower and more realistic posterior estimate for σ.
However, when forecasting future SAP values at apogee passes, the KOH method predicts a faster increase in the 95% CI width over time compared to the DBC method. This is due to the assumption that CLU2 will absorb significant radiation while crossing the inner Van Allen belt, leading to fluence values outside the training dataset. Consequently, due to the properties of the exponentiated quadratic kernel, SAP predictions under the KOH method exhibit increasing uncertainty over time—an expected outcome when extrapolating beyond the training region. The key advantage, however, is that this uncertainty can be quantified, resulting in more robust and reliable SAP forecasts.
Finally, despite using only a subset of the available training data to reduce the computational burden of the KOH method, the GP model demonstrates strong generalization in the test region without overfitting.

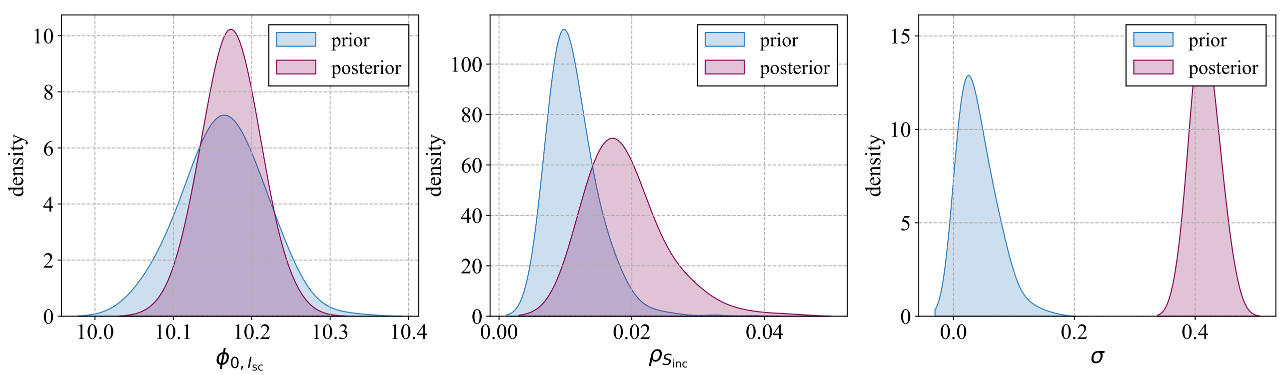
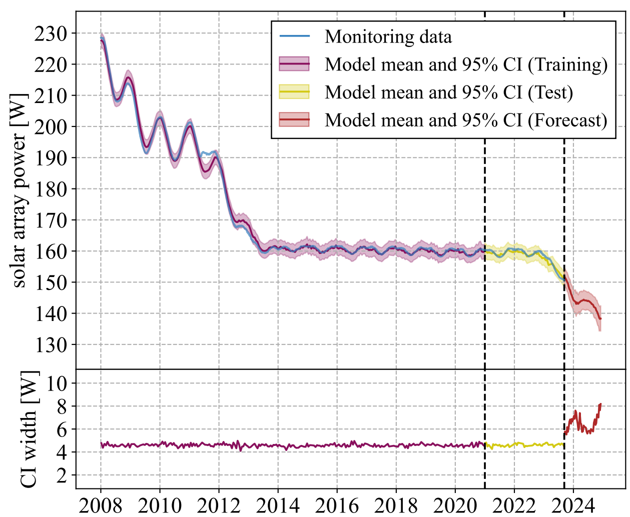


Fig. 2. Comparison of the posterior and prior distributions of three model parameters for the KOH method, in the case of CLU2.

Table 4. Mean and 95% CI of the posterior estimates for all the calibrated parameters and for both the DBC and KOH methods, in the case of CLU2.

	DBC		KOH	
Parameter	**Mean**	**95% CI**	**Mean**	**95% CI**
$\alpha_{I_{sc}}$ [mA/°C]	0.948	[0.867; 1.027]	0.934	[0.856; 1.013]
$\alpha_{V_{oc}}$ [mV/°C]	-2.721	[-2.836; -2.612]	-2.715	[-2.835; -2.597]
$C_{I_{sc}}$ [ ]	0.06729	[0.06652; 0.06811]	0.06748	[0.06668; 0.06843]
$C_{V_{oc}}$ [ ]	0.550	[0.525; 0.573]	0.549	[0.526; 0.575]
$\phi_{0,I_{sc}}$ [count/cm^2]	1.462×10^{10}	[1.281; 1.656]$\times10^{10}$	1.496×10^{10}	[1.281; 1.750]$\times10^{10}$
$\phi_{0,V_{oc}}$ [count/cm^2]	3.85×10^{15}	[3.60; 4.09]$\times10^{15}$	3.86×10^{15}	[3.59; 4.16]$\times10^{15}$
$\rho_{S_{inc}}$ [ ]	-	-	0.0190	[0.0113; 0.0321]
$\rho_{\Delta SAT}$ [°C]	-	-	4.58	[2.82; 7.33]
ρ_{ϕ} [count/cm^2]	-	-	4.35×10^{14}	[3.47; 5.28]$\times10^{14}$
η [W]	-	-	1.15	[0.95; 1.37]
σ [W]	1.15	[1.01; 1.32]	0.42	[0.37; 0.46]



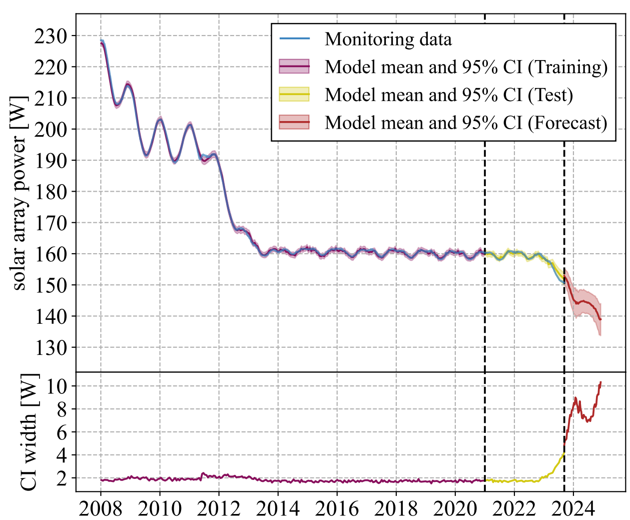


Fig. 3. Results obtained for CLU2 with the DBC (left) and KOH (right) methods. SAP monitoring data are compared with the predictions of the calibrated model on both the training and test sets. Forecasts for SAP are also shown. The different data sets are visually separated by vertical dashed black lines.

4. Conclusions

A Digital Twin (DT) relies on simulation models that must be carefully calibrated to accurately represent the behavior of the actual system. Additionally, the calibration process should incorporate uncertainty quantification (UQ) to ensure precise and reliable model predictions. In this context, we propose a Bayesian framework for model calibration under uncertainty and apply it to ESA's Cluster spacecraft fleet.

The results indicate that:

i) Both the DBC and KOH methods enhance Cluster SAP modeling compared to previous optimization-based calibration approaches, as they provide comparable SAP predictions while also accounting for uncertainty.

ii) The Gaussian Process (GP) effectively refines the physics-based model, leading to more realistic credible intervals for SAP predictions.

iii) The KOH method successfully corrects artificially introduced strong model discrepancies, demonstrating its robustness and effectiveness for model calibration under uncertainty.

For future research, one potential direction is exploring sequential Bayesian techniques, such as particle filtering, to enable continuous and real-time calibration of the simulation model. Additionally, further investigation will focus on assessing the impact of input data uncertainty on forecasting accuracy.

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] C.P. Escoubet, M. Fehringer, M. Goldstein, The Cluster mission, Ann Geophys 19 (2001) 1197–1200.

[4] R. Letor, J. Marie, S. Sangiorgi, H. ~J. Volpp, 10 Years Evolution Of Cluster Solar Arrays And Forecasting Their Degradation After Entering The Inner Radiation Belt, in: 9th European Space Power Conference, 2011: p. 107.

[5] 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

[6] 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.

[7] 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).

[8] 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.