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Surrogate Model-Based Calibration of a Flying Satellite Battery Digital Twin

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At the European Space Agency (ESA), Modeling and Simulation (M&S) plays a fundamental role during the lifetime of a spacecraft, being used from the design phase to the testing and during operations in space. In particular, the European Space Operation Center (ESOC) makes use of M&S tools for various tasks such as monitoring and control, procedure validations, training, maintenance, planning and scenarios investigation, to mention a few. Moreover, moving towards the digital twin paradigm, simulation models are gaining growing attention with the expectation to provide ultra-fidelity capabilities to represent the live status and dynamics of flying spacecraft. In this respect, M&S tools embed general physics-based models and disciplines characterized by configurable parameters which have to be calibrated in order to mimic the behavior of the actual flying spacecraft. However, their calibration requires a large number of simulations which are unfeasible to be obtained through computationally expensive high-fidelity simulation models. In this light, the present work proposes the use of a surrogate model-based approach for the calibration of simulation models of spacecraft. The approach integrates a computationally inexpensive deep-learning-based surrogate model. The approach's effectiveness is shown by its application to real flying Earth observation satellite data and simulation models.

Keywords: Spacecraft, European Space Agency (ESA), Modeling and Simulation, Calibration, Deep-learning, Artificial Intelligence, Surrogate Model, Spacecraft, Satellite Battery, Digital Twin.

1. Introduction

The use of Modeling and Simulation (M&S) tools plays a vital role in the design, testing, and operations of European Space Agency (ESA) spacecraft (Crues et al., 2022). In particular, the European Space Operations Center (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). Also, M&S is recently gaining traction, with the expectation of providing ultra-fidelity capabilities to represent the live status and dynamics of flying spacecraft and leading, eventually, to the development of spacecraft digital twins, which are dynamic and self-evolving digital replicas of spacecraft representing their exact status and any given point in time and able to enable diagnostics, prognostics, decision making and automation (Thelen et al., 2022). Digital twin-based simulation tools incorporate general physics-based models and configurable parameters that need to be calibrated to mimic the behavior of actual flying spacecraft (Ward et al., 2021). Thus, by adjusting the simulation model's parameters to match the real-world system's behavior, model calibration allows *i*) creating of more accurate and reliable digital twins, ensuring that simulation models faithfully reflect the behavior of the real-world system; *ii*) identifying and resolving discrepancies between the simulated and real-world behavior of a spacecraft, avoiding unexpected results and costly errors, which can have severe consequences for spacecraft missions; *iii*) adapt M&S tools to simulate the spacecraft behavior under a wide range of conditions, by optimizing the configurable parameters reflecting the environmental and condition situation (Ward et al., 2021; Tian et al., 2022).

The calibration of complex high-fidelity models simulating spacecraft behavior and operations, such as digital twins, rely on computationally expensive high-fidelity simulation models; therefore, their direct use for calibration techniques requiring a large number of simulations is unfeasible (Sapkota et al., 2022). In this light, the use of surrogate models, which are simplified approximations of more complex simulation models, has gained attention in recent years as they have shown to provide efficient and accurate alternatives to traditional methods for the calibration of complex models (Antonello et al., 2023; Radaideh & Kozlowski, 2020). Surrogates approximate the response surface of the simulation model in a lower-dimensional space, allowing for faster and computationally inexpensive simulations (Benner et al., 2015). Concerning model calibration, surrogates have been adopted in (Sapkota et al., 2022) to calibrate the configurable parameters of a digital twin. They used a polynomial regressor to surrogate a complex and time-consuming simulation model of cathodic protection for underwater metallic infrastructures. The developed surrogate is then used in an exploratory search to find the optimal set of configurable parameters. Similarly, (Song et al., 2022) proposed an online calibration of a digital twin of a nuclear power plant. They used digital twin simulated data to develop an ANN-based surrogate model, which is then used to find the optimal set of configurable parameters reducing the error in the difference between digital twin simulations and experimental data. Finally, (Tian et al., 2022) presented the use of an ANN surrogate of an aero propulsion system simulation and a reinforcement learning framework to calibrate key model parameters. It is worth noticing that the works mentioned above provide successful examples of surrogate models for complex simulation model calibration. However, up to the authors' knowledge, such approaches have not yet been investigated for the calibration of simulation models of real flying spacecraft.

This work proposes a method for using surrogate models to calibrate complex simulation models of spacecraft. The method used DNN-based surrogate models, which are trained to replicate spacecraft simulations models and have been selected for their proven advantages with respect to ROMs and other ML-based surrogates (Tripathy & Bilionis, 2018).

The effectiveness of the proposed method is shown by means of its application to a simulation model and real data of a battery of a flying Earth observation satellite operated at ESOC.

The remainder of the paper is as follows: Section 2 presents the spacecraft battery case study. Section 3 describes the proposed method and introduces the considered DNN and GA. Section 4 presents and discusses the obtained results. Finally, Section 5 gives some conclusions.

2. Earth Observation Satellite Battery

The monitoring and study of the Earth's environment, climate, and natural resources are essential, and Earth observation satellites play a crucial role in this. These satellites come equipped with a variety of sensors and instruments that, while orbiting around Earth, gather data on several environmental factors such as temperature, humidity, vegetation cover, and ocean salinity (Melloni et al., 2018). Generally, Earth-orbiting spacecraft utilize Electrical Power Systems (EPS) equipped with both solar array power generation and rechargeable batteries for storing energy. The solar arrays supply power to the spacecraft bus and payload subsystems while also charging the batteries when exposed to sunlight. On the other hand, during orbital periods when the spacecraft is in eclipse, the rechargeable batteries power all the subsystem loads on the spacecraft (Dalton et al., 2022). In this work, we consider a flying Earth-orbiting satellite battery and the corresponding simulation model to show the capabilities of the proposed calibration approach.

The basic parameters usually considered to develop a simulation model of a battery are the capacity C, voltage V, current I, temperature T, state of charge SoC, load L and internal resistance R_{in}, to mention a few (Acharya et al., 2019). Notice that, among the various configurable parameters of the above mathematical models, the capacity, C, is usually considered of particular interest for its ability to drive the battery behaviour and being associated to its degradation (Dominguez-Jimenez et al., 2020). For such reasons, in this work, the capacity, C, is the parameter to be calibrated by the proposed approach.

For the satellites operated at ESOC, the simulation model of the battery is embedded in a complex operational simulator representing all the spacecraft subsystems and also mimicking the onboard computer and running an image of the onboard software (OBSW), which lead the response of the satellite to telecommands and its behavior under the possible operating conditions and modes. 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, running thousands of long simulations is unfeasible and surrogate models are needed to enable the use of genetic algorithms and other optimization tools.

Notice finally that, for confidential and proprietary reasons, further details on the mathematical models used in the simulation model 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.

3. Proposed method

This Section describes *i*) the mathematical formulation of the problem, and *ii*) the developed DNN-surrogate model.

3.1. Mathematical formulation of the problem and simulated data generation

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, 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 configurable parameters of the simulation model, $Y = [\overline{y_1}, \overline{y_2}, \dots, \overline{y_T}] \in R^{TxN}$ the model output, and $\overline{y_t} = [y_{t,1}, y_{t,2}, \dots, y_{t,N}] \in R^N$ the set of simulated variables at a time *t*. In this light, the simulation model calibration consists in the identification of the optimal set of configurable parameters $\overline{X'}$ which minimizes the following absolute error (Eq. 1) between the simulated time evolution of the variable of interest Y and the corresponding telemetry observations Y^*:

$$Err(Y^*, Y) = \sum_{t=1}^{T} \left(\sum_{i=1}^{N} abs(y_{t,i} - y_{t,i}^*) \right) \qquad (1)$$

3.3. DNN-based surrogate model

The development of the proposed surrogate model requires to *i*) define the simulation model output variables of interest, *ii*) identify the set of configurable parameters and their possible range of values during operations, *iii*) sample a sufficient number of sets of configurable variables and perform the corresponding simulation, in order generate a dataset to train, validate and test the surrogate model, *iv*) determine the input-output relationship to be modeled by the DNN and select the network architecture and hyperparameters, and *v*) train, validate and test the DNN.

Table 1 reports the considered configurable parameters, with their range of values, and output parameters. Notice that the values and their ranges have been masked and the unit of measures not given for confidential reasons.

Table 1. Simulation model input and output parameters

Configurable variables		Range		Output variables	
x_1	Initial State of Charge (SoC)	[0-100]		y_1	Current (I)
x_2	Battery Capacity (C)	[0.5-2]		y_2	Voltage (V)
x_3	Load (L)	[-3,3]			

Then, 250 sets of configurable variables have been sampled through the Latin Hypercube Sampling (LHS) strategy (Helton & Davis, 2003) and the corresponding simulations performed.

Then, in order to calibrate the capacity, C, we here develop a DNN which, given the values of voltage, V_t, capacity, C, load, L, at a given time t, and the expected current at the $t+1$, I_{t+1}, predicts the voltage at the $t+1$, V_{t+1}. Table 2 gives the details of the considered DNN architecture, along with the hyperparameters, which have been chosen through a trial-and-error process. The available data has been scaled using a traditional min-max scaler, and the models have been trained on 70% of the simulations while being validated on 15% to calibrate the hyperparameters. The remaining 15% of the simulations have been used for testing. The training process has been carried out for 1000 epochs, and a callback method has been utilized to select the best-performing network on the validation dataset. The Adam optimizer, a first-order gradient-based optimizer that utilizes adaptive estimates of lower-order moments, has been chosen for its ease of implementation and computational efficiency (Kingma & Ba, 2015). The Exponential Linear Unit (ELU) activation function has been utilized due to its characteristic of decreasing bias by driving the mean activation towards zero, which has been shown to be effective when compared to other non-linear activation functions (Pedamonti, 2015).

Table 2. DNN architecture and hyperparameters

Number of layers	4
Number of neurons per layer	64, 32, 32, 2
Optimizer	Adam
Activation function	Elu
Batch size	32
Learning rate	0.001
Maximum training epochs	2000

Figure 1 compares the voltage values of a simulation and the corresponding values reconstructed by the developed surrogate model for four different simulations of the test set. It is worth noticing the good agreement between the two models which is also proven by an overall Mean Squared Error (MSE) of $1.5 \cdot 10^{-6}$ on the scaled test set. It is worth also noticing that each simulation run requires 2,040 seconds for a total of 510,000 seconds to generate the entire dataset, whereas the training of the DNN requires 943 seconds on an Intel core (TM) i7 CPU@ 3.6 GHz, 16 GB RAM. On the other hand, given the trained DNN, the computational time required to reconstruct the entire transient, which is the term of reference for surrogate model performances, is a few seconds.

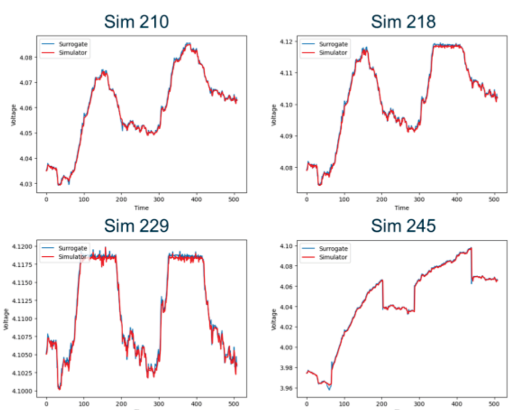

Figure 1. Comparison between the voltage values of a simulation and those reconstructed by the developed surrogate model for four different simulations of the test set.

3.4. Workflow of the proposed method.

Figure 2 summarizes the workflow of the proposed method. The first step requires the identification of the telemetries of interest and the corresponding simulation model configurable parameters which drive their evolutions in time. The second step involves the sampling the of sets of configurable variables for generating the simulations which are used in the third step to develop and train the metamodel. In the fourth step the real telemetries are acquired, and the developed surrogate model is to run tens of thousands of simulations in order to identify the optimal set of configurable variables which minimizes the difference between the simulated and the real telemetries.

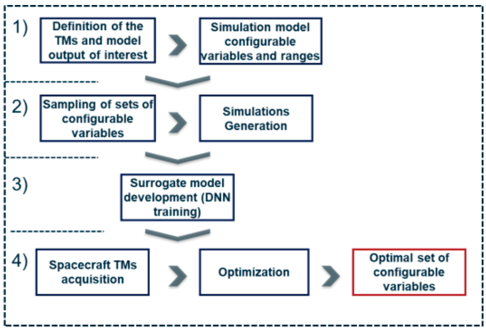

Figure 2. General workflow proposed method.

4. Results

Figure 3 shows the comparison between the voltage values monitored by the telemetries and the values reconstructed by the surrogate model before the capacity calibration and when the parameter has been calibrated. It is worth noticing the larger correspondence between the values when the model is calibrated, which highlights the effectiveness of the proposed approach.

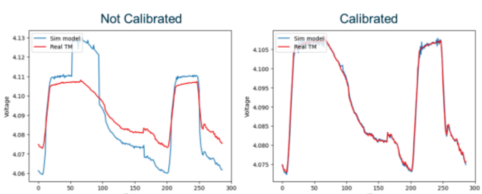

Figure 3. Comparison between the voltage values monitored by the telemetries and the values reconstructed by the surrogate model before the calibration of the capacity and when the parameter has been calibrated.

The proposed calibration approach has also been applied to datasets collected in different periods of time, in order to analyze possible degradation mechanisms and seasonal effects. In particular, a total of fifteen datasets containing telemetry data at monthly intervals have been analyzed. Figure 4 shows, for four of the considered datasets, the comparison between the voltage values monitored by the telemetries and the values reconstructed by the surrogate model. The good correspondence between the real monitored telemetries and the reconstructed values shows the capability of the proposed approach to be used to calibrate configurable parameters in different operating conditions.

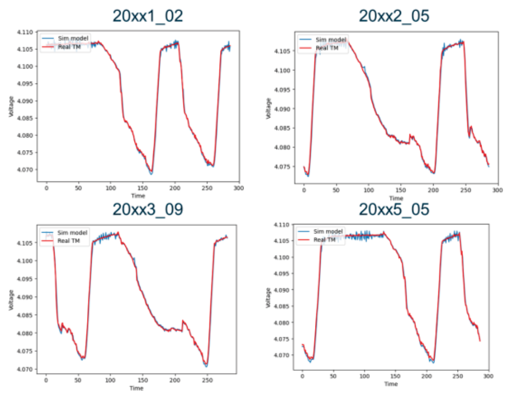

Figure 4. Comparison between the voltage values monitored by the telemetries and those reconstructed by the surrogate model for four different datasets.

5. Conclusions

The paper proposes a surrogate model-based approach for the calibration of configurable variables of spacecraft simulation models. The approach integrates a computationally inexpensive deep-learning-based surrogate model and a metaheuristic optimization algorithm to identify the optimal values of the configurable parameters. This approach is particularly relevant in the context of the digital twin paradigm, where simulation models are gaining attention with the expectation of providing high-fidelity capabilities to represent the live status and dynamics of flying spacecraft. The proposed approach offers a computationally efficient and effective solution to the computational burden requires to calibrate such high-fidelity simulation models, improving their accuracy and reliability, which is critical for the design, testing, and operations of spacecraft.

The effectiveness of the approach is demonstrated by its application to a real flying Earth observation satellite. The results show *i*) the capabilities of the approach to replicate the high-fidelity spacecraft simulation model with a computationally cheaper but accurate surrogate model; *ii*) the effective configurable parameter calibration, which improves the simulation model's adherence to actual monitored data; and *iii*) the ability of the approach to be applied to different datasets with different operating conditions, which increases its versatility and applicability.

In summary, the proposed approach offers a promising solution to the challenge of calibrating high fidelity simulation models more efficiently and effectively, with the potential to improve the accuracy, reliability and predictive capabilities of simulation models.

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