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# Hybrid Digital Twin for Satellite Attitude Control System Based on FMI Co-Simulation Technology

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## Abstract

State-of-the-art technologies, such as artificial intelligence, big data analytics, cloud computing, and Internet of Things, have greatly stimulated the development of digitization to achieve more efficient optimization, more intelligent integrated control, and lower cost. As a virtual representation of a specific physical asset, the digital twin has great potential for realizing the intelligent control algorithm of satellite. However, the digital twin of satellite attitude control system involves many disciplines, which need the interaction between physical field input and control system feedback. For each level, modeling is usually completed by its unique commercial softwares and tools, which makes cross-level model real-time integration, simulation, and testing pretty challenging. To solve this problem, this work develops a methodology for creating a multiphysics system hybrid digital twin of satellite attitude control system by combining various modeling techniques such as deep learning methods and Modelica modeling language. Firstly, the temperature field reconstruction (TFR) of the satellite surface is modeled by neural networks from limited monitoring sensors. Then, an attitude control system consisting of sensors, thruster models, and gesture controllers is developed by the multi-domain modeling language Modelica. Finally, a co-simulation method based on Functional Mock-up Interface (FMI) standard is proposed to integrate different level models, leading to successful full-digital co-simulation with time delays of less than 100ms.

## 1. Introduction

Satellite attitude control systems are fundamental to ensuring the proper orientation and stability of satellites in space. These systems enable precise pointing, stability, maneuverability, and thermal management of spacecraft by controlling various components, such as thrusters, reaction wheels, and control moment gyros. The successful operation of satellites in space and the achievement of their intended mission objectives depend heavily on the effective functioning of these attitude control systems. As the space environment grows progressively inhospitable, satellites in orbital are increasingly susceptible to external interferences, presenting substantial obstacles to their secure operation. Cosmic rays and high-energy particles have emerged as tangible hazards that jeopardize the secure operation of satellites. Conventional thermal management approaches are no longer sufficient in effectively mitigating the abrupt influx of external energy. In such circumstances, satellites must execute pragmatic attitude adjustments to prevent localized overheating.

The existing methods for in-orbit service and maintenance lack sufficient capabilities in terms of monitoring and timely response. Consequently, there is a compelling requirement for a novel approach that can effectively reflect the status and condition of satellites. The digital twin,[1] a concept that aims to establish a dynamic correlation between physical and digital space, offers substantial promise in achieving this goal. Serving as an accurate and virtual replica of the physical entity, the digital twin can effectively mirror the real-time behavior of the physical system under operational circumstances throughout its entire lifecycle.[2] This capability addresses the growing demand for resolving complexities associated with equipment health maintenance.[3]

In recent years, numerous endeavors have been made to apply digital twin technology in the aerospace industry.[4,5] Nevertheless, the studies mentioned before primarily concentrated on system-level models, neglecting the incorporation of physical field-level information. In general, physical fields encompass a vast array of valuable information

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and can serve as input to the control systems. The reconstruction of physical fields holds significant importance in the measurement and control of engineering systems.[6] Specifically, the reconstruction of the temperature field from a restricted set of observations plays a crucial role in the realm of satellite thermal management.[7] This paper focuses on establishing a hybrid digital twin (HDT) for satellite attitude control system integrating real-time temperature field sensing.

As for temperature field reconstruction, the majority of prior studies utilized numerical simulation techniques, such as the finite element method (FEM)[8] and finite difference method (FDM),[9] to compute the temperature distribution at various points or domains. Despite the capability of these numerical methods to yield accurate evaluations, they often require significant computational time, particularly when employing a highly refined mesh for achieving high precision. However, in practical engineering scenarios, such computational requirements can be impractical and cost-prohibitive. To address this challenge, utilizing surrogate models as an alternative to physics simulations has emerged as a viable option for addressing computationally intensive optimization problems and achieving end-to-end, near-real-time temperature field reconstruction. Deep neural networks (DNNs), renowned for their outstanding performance in various domains, such as computer vision, speech recognition, and natural language processing, offer a robust approach for attaining real-time predictions.[10,11]

Regarding to attitude control systems, it is a typical complex system with mechanics, electronics, thermotics, and control coupling. The existing multi-domain simulation approaches primarily rely on single-domain software, such as Ansys, Adams, and Simulink, to construct individual discipline models.[12,13] These models are subsequently solved through software interfaces to enable single-disciplinary simulation and co-simulation of certain disciplines. However, these approaches fall short of supporting comprehensive multi-system modeling and simulation, resulting in limited model reusability and scalability. Modelica, a multi-domain modeling language, has made significant strides in this aspect owing to its capabilities in supporting multi-domain unified modeling, non-causal modeling, object-oriented physical modeling, and continuous-discrete mixed modeling. These features have contributed to the notable achievements of Modelica in the aerospace area.[14,15]

In this study, we utilize deep learning and Modelica language to construct physical field-level digital twin and system-level digital twin. Subsequently, a co-simulation method based on the Functional Mock-up Interface (FMI)[16] is developed, effectively achieving cross-level information interaction.

## 2. Temperature field reconstruction

### 2.1 Mathematical modeling

This study focuses on heat source systems consisting of multiple components (namely heat sources) that generate internal heat. To simplify the analysis without sacrificing generality, the system is modeled as a two-dimensional domain where thermal conduction takes place along this domain. We expect to employ DNN to rapidly give temperature field predictions for heat source layout. The proposed methodology is validated using the volume-to-boundary (VB) heat conduction problem[17,18] as illustrated in Fig. 1. The TFR task can be formulated as the following optimization problem:

$$T^* = \arg\min_T \left( \sum_{k=1}^{m} |T(x,y) - O_k| \right) \tag{1}$$

where $T(x,y)$ is the reconstructed temperature field. The steady-state temperature field over the domain satisfies the Poisson?s equation, which can be expressed as:

$$\frac{\partial}{\partial x}\left(\lambda \frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y}\left(\lambda \frac{\partial T}{\partial y}\right) + \phi(x,y) = 0 \tag{2}$$

Boundary :

$$T = T_0 \text{ or } \lambda \frac{\partial T}{\partial \mathbf{n}} = 0 \text{ or } \lambda \frac{\partial T}{\partial \mathbf{n}} = h(T - T_0) \tag{3}$$

where $\lambda$ represents the thermal conductivity of the domain, $\phi_i(x,y)$ is the power intensity distribution function. Below the governing equation denotes three boundary conditions, including Dirichlet boundary conditions, where $T_0$ is the isothermal boundary temperature value, Neumann boundary conditions, where zero heat flux is exchanged, and Robin boundary conditions, where $T_0$ denotes the surrounding fluid temperature value and $h$ defines the convective heat transfer coefficient.

In conclusion, the TFR task can be formulated as the optimization problem Eq. 1 subject to constraints Eq. 2 and Eq. 3. This study investigates effective and efficient prediction techniques aimed at replacing the time-intensive numerical simulation process and enabling nearly real-time predictions.

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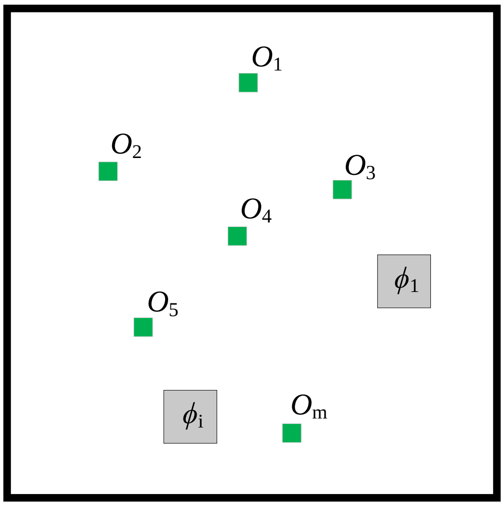


Figure 1: The illustration of the VB problem with $n$ heat source and $m$ temperature sensors in a square domain. $O_m$ denotes temperature sensor and $\phi_i$ represents $i$-th component power distribution.

### 2.2 Deep neural network

In what follows, a deep learning method based on multilayer perceptron (MLP) is employed to reconstruct the temperature field from limited observation. Fig. 2 illustrates the structure of the network. In this study, we arrange 9 sensors

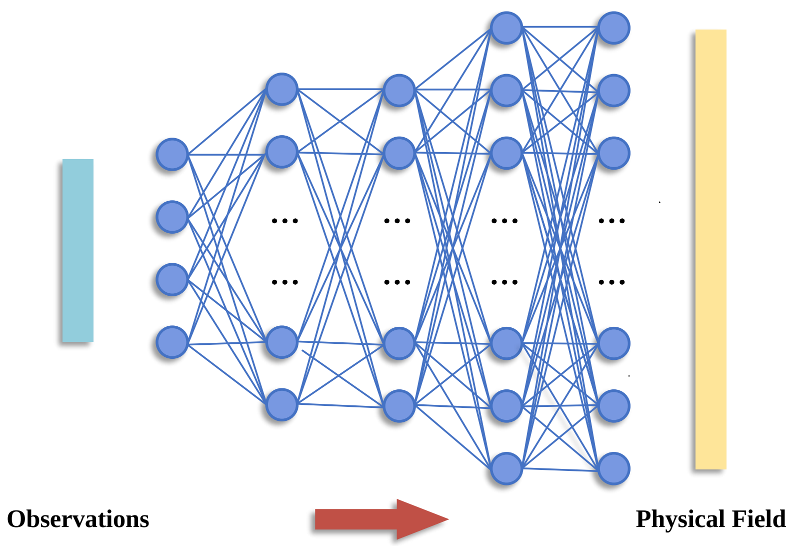


Figure 2: The structure of MLP

on a square cabin with a side length of 1.2 meter. The sensor layout is shown in Fig. 3. The structure of the MLP is set to '9-512-2048-14,400'. We split a total of 10,000 heat source layout maps into 8,000, 1,000, and 1,000 for training, validation, and testing. Chen et al.[9] proposed a variety of metrics to evaluate the neural network performance for temperature field prediction. In this paper, we adopt the following metrics, namely the mean absolute error on the entire domain (MAE) and the mean squared error (MSE),which are presented in Table 1. Fig. 3 displays two randomly selected cases from the test dataset, showcasing the corresponding reconstructed temperature fields and the associated error. Experiments prove the effectiveness of the method.

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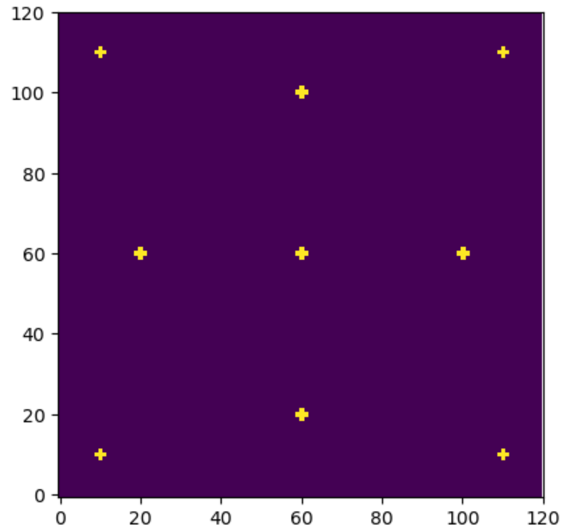
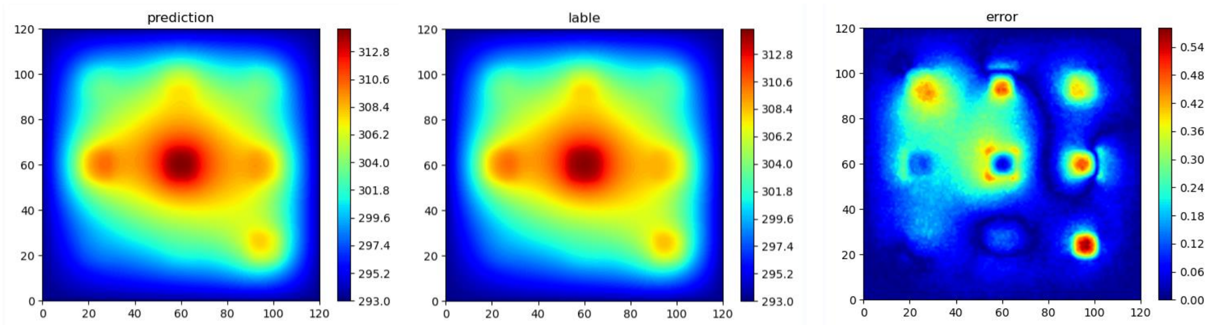
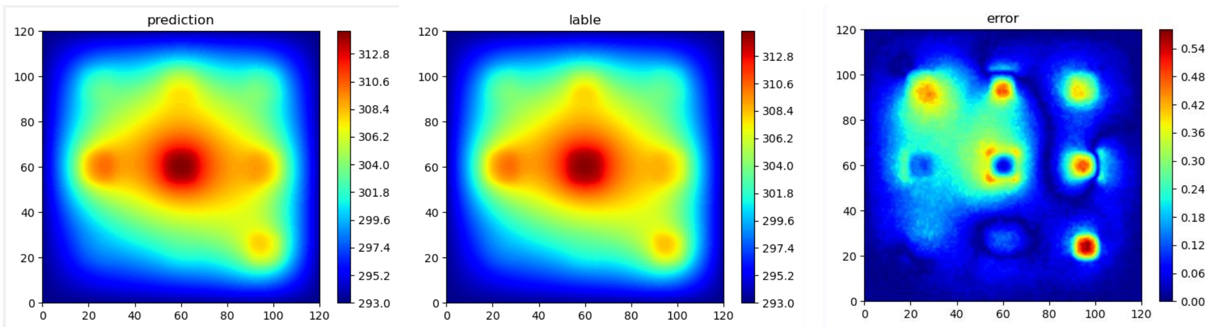



Figure 3: The layout of sensors




(a) case 1




(b) case 2

Figure 4: Two randomly selected cases of reconstruction results.

# 3. Attitude control system

## 3.1 Modelica language

Modelica is an object-oriented, equation-based, and declarative modeling language widely used in the field of physical and cyber-physical systems.[19] It provides a versatile framework for the modeling, simulation, and analysis of complex dynamic systems, including mechanical, electrical, thermal, and control systems. One of the key features of Modelica is its ability to express systems using a mix of differential, algebraic, and discrete equations in a single unified framework.

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Table 1: The performances of the MLP surrogate model.

| Network | MAE | MSE | Prediction time (s) |
|---|---|---|---|
| MLP | 0.0121 | 0.0973 | 0.000828 |

This makes it possible to model a wide range of dynamic phenomena, including transient behavior, nonlinearities, and event-driven dynamics. Another notable aspect of Modelica is its support for acausal modeling, where the connections between components are defined based on the physical relationships, rather than the specific order of execution. This leads to a more modular and flexible approach to modeling, enabling the reuse and exchange of models across different domains and applications.[20]

Modelica is supported by various modeling and simulation environments, such as Dymola, OpenModelica, and MWorks. These tools provide graphical user interfaces for model development, simulation environments for running simulations, and post-processing capabilities for analyzing and visualizing simulation results. In conclusion, Modelica is a powerful and expressive modeling language that facilitates the creation of detailed and accurate computer models of physical systems. Its versatility, modular nature, and support for acausal modeling make it a preferred choice for researchers and engineers working in diverse fields, ranging from automotive and aerospace engineering to energy systems and robotics.[21]

### 3.2 Construction of models

Based on the principles of structural hierarchy, reusability, and extensibility, the dynamics and control system of the satellite is decomposed into several components. These components include the satellite cabin, thrusters, sensors, GNC unit, and the environment, etc.

**Satellite cabin.** Fig. 5 depicts the model of the satellite cabin, which is constructed based on the Modelica standard library incorporating fundamental components. Specifically, the utilization of the well-documented multi-body dynamics library within this framework aids in reducing the modeling engineer?s time allocated to formula derivation. The satellite cabin model is constructed using building blocks, aligning with the actual physical topology of the satellite, and additionally includes the specification of the position of solar array and antennas. This model primarily accounts for the cabin?s mass and inertia attributes.

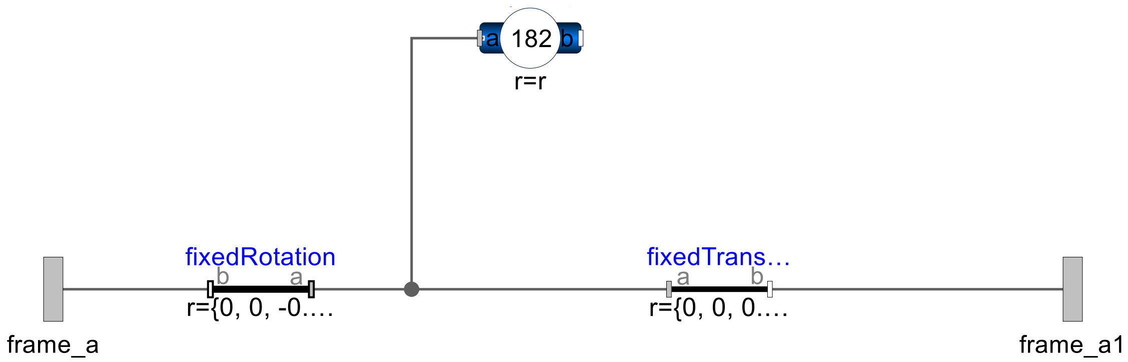


Figure 5: The satellite cabin model.

**Thrusters.** The thruster is a critical actuator for satellite attitude and orbit control. Their model encompasses various components, such as the thruster nozzle, propellant tanks, valves, and the associated control algorithms. We incorporated established physical principles and mathematical descriptions to accurately represent the behavior and performance of these components. We employ Modelica?s acausal modeling paradigm, which allowed us to seamlessly integrate the thruster model within larger satellite system models. This integration facilitated the analysis of the overall system?s performance and enabled optimizations for various mission scenarios. Fig. 6 shows the thruster model.

**Sensors.** Modelica library offers various sensor models. We can also create accurate and detailed models of satellite sensors. These models have the capability to provide real-time simulation data on attitude angles and angular velocities.

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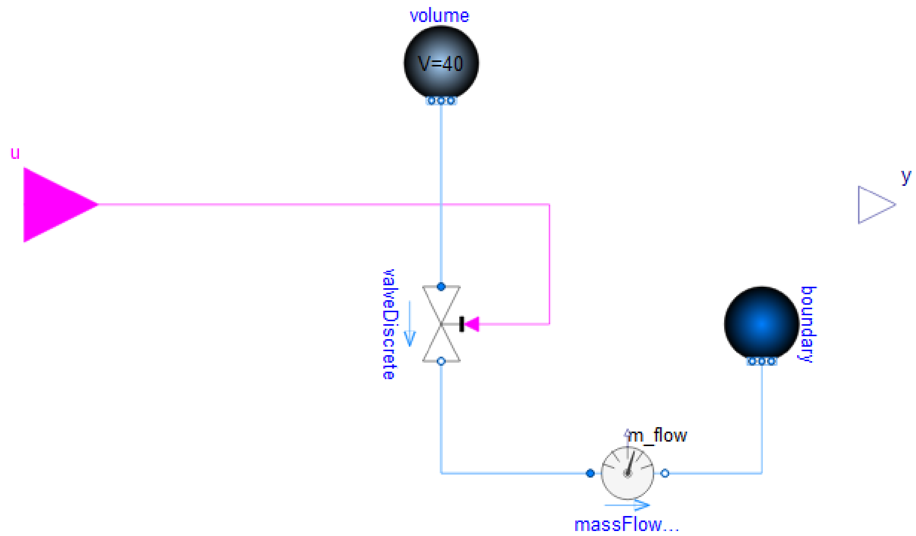


Figure 6: The thruster model.

**GNC unit.** The GNC unit functions as the central component for satellite attitude control, as shown in Fig. 7, which is mainly responsible for the attitude and orbit control of the satellite. It primarily consists of a PID controller, control strategy, jet timing control, and control signal transformation. GNC calculates the control voltage signal by utilizing inputs such as the satellite's attitude angles, attitude angular velocities, and control modes. Given a sinusoidal command signal in a certain direction, its control result is shown in Fig. 8. Observably, the controller demonstrates a commendable control efficacy.

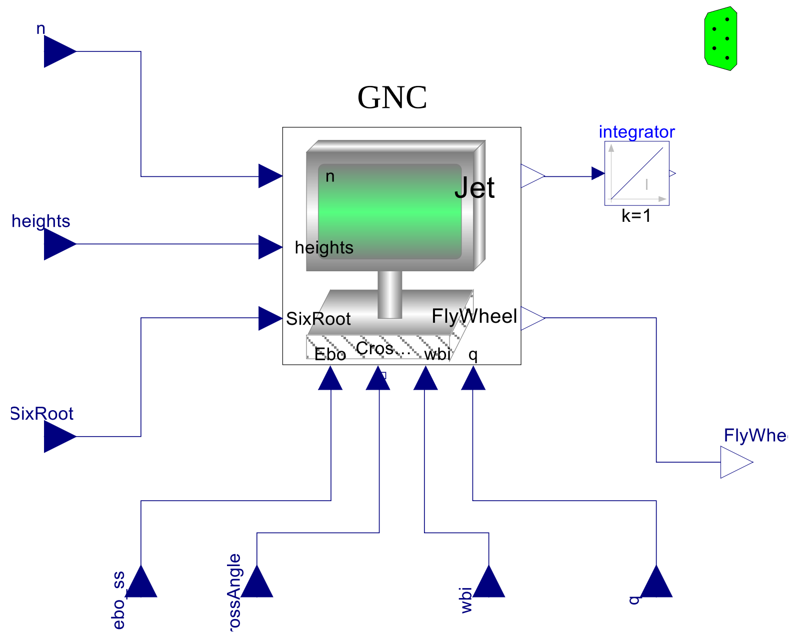


Figure 7: The GNC model.

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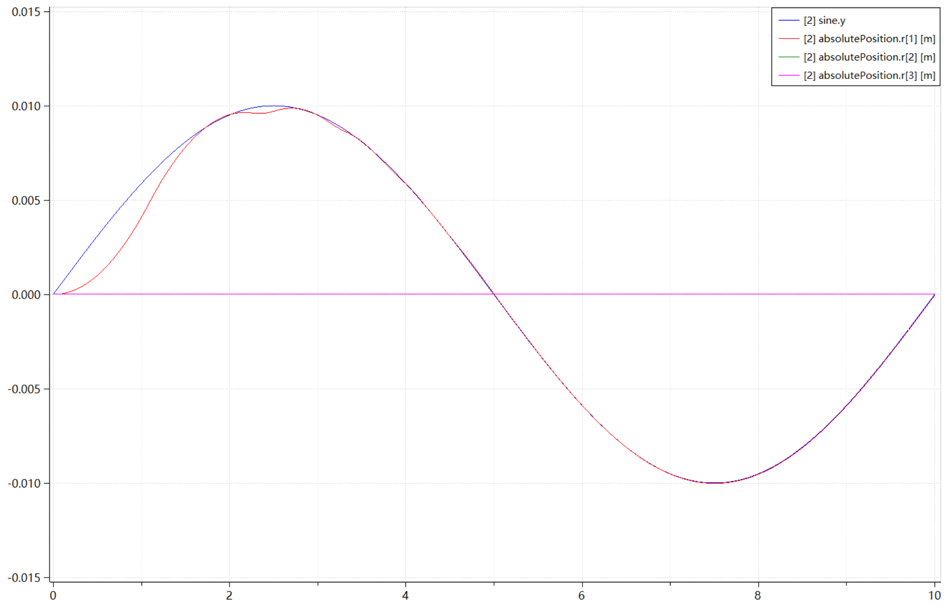


Figure 8: Attitude angle curves of satellite. The blue line represents the target command and the red line indicates the actual status.

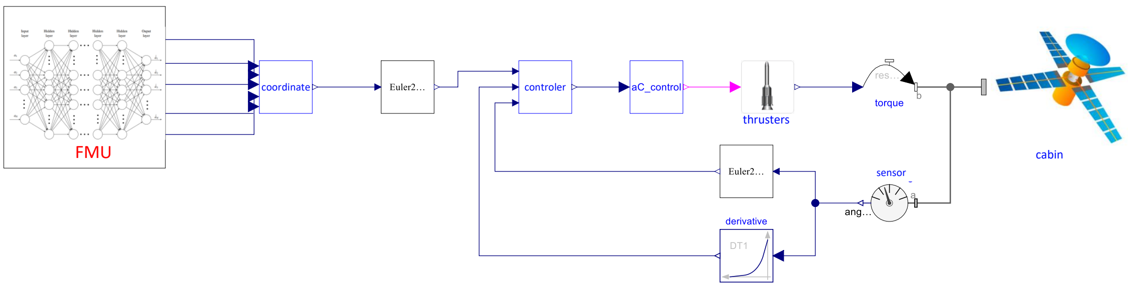


Figure 9: The complete model combining temperature sensing and attitude control.

## 4. Cross-level co-simulation based on FMI

The Functional Mock-up Interface (FMI) standard is a widely recognized and adopted framework in the field of model-based systems engineering.[22] FMI provides an open standard for model exchange and co-simulation, enabling seamless integration and interoperability among various modeling and simulation tools. The standard defines a set of specifications and APIs that allow for the exchange of models between different simulation environments, facilitating collaborative development and analysis of complex systems.[23] FMI supports both functional and structural model representations, allowing users to share and reuse models across different domains and disciplines. By promoting model reusability and facilitating cross-domain collaboration, FMI plays a crucial role in advancing system-level modeling and simulation practices, fostering innovation, and enhancing the efficiency and reliability of engineering workflows.[24]

This paper leverages the FMI to construct a deep learning surrogate model in the form of a FMU, which is subsequently imported into the Modelica simulation platform for conducting integrated simulation studies. The complete model is shown in Fig. 9. The temperature field reconstruction surrogate model can output the coordinates of the anomalous heat source position to the attitude control system, enabling the system to determine the necessary adjustments in Euler angles and subsequently execute the corresponding actions.

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## 5. Conclusion

This paper endeavors to integrate both the physical field-level digital twin and the system-level digital twin. The physical field-level digital twin comprises a data-driven model, while the system-level digital twin relies on a physics-based model. By fully integrating these two distinct modeling approaches, the study capitalizes on their respective strengths and benefits. Significantly, this study presents a promising direction with widespread applicability. It can extend beyond spacecraft to encompass other types of vehicles, such as engineering machinery, suggesting the hybrid digital twin's broad utility and versatility.

## 6. Acknowledgments

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