Exploration of Multifidelity Modeling in Spacecraft Digital Twin Architectures

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Introduction

This work presents investigates a multifidelity framework for the simulation of small satellites. Taking into account the concept of digital twin, our work focuses on handling a constant stream of live data. Towards this end, current multifidelity modelling(MFM) methods and low fidelity surrogate models for timeseries were surveyed.

Multifidelity Modelling

Models describing the same phenomenon often differ in the quality of the approximation and computational cost. Highfidelity models (HFMs) estimate the output with the accuracy that is necessary for the current task, while low-fidelity models(LFMs) estimate the output with a lower accuracy than the HFM typically in favor of lower costs.

Cokriging

To approximate the expensive, high fidelity model, the cheap, low fidelity model is transformed by a comprehensive correction with a constant scaling factor ρ and a Gaussian process for δ.

$$Z_H(x) = \rho Z_L(x) + Z_d(x)$$

Z_L is also a Gaussian process fitted on low fidelity data. Can be easily readjusted when more HFM data become available.

Low Fidelity Model(LFM)

- Recurrent Neural Networks(GRUs)

High Fidelity Model(HFM)

- A finite differences analysis using Thermal Desktop
- Sensor data, thermal vacuum chamber test

Impact

1. Discusses how multifidelity modelling can enable a satellites digital twin architecture.
2. Strives to correct the shortcomings of telemetry data.
3. Takes into account multiple features for s/c thermal simulation.

Application

Spacecraft thermal simulation with multiple features.

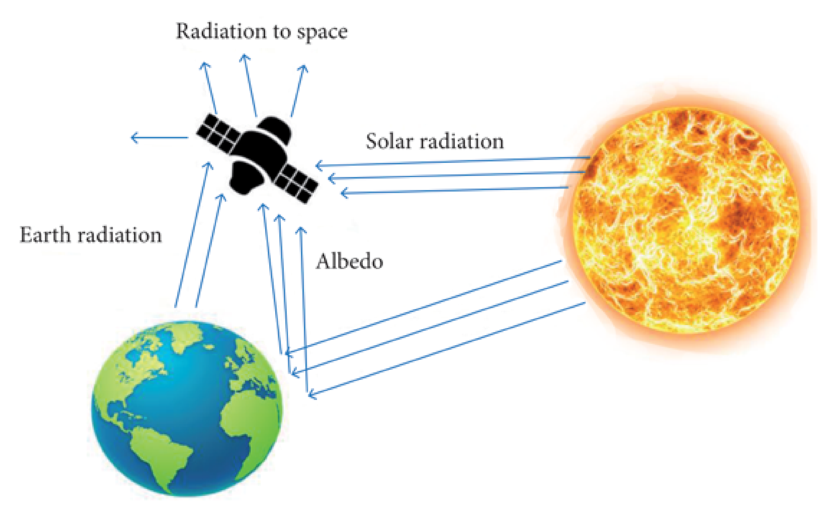

Figure 3: Sources of Radiation

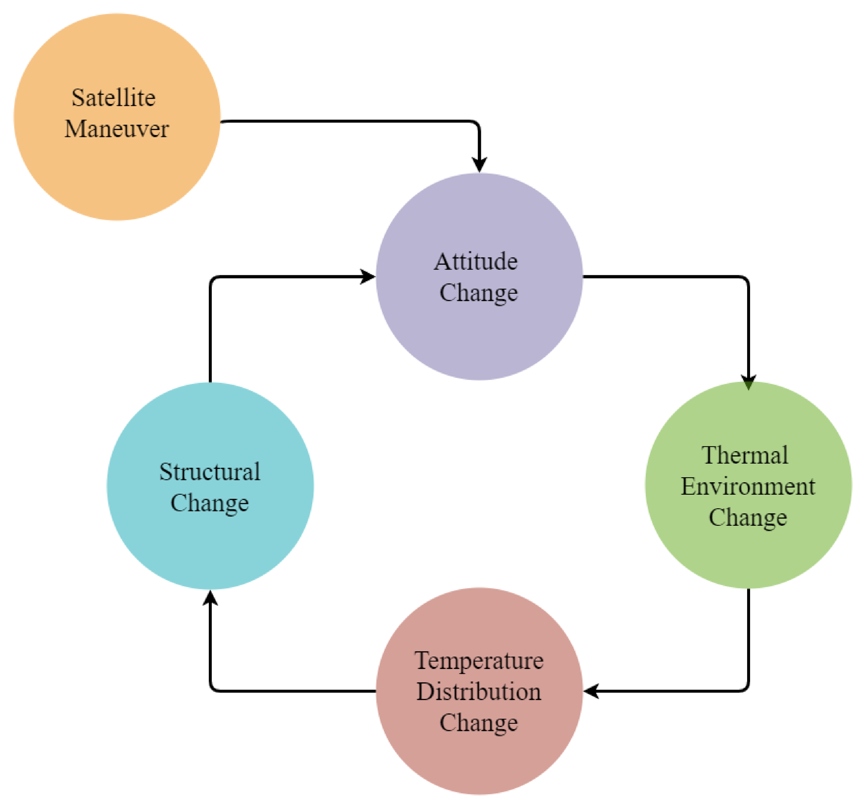

Figure 4: Thermal effects on spinning satellites.

Proposed Framework

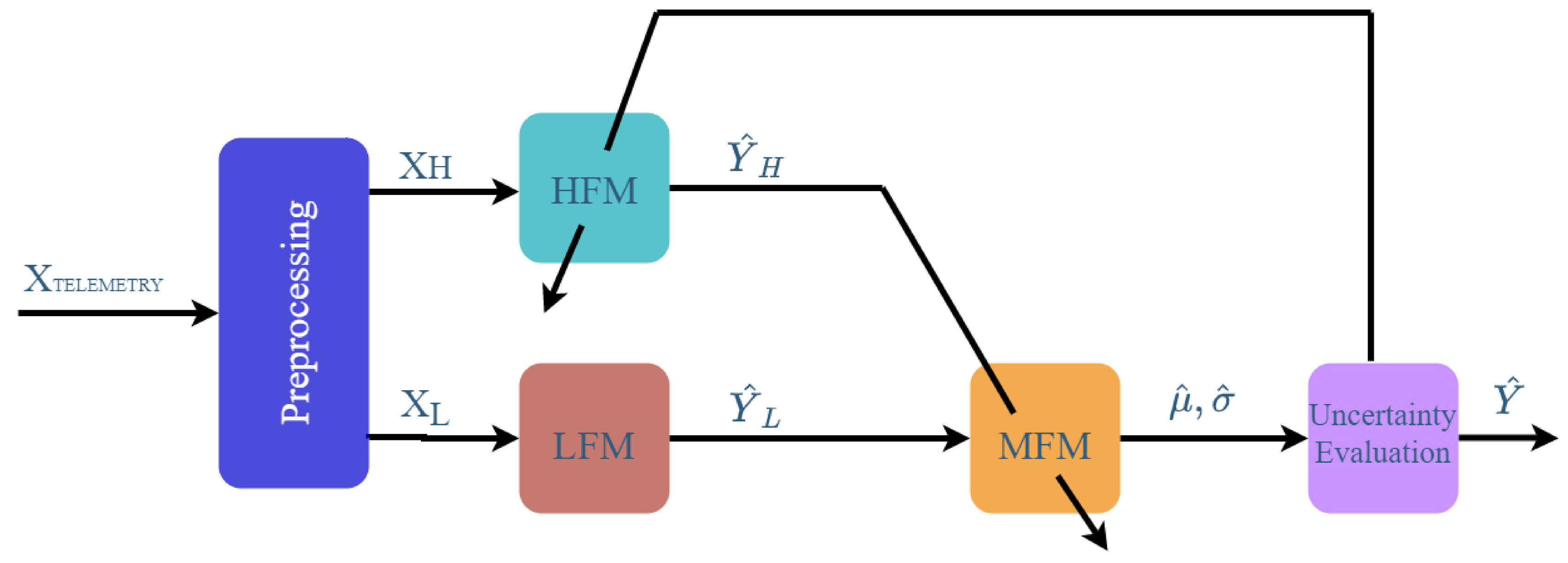

Figure 1: Proposed Framework

As illustrated in Fig.4, the current state X_t is fed as input to two separate systems. We distinguish between X_L and X_H and input is a sequence with different sampling rates, with the rate of the LFM being much higher than the HFM's. High fidelity and low fidelity predictions for the next thermal state $\hat{Y}$ are produced. A meta predictor corrects the LFM with HFM data through cokriging. The produced estimated mean $\hat{\mu}$ and standard deviation $\hat{\sigma}$ are compared with a desired value for uncertainty. If found undesirable, more HFM data are incorporated in the next time steps. The framework should produce data with the a rate close to the LFM's sampling rate and an accuracy closer to the HFM.

Discussion

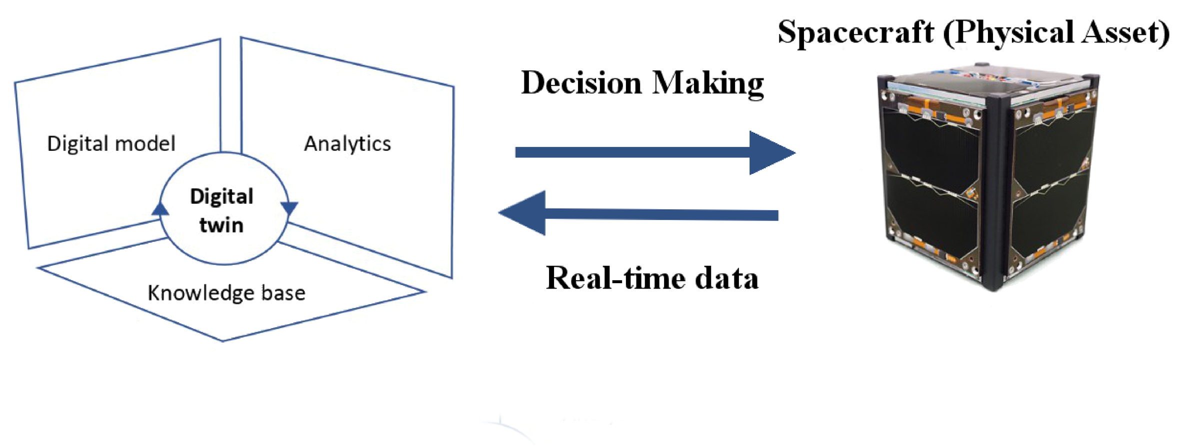

Figure 2: Digital Twin

The finite element simulator will be used as the HFM. On the other hand, the LFM will be implemented with both an LSTM and ARIMAX and compared for accuracy and computation time. The HFM can be replaced by onboard measurements, received by telemetry. Telemetry data arriving are sparse, however, this is not an issue for the framework because it can update if and when new data arrive for a minimum computational cost, since it only requires refitting the model with the new data.

Our framework reflects the digital twin framework in Fig. 2

- MFM is the corresponding digital model.
- An established knowledge base is utilized to construct the low fidelity mode.
- Analytics decide whether or not to increase the number of data taken into account.

References

https://drive.google.com/file/d/1dJP13Rbc3vF97cUQ1TBS5RcoUXTxVSJG/view?usp=sharing

Future Research

Our framework will be applied on a small cube satellite. It will be validated initially through synthetic exclusively high fidelity data, and subsequently with real data provided by the Intelligent Space Systems Laboratory of the University of Tokyo. Accuracy, computation times and memory usage will be benchmarked against purely low fidelity and high fidelity simulations.

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