Towards a Digital Twin Enabled Multi-Fidelity Framework for Small Satellites

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ABSTRACT

In this work, a multi-fidelity framework for the simulation of small satellites is investigated. Taking into account the concept of digital twin, our work focuses on handling a constant stream of live data. Towards this end, current multi-fidelity modelling methods and low fidelity surrogate models for time series were surveyed. A multi-fidelity approach is used to combine a low fidelity surrogate model with a high fidelity model. As a high fidelity model, a previously investigated finite element model is assumed. As a low fidelity model, auto-regressive and recurrent neural network-based models are investigated. Through cokriging, the low fidelity data is corrected by the high fidelity data through a comprehensive correction, where the parameters are given through Gaussian processes in order to perform uncertainty quantification. As an application, the thermal simulation of a small satellite, and the use of this framework in conjunction with sparse telemetry data is proposed. This online, statistical approach aims to provide a tool for performing fault detection.

1. INTRODUCTION

Simulations are an indispensable tool for supporting the operation of satellites during their life cycles. A dynamic system simulation can enhance the operational phase of a satellite. In space, where human intervention is not possible, faults must be autonomously detected and dealt with by the health management system. Inaccuracies, causing instrument failures during operations, can lead to significant costs. It is of paramount importance to continuously monitor the state of the satellite, in order to both react and notify the on-board health management system. In addition, with a dynamic simulation, it is possible to test the spacecraft status in real time with respect to the requirements, to ensure that the performance will satisfy all needs. If estimated values surpass tolerances, the health monitoring system can raise an alarm. Due to the remote nature of space, space agencies recognized early the benefits of simulation, which eventually led to the development of the concept of digital twin. NASA coined the term digital twin during the Apollo Program, referring to two identical space vehicles built so that the space vehicle on earth can mirror, simulate, and predict the conditions of the other in space. Since its introduction, multiple definitions have been attached to the concept of the digital twin.

Initially, digital twin was treated as a high fidelity model or multidisciplinary simulation, and the real-time component had not yet been under consideration (Liu, Fang, Dong, & Xu, 2020). However, the definition has evolved to encompass dynamic modelling and bidirectional communication and mapping to the physical system. In essence, the digital twin is based on the simple idea of linking a physical object with its digital counterpart accurately and in real-time. However, a fit-all concept architecture has not been developed (D. Jones, Snider, Nassehi, Yon, & Hicks, 2020). In particular, Xu, Sun, Liu and Zheng (2019) defined digital twin to be a dynamic representation of physical entities with their functions, behaviors, and rules. Fig. 1 describes our conception for the digital twin. The framework consists of three components; the digital model which describes the physical object, a knowledge base which is used to build the framework and an analytics component used to assess its performance. Utilizing real time data, the system should be able to communicate accurately predict its state and react. Through our proposed framework, the dynamic digital twin will act as a living entity or a true representation of the system.

The purpose of this research is to propose a multi-fidelity framework for small satellites. To incorporate this in a digital twin architecture, there is a need to satisfy two usually competing requirements, i.e., fast computation time and high accuracy. To reconcile these requirements, a multi-fidelity approach will be used, which will take advantage of the accuracy of a computationally expensive high fidelity simulator

Table 1. Extensions of the basic Cokriging model.

Year	Application	Novelty	Reference
2006	Material Science	The scalar ρ is replaced by linear regression and GP to model the low fidelity data.	(Qian & Wu, 2008)
2011	Airfoil Optimization	Employed cokriging to reduce the number of simulations in CFD.	(Toal & Keane, 2011)
2013	Hydrodynamics	Used Markov Chain Monte Carlo to calculate the posterior. Multiple simulators.	(Goh et al., 2013)
2015	Fluid Dynamics	Enchanced computation using the recursive method in Le Gratiet & Garnier(2014).	(Perdikaris, Venturi, Royset, & Karniadakis, 2015)
2017	Fluid Dynamics	Generalized the Kenedy and o'Hagan (2000) scheme with non-linear autoregression.	(Perdikaris, Raissi, Damianou, Lawrence, & Karniadakis, 2017)
2018	Various Datasets	Different fidelity data were generated by proper orthogonal decomposition model reduction with varying number of basis vectors.	(Xiao, Zhang, Breitkopf, Villon, & Zhang, 2018)
2020	Various Datasets	An extension of two-level cokriging for multiple levels is developed.	(Ruan, Jiang, Zhou, Hu, & Shu, 2020)

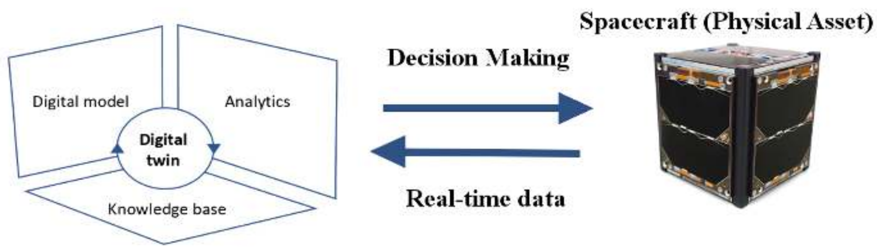

Figure 1. Digital Twin

and the speed of a low fidelity surrogate model. In order to narrow the scope of this study, a few assumptions were made. The framework takes into account a small spinning satellite, such as eATOMS(Akita, Takaki, & Shima, 2012), without control capabilities. This eliminates the need to define a particular output required for control, e.g. the demand for linear outputs in model prediction control. Additionally, the framework should support satellite operation, but not necessarily the design phase. The framework is not limited to any particular application. Potential applications include power simulation, communications, attitude etc. However, to demonstrate its effectiveness we intend to apply it on thermal simulation, one of the most demanding simulations to be performed. In the thermal simulation, discretizing the heat conduction equation, computation cost is generally high due to the small computation time step. There is a need for the surrogate model to reduce the computation cost.

The paper is organized as follows. In section 2, the literature review on some necessary concepts is presented. In section 3, the thermal environment of the satellite is discussed. Section 4 illustrates our proposed framework. Discussion and conclusion are in sections 5 and 6.

2. Literature Review

2.1. Multi-Fidelity Modeling

Typically, data is either too expensive to obtain through experiments or unavailable. For this reason, multiple models must be developed to describe the same process or output quantities. These models attempt to establish a relationship between sets of input and output data. However, they often differ in the quality of the approximation and computation cost. These models can be distinguished into two categories. High-fidelity models (HFMs) estimate the output with the accuracy that is necessary for the current task (Peherstorfer, Willcox, & Gunzburger, 2018). For our research, HFMs will represent the true behavior of the system. On the other hand, low-fidelity models (LFMs) are models that estimate the output with a lower accuracy than the HFM typically in favor of lower costs (Peherstorfer et al., 2018). Lower fidelities are generally ranked in three categories by:

1. Simplifying the mathematical model, e.g., simplifying the geometry / boundary conditions;
2. Varying the spatial and temporal resolution;
3. Using real-time data.

While LFMs and HFMs can describe the same process, they may not produce the same estimation, e.g., the LFM might not capture some underlying processes successfully compared to the HFM. However, if one attempts to analyze a complex problem using only a HFM, the cost will quickly become impractical. Multi-fidelity modelling attempts to construct a multifdelity model (MFM) by combining the strengths of both models, particularly the accuracy of the HFM and the low computation cost of the LFM. The principal challenge of multi-fidelity approaches in multidisciplinary problems, is the mitigation of computation cost, which scales with the increase in available models. Peherstorfer et al. (2018) categorize the approaches to combine fidelities in three, fusion, filtering and adaptation which enhances the LFM with information from the HFM. Not all approaches can be strictly placed into one of these categories. MFM approaches can additionally be separated into two broad categories, deterministic (DAs) and non-deterministic approaches (NDAs), based on the properties of the model used to make a prediction. In DAs, the MFM is constructed by fitting the sampling points using distance based metrics such as the minimum root mean square error (RMSE) or the minimum cross-validation error (CVE). NDAs are constructed using the maximum likelihood criterion instead. DAs can be applied to any surrogate model. NDAs require an uncertainty structure. In addition, NDAs were found to be more accurate than DAs in Keane (2012) and in Park, Haftka and Kim (2017).

In satellite development where uncertainty quantification(UQ) is crucial, NDA methods, and in particular Bayesian theory, are well suited for their ability to produce an estimation for the quantity of interest and also estimate the uncertainty. The difference between Bayesian methods and classical statistics is that the former takes advantage of prior information. Both approaches can be applied on the same model, e.g., a Kriging surrogate can be constructed with both Bayesian and non-Bayesian methods. Popular MFM approaches use Gaussian processes (GP) to model each fidelity response. A GP is a collection of random variables with the property that the joint distribution of any finite subset is Gaussian.

2.2. Kriging

Even though our framework incorporates cokriging, the reader must first be accustomed with the standard kriging method, of which cokriging is an extension for models with multiple fidelities. Kriging is a popular surrogate for multi-fidelity applications. This is due to the fact that it has an uncertainty structure that easily facilitates a probabilistic MFM. The uncertainty prediction in kriging surrogates can be constructed using GPs. Kriging is based on the idea that if two points x_i, x_j are close then the random variables $Y(x_i)$, $Y(x_j)$ will be similar. This is expressed through their correlation,

$$\begin{aligned} R &= Corr[Y(x_i), Y(x_j)] \\ &= \exp\left(-\Sigma_{l=1}^{d} 10^{\theta_l} ||x_{il} - x_{jl}||^{p_l}\right), \end{aligned} \tag{1}$$

where θ_l and p_l represent the hyperparameters of the lth variable. These hyperparameters are chosen via a maximization of the concentrated log likelihood function (D. R. Jones, 2001). If n is the number of data points, the log likelihood ϕ is

$$\phi = \frac{n}{2}\ln(\hat{\sigma}^2) - \frac{1}{2}\ln(|\mathbf{R}|), \tag{2}$$

where optimal variance σ^2 and mean μ are:

$$\hat{\sigma}^2 = \frac{1}{n}(\boldsymbol{y} - \mathbf{1}\hat{\mu})^T \boldsymbol{R}^{-1}(\boldsymbol{y} - \mathbf{1}\hat{\mu}), \tag{3}$$

$$\hat{\mu} = \frac{\mathbf{1}^T \boldsymbol{R}^{-1}\boldsymbol{y}}{\mathbf{1}^T \boldsymbol{R}^{-1}\mathbf{1}}. \tag{4}$$

The concentrated likelihood function only depends on the hyperparameters through the correlation matrix. The main computation cost of this method arises from the optimization problem of maximizing the likelihood. Attempts have been made to improve computation, such as in Toal, Bressloff, Keane and Holden (2011) and Giles (2008), in which the adjoint of the correlation matrix can reduce computation time. A comprehensive guide on kriging is found in Jones (2001).

2.2.1. Cokriging

Kennedy and OHagan (2000) proposed a base methodology, often used as the basis for further research using adaptation, and in particular a comprehensive correction, for the MFM. A comprehensive correction is a combination of a multiplicative and additive correction or $\hat{Y}_H = \rho Y_L + \delta$. To approximate the HFM, a LFM is transformed by a comprehensive correction with a constant scaling factor ρ and a GP Z_d for δ. Z_L is a GP fitted on LFM data,

$$Z_H(x) = \rho Z_L(x) + Z_d(x). \tag{5}$$

An important assumption is that in points where high fidelity estimation exists, a low fidelity estimation also exists. Its covariance matrix $\boldsymbol{C}$ can be given as

$$\boldsymbol{C} = \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix}, \tag{6}$$

$C_{11} = \sigma_L^2 \boldsymbol{R}_L\left(\boldsymbol{X}_L, \boldsymbol{X}_L\right)$,
$C_{12} = \rho\sigma_L^2 \boldsymbol{R}_L\left(\boldsymbol{X}_L, \boldsymbol{X}_H\right)$,
$C_{21} = \rho\sigma_L^2 \boldsymbol{R}_L\left(\boldsymbol{X}_H, \boldsymbol{X}_L\right)$ and
$C_{22} = \rho^2\sigma_L^2 \boldsymbol{R}_L\left(\boldsymbol{X}_H, \boldsymbol{X}_H\right) + \sigma_d^2 \boldsymbol{R}_d\left(\boldsymbol{X}_H, \boldsymbol{X}_H\right)$,

where X_H and X_L are predicted high and low fidelity data points, respectively. While the correlations are the same as in the standard kriging, the number of hyperparameters doubles. If more fidelities are used, the number increases even further.

The hyperparameters of the LFM, assuming the LFM data is independent of the HFM data, can be calculated as in the standard kriging. However, to calculate the hyperparameters corresponding to the HFM, the difference $\boldsymbol{d}$ between the expensive and cheap data at known points should be calculated as

$$\boldsymbol{d} = \boldsymbol{y}_H - \rho \boldsymbol{y}_L \left(\boldsymbol{X}_H \right). \tag{7}$$

The concentrated log likelihood for the HFM data is

$$\phi_d = -\frac{n_H}{2} \ln \left(\hat{\sigma}_d^2 \right) + \frac{1}{2} \ln \left(\left| \boldsymbol{R}_d \left(\boldsymbol{X}_H, \boldsymbol{X}_H \right) \right| \right). \tag{8}$$

The variance and the mean are given by the same Eq. (4), (3), however these parameters are replaced by their equivalents, obtained through the difference model, $\boldsymbol{R}_d \left(\boldsymbol{X}_H, \boldsymbol{X}_H \right)$, $\boldsymbol{d}$ and n_H. Methods from standard kriging, such as Giles (2008), can again be used to reduce computation time. Toal (2015) outlined the requirements for successful cokriging to be

1. The correlation between the low and high fidelity function should be reasonably high, $R^2 > 0.9$.
2. No more than 80% of the total evaluation budget should be converted to cheap evaluations, $f_r < 0.8$, where f_r is the fraction of the expensive functions replaced by cheap functions.
3. More than 10% of the total evaluation budget should be converted to cheap evaluations, $f_r > 0.1$.
4. There should always be slightly more cheap data points than expensive, with $fr > \frac{1.75}{1+1/C_r}$ giving a conservative bound for this condition, where C_r is the ratio between the cost of the cheap model over the cost of the expensive model.

Many other popular MFM approaches use GPs to model each fidelity response. In particular, Qian and Wu (2008) expanded on the work by Kennedy and o'Hagan (2000). The main idea was a two-step approach in which again 1) uses low fidelity data to provide a base surrogate model, and 2) adjusts the model accordingly by utilizing HFM data. The application required two assumptions, a) the prediction of uncertainty of one fidelity is independent to that of the other fidelity and b) the HFM data is considered ground truth and therefore the error between them and the true process can be neglected. In more detail, in the first step, the LFM was estimated through a GP using LFM data. Subsequently, assuming both HFM and LFM predictions for the same input x are available, the discrepancy could be modeled as $\hat{y}_{HF} = \rho \cdot y_{LF} + \delta$, where both ρ and δ are constants. However, many applications require more information to estimate discrepancies. Qian and Wu (2008) replaced the scalar ρ of Eq. (5) with a linear regression.

This method offers a significant number of advantages. It builds a surrogate model that is both more accurate than a low fidelity surrogate model and at the same time computationally cheaper than its high fidelity counterpart. In addition, it allows the surrogate to update using new HF data as they become available for a minimum computation cost, since it only requires refitting the model with the new data. Through this process, the model can be improved to the level of desired accuracy. Both works can be expanded for multiple models with various levels of fidelity. However, they suffer from limitations often encountered in kriging methods. Severe computation costs are introduced when training a metamodel on a set of known observations by repeatedly inverting large, ill-conditioned covariance matrices.

Le Gratiet and Garnier (2014), suggested that emerging cokriging schemes with s-levels of fidelity can be decoupled and formulated in a recursive fashion as s-independent kriging problems. This eases computation by solving a sequence of simpler kriging problems with covariance matrices of smaller dimensions. In Table 1, a summary of some notable works which employed the basic Kenedy and O'Hagan (2000) framework are presented.

2.3. The Low Fidelity Surrogate Model

2.3.1. Multivariate Time Series

Time series are a set of observations x_t, sampled at time t. According to Brockwell, Davis and Fienberg (1991), many time series X_t should be considered vector valued (multivariate), having both serial dependence within each component series X_{ti} and interdependence between the different component series X_{ti} and X_{tj}, $i \neq j$.

Satellites generate a large amount of data through a variety of sensors, logging the values periodically. Our goal is to build a reduced order model with these time series data, enabling quick and computationally cheap calculation. Amongst a variety of options, two data-fit models will be considered for this study, Neural Networks (NN) and Vector Autoregression (VAR). These methods are chosen as simple representatives of classes of methods, are well understood and are included in many comparison studies (Reikard, 2009), (Hamzaçebi, Akay, & Kutay, 2009), (Deb, Zhang, Yang, Lee, & Shah, 2017).

2.3.2. Autoregression

Before employing more complicated machine learning techniques, classical linear techniques for time series forecasting need to be exhausted. Since these focus on linear relationships, they are not expected to have the performance of more advanced methods. However, if they are calibrated and preprocessed, they can tackle a wide variety of problems. Their main strength is easy implementation and fast computation. Many methods have been developed but they are heavily dependent on the type of data available. A crucial assumption is the inclusion of some form of statistical equilibrium, expressed by the concept of stationarity[1]. Autoregression methods work well on stationary data. If the series is non-stationary, it can be transformed to stationary through proper operations (Box, Jenkins, Reinsel, & Ljung, 2015).

Our data is multivariate since satellites have many relevant features, including position, attitude etc. Auto-regressive Integrated Moving Average with eXogenous input (ARIMAX) is suitable for analyses where there are additional explanatory variables. ARIMAX can be viewed as a multiple regression model with one or more auto-regressive terms and one or more moving average (MA) terms. This makes it suited for multivariate, non-stationary data. It is described by adding the exogenous X scaled by a parameter to the ARIMA model as

$$Y_t = ARIMA(p, d, q) + \beta X_t. \tag{9}$$

In ARIMA (p,d,q) model, the 'p' lags of each variable are used as regression predictors for each variable, 'q' is the order of the MA term, referring to the number of lagged forecast errors that should go into the ARIMA Model and 'd' is the minimum number of differencing needed to remove the trend and make the series stationary. The effect of parameter β is not as straight forward as it looks at first glance. If Eq. (9) is rewritten, assuming the data is already stationary, ignoring integration and using the lag or backshift operator $B^k z_t = z_{t-k}$, which expresses the value of a variable k time steps in the past, it becomes

$$\begin{aligned}\phi(B)Y_t &= \beta X_t + \theta(B)e_t \Rightarrow \\ Y_t &= \frac{\beta}{\phi(B)}X_t + \frac{\theta(B)}{\phi(B)}e_t,\end{aligned} \tag{10}$$

where $\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \dots - \theta_q B^q$. An increase of X_t by 1 would not increase Y_t by β since it is conditional on the past values of Y. If integration is to be considered, $\phi(B)$ can be replaced with $\nabla^d \phi(B)$, where $\nabla = (1 - B)$ denotes the differencing operator. Rewriting the equation this way reduces the number of parameters to be estimated and also makes use of data more efficiently.

The parameters can be estimated with two methods, one proposed by Box and Jenkins(Box et al., 2015), which is difficult to implement when there are more than one exogenous variable, and another called Linear Tranfer Function (LTF) described in detail by Pankratz (2012). The reader is encouraged to refer to Pankratz (2012) for ARIMAX, which in the book is indicated as dynamic regression. ARIMAX has been applied to many problems such as epidemiology (Jing et al., 2018), urban planning (Williams, 2001) and macroeconomics (Anggraeni, Andri, Sumaryanto, & Mahananto, 2017). ARIMAX is often juxtaposed to neural networks.

[1]A stationary time series is one whose properties do not depend on the time at which the series is observed. This implies the absence of a trend or seasonality.

2.3.3. Recurrent Neural Networks

Neural networks are a prime candidate for time series forecasting. While their training is costly, their forward operations are fast and can handle multivariate inputs, and capture inter-dependencies between data and non-linear trends. A popular choice for time-series forecasting are Long-Short Term Memory (LSTM) networks.

LSTMs have been successfully applied to problems with similar assumptions and goals, e.g., Zhao, Chen, Wu, Chen and Liu (2017) applied LSTMs for short-term forecasting of traffic conditions, taking advantage of spatial and temporal correlations. Moreover, LSTM consistently shows strong performance against other methods for non-linear spatial-temporal data forecasting (Mettu & Sasikala, 2019), (Mussumeci & Codeço Coelho, 2020). LSTMs constitute a strong alternative to auto-regressive methods. LSTMs can capture temporal inter-dependen- cies in addition to inter-dependencies between features and work well for short term forecasting and non-linear data. A series of studies have compared LSTMs to auto-regressive methods. Siami-Namini, Tavakoli, and Siami Namin (2019) showed 85% improvement over ARIMA for univariate, non-linear financial data. In Li, Pan, Liu, Song and Wang (2020), LSTM and ARIMAX performance was directly compared in predicting tuberculosis incidents in eastern China with the inclusion of metereological factors as additional variables. ARIMAX performed better than the neural network. In another example, Serafini, Yi, Zhang, Brambilla, Wang, Hu and Li (2020) applied both forecasting models to predict the behavior of the BITCOIN market through financial and sentiment features extracted from economic and crowdsourced data. ARIMAX again outperformed the LSTM.

ARIMAX seems to hold an edge over LSTM in the aforementioned applications. This is because tuning the hyperparameters of a neural network is a difficult task. In contrast ARIMAX can achieve good results with minimum input from the analyst. However, autoregression models are linear models and there is always the risk of them not capturing important information in a particular application. For this reason our own comparison of the two methods will be performed on satellite data with a trade off between computation time and model accuracy. The accuracy will be evaluated with three metrics, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). The computation time will be evaluated as the input vector arrives to the time a prediction is generated.

2.4. High Fidelity Model

An adaptive estimation method for spacecraft thermal simulation was presented by Akita, Takaki and Shima (2012). They employ a finite element analysis of a spacecraft thermal mathematical model, with the status of the central point, or node, of each element representing its status. The heat balance equation of each node is

$$C_i \frac{dT_i}{dt} = Q_i - \sum_{j=1}^{N} C_{ij} \left(T_i - T_j\right) - \sum_{j=1}^{N} R_{ij} \sigma \left(T_i^4 - T_j^4\right), \tag{11}$$

where N is a total number of nodes, T_i and C_i are temperature and a capacitance of node i, respectively, Q_i is an external or internal thermal load to node i, C_{ij} and R_{ij} is a linear conductor and a radiation factor between node i and j, respectively, and σ is the Stephan-Boltzmann constant. Eq. (11) is solved for all nodes simultaneously to calculate temperature changes. The heat load Q_i can be obtained through either the orbital environment or instrument power level, while C_{ij} and R_{ij} have to be identified through thermal-vacuum tests.

3. APPLICATION

3.1. Thermal Simulation

A small spinning satellite in orbit around the Earth is subject to multiple sources of thermal radiation. As a result, the satellite's behavior can be severely affected, especially in the areas of orbital evolution, attitude and instrumentation. The most relevant thermal loads for our study are in the low earth environment. As illustrated in Fig. 2, a satellite in LEO is subject to several radiation sources.

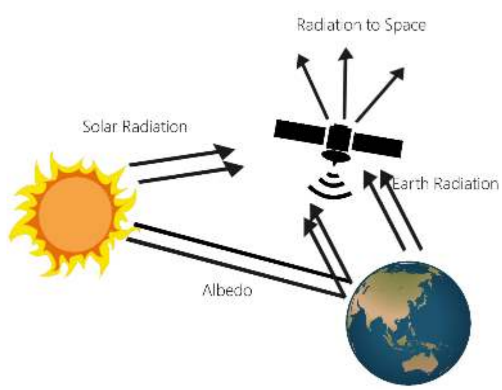

Figure 2. Sources of Radiation

The thermal forces acting on satellites are generated when the incoming radiation from a thermal radiation source, e.g. the Sun, heats in a larger degree the surface facing it, compared to the dark side of the satellite. The uneven distribution of incident radiation results in asymmetric temperature distribution on the surface of the satellite. Consequently, the balance in photon re-emission is compromised, with the hot side losing more momentum than the cool side. The effect of this anisotropic behavior is observed as a total linear momentum, creating a recoil force on the satellite. This force is time-variate, due to the varying amount of incidence radiation from the source to the surface, which depends on coordinates controlled by the orbital characteristics of the satellite (spin axis, rotational motion, orbital motion). In the relative system of the satellite the thermal distribution is described by asymmetries along the spin axis (summer-winter effect) and along the equatorial direction (day-night effect) (Duha & Afonso, 1999). Furthermore, sudden heating and cooling on the satellite's surface may create temperature gradients and thus bending moments due to thermal stresses. These deformations in the structure affect the energy efficiency and the reliability of the satellite. Over the last decades, instrument failures are thought to have been caused by excessive thermal deformation. In a study on a 3D CubeSat, it was shown that the thermal deformation of the satellite structure, which was in orbit of 450 km high and angle $B = 90°$, caused a deviation of about $0.03°$ from the normals to the opposite small sides of the satellite (Gorev, Pelemeshko, Zadorozhny, & Sidorchuk, 2018). Such a deviation is commensurate with the required satellite pointing accuracy on the order of $0.1°$ necessary for laser communication. A spinning satellite, having no control capabilities, cannot correct for external forces influencing its behavior. In the context of thermal effects, as illustrated in Fig. 3, a maneuver performed by the spacecraft would inevitably change its attitude, changing the thermal environment. In turn, the temperature distribution also changes, altering the structure through stresses and strains along the surface. The additional Summer-Winter and Day-Night effects will further distort the satellite's attitude and repeat the vicious cycle.

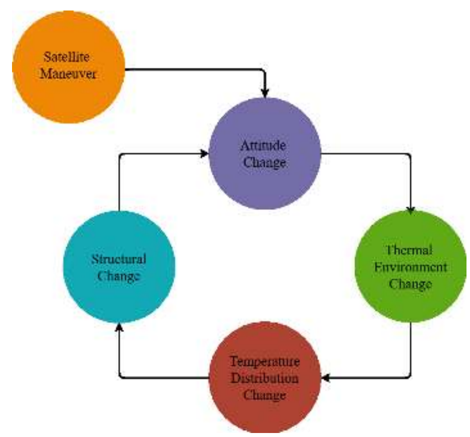

Figure 3. Thermal effects on satellite.

3.2. eATOMS

Our research was motivated by the work of Kato, Ando and Fukuzoe (2019). Kato et al. (2019) constructed an emulator using GP regression and Least Absolute Shrinkage and Selection Operator (LASSO) to estimate the thermal margin based on given uncertainties. A sensitivity analysis was performed, based on multiple regression analysis, in order to reduce risk in the thermal design of the satellite. Kato et al. (2019) applied the scheme on a pseudo-small satellite called eATOMS and demonstrated that the emulator can reduce the uncertainty quantification cost compared to an ordinary simulator and that the sensitivity analysis shows that only two factors are dominant in pseudo-small satellite thermal design uncertainty. Our intention is to use the same satellite for our future research.

eATOMS was originally employed for educational purposes (Shigehara & Toriyama, 2002). It is a 50-kg cubic satellite with six outer panels, the side length of which is 500 mm, and three inner panels. eATOMS is shown in Fig. 4. Each panel is discretized by a single arithmetic node, and a boundary node is set to the deep space, whose temperature is constant ($3K$). The total number of nodes is 16 (Akita et al., 2012).

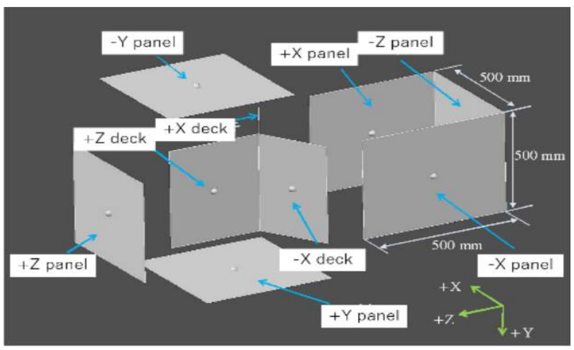

Figure 4. Exploded view of eATOMS.

4. METHODOLOGY

The requirements this framework needs to fulfill need to be summarized. The framework should be able to:

1. Perform high accuracy simulation;
2. With short computation times to support an online stream of data;
3. The requirements proposed by Toal (2015) and described in Sec. 2.2.1 need to be considered;
4. To provide UQ for risk assessment.

Due to the limited computation capacity of small satellites to generate high fidelity data, the simulation will be carried out on the ground, using telemetry data, which for the scope of this review is considered reliable, i.e. it is not corrupted with noise and not too sparse.

4.1. Proposed Framework

In this subsection a framework for satellite simulation is presented. To satisfy the requirement described, a multi-fidelity approach taking advantage of both the accuracy of - hard to obtain - high fidelity data and the abundance of low fidelity data, is proposed. A high fidelity model produces sparse high fidelity data describing the satellite's state. On the other hand, abundant low fidelity data are taken advantage of to speed up the process.

As illustrated in Fig. 5, the current state X_t is fed as input to two separate systems. A distinction between X_L and X_H is drawn because, since the LFM runs much faster than the HFM, each input is fed with a sequence with different sampling rates, with the rate of the LFM being much higher than the HFM's. Each system produces a set of predictions, particularly a high fidelity model and a low fidelity surrogate model, as two predictions for the next thermal state $\hat{Y}$. Subsequently, a meta predictor combines both predictions appropriately through a multi-fidelity scheme to produce a multi-fidelity surrogate model for X_{t+1}, which will follow LFM's sampling rate. The produced estimated mean $\hat{\mu}$ and standard deviation $\hat{\sigma}$ are compared with a desired value for uncertainty and fed back to the HFM.

5. DISCUSSION

The simulator proposed by Akita et al. (2012), and discussed in section 2, is the HFM. On the other hand, the LFM is implemented with both an LSTM and ARIMAX. To avoid complicating the analysis and increasing the computational burden, in the final stage, the one that describes the true behavior of the satellite's thermal state more accurately will be used as LFM. For the multi-fidelity component, the basic cokriging framework proposed by Kennedy and O'Hagan (2000), described in section 2, and Le Gratiet and Garnier's (2014) work, on decoupling the cokriging scheme into two parallel kriging schemes for easy computation is used. A limitation of this framework is that its individual constituents have been demonstrated to work on Multiple Input Single Output (MISO). However, a future expansion will focus on implementing a system that can also handle multiple outputs. When working with online data, low fidelity predictions will be corrected to estimate the high fidelity prediction. Whenever a true high fidelity prediction is generated, the model will be updated for a minimum computational cost, since it only requires refitting the model with the new data. In order to optimize the process for computation time, the estimated uncertainty will be constantly compared to a predetermined, application dependent, value. If found undesirable, the model can be updated with high fidelity information at a cost of computation time.

Concerning our choice of surrogate models for the low fidelity prediction of time series, a multitude of methods in the bibliography have been developed. However auto-regressive methods and recurrent neural networks have been shown to produce good results. While the main drawback of neural networks is that that they are not explainable, it is not an issue in this particular case since they do not need to produce

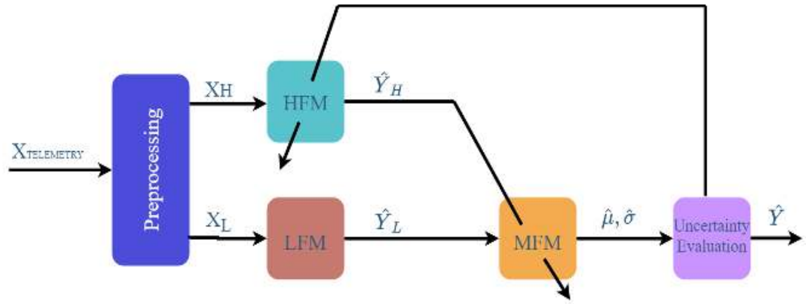

Figure 5. Proposed Framework

an estimate for uncertainty. UQ will be carried out using the MFM. As input features, the framework will accept attitude parameters, orbital elements, the Earth's radiation parameters and previous thermal states. These data will also have to be preprocessed in order to be in suitable format for the two separate models. Even though multiple applications of cokriging have been presented , to our knowledge, there is limited work that:

1. Discusses how multi-fidelity modelling can enable a satellites digital twin architecture;
2. Addresses the shortcomings of telemetry data;
3. Investigates multiple features to improve the results from solving the thermal equations.

When considering a physical application of the framework and its incorporation in a digital twin architecture, onboard measurements, received by telemetry, can replace the HFM. The main drawback of telemetry is sparsely arriving data. However, this is not an issue for the proposed framework which reflects a 'living' digital twin as described in Section 1. The MFM corresponds to the digital model. An established knowledgebase is utilized to construct the low fidelity model. Analytics are performed to decide whether or not to increase the number of data points. This is achieved through continuous communication with the physical satellite. Besides the development of another framework for satellite simulation, the main impact of our approach is to compliment efforts by other researchers to tackle the unreliability of telemetry data. This will enable fault detection systems on the ground to have accurate information on the satellite. A recent paper applied a cokriging scheme on all-electric geostationary orbit satellite systems for optimization. Their research supports our work, however our end goal is different (Shi, Liu, Long, Wu, & Gary Wang, 2020). This research focuses on:

1. Handling real-time data within the digital twin framework, instead of optimization;
2. The problem of processing telemetry data;
3. Testing various methods to construct the low fidelity surrogate model.

Finally, the framework will be validated initially through synthetic data, generated by the high fidelity simulator proposed by Akita et al. (2012) and subsequently with real data provided by the Intelligent Space System's laboratory of the University of Tokyo. In particular, accuracy, computation times and memory usage will be benchmarked against purely low fidelity and high fidelity simulations. However, the absolute accuracy requirement to be achieved depends on the particular application and is to be determined at a later time.

6. Conclusion

This paper proposes an online multi-fidelity framework for small satellites. After reviewing each individual component, i.e., the low fidelity surrogate model, the high fidelity model and the multi-fidelity methods; it is observed that individually they can function effectively. Gaps in the body of work on the digital twin for satellites have been identified. A method for online data processing was investigated and is expected to be appropriate for the thermal simulation of a small satellite. In our future work, the feasibility of this digital twin enabled framework is being implemented.

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