**REDUCED ORDER MODELS AND MACHINE LEARNING ALGORITHMS TO DEVELOP PREDICTIVE THERMAL TOOLS FOR SPACECRAFT SIMULATIONS**

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**ABSTRACT:**

In the spacecraft industry, particularly for satellites, accurate predictions of transient thermal behaviour of their components is critical. Unfortunately, such simulations are very time consuming and computationally expensive. As a result, there is a great need to reduce simulation time as much as possible to be able to analyse the full transient thermal behaviour of spacecraft. *Reduced Order Models* (ROMs) and machine learning techniques can thus be very useful to address these challenges while maintaining the high level of accuracy required in thermal spacecraft analysis.

In this paper, we review the various techniques and concepts of ROMs, and detail a novel method for coupling thermal modelling tools (commercial software Simcenter™ 3D Space Systems Thermal (SST) developed by Maya HTT) with machine learning (ML) algorithms to develop predictive thermal tools for spacecraft simulations. Additionally, we utilize a model reduction method to reduce the complexity of the models, the results of which can then be mapped back onto the original high fidelity models. The ML are trained on existing or generated simulation data and used as a predictive tool to drive thermal physics solutions without the need to explicitly resolve the conductance networks over the entire lifetime of the simulation, thus greatly reducing the burden to run explicit simulations.

# **INTRODUCTION**

Engineers increasingly use numerical models and analysis at every stage of the design and development of spacecraft. Every component needs to be assessed to ensure that its temperature and thermal distortion remain within pre-established operating conditions, and meet all the thermal requirements during the entire mission sequence. These numerical models can be very detailed and complex [1], based on approximate thermal analytical models [2] or even simply on experience and / or heuristic models [3].

Detailed numerical models, based on the discretization of the governing Partial Differential Equations (PDEs) of heat transfer can be computationally intensive, with solution times taking between a few hours to a few days for one transient simulation. On the other hand, approximate and heuristic models, although very fast to generate, are often not accurate enough, leading to large uncertainties which do not fulfil the stringent requirements of the spacecraft industry.

In this context, the use of ROMs is particularly interesting. ROMs are mathematical models that provide accurate descriptions of the dynamics of a system with a much lower computational cost than the fully detailed models. *Proper orthogonal decomposition* (POD) is a widely used model reduction technique for complex non-linear problems [4]. The POD generates a reduced set of base functions for Galerkin representations of the PDEs. In other words, given an ensemble, consisting of *N* data vectors of length *Nx*, the POD theory dictates that we can find a set of orthonormal basis functions such that the variance of the dataset in this coordinate system becomes maximal. Therefore, when the PDEs are projected onto this basis set, a reduced order model is generated.

In the last decade, the fields of artificial intelligence (AI), machine learning (ML) and deep learning have blossomed. Their applications include: computer vision, speech and language processing, robotics, video games, search engines, online advertising, and finance. These fields benefit from having large sets of data which can be used to train the machine learning algorithms. In the field of engineering simulation, the relatively small number of data samples available to a simulation analyst has historically precluded them from taking advantage of machine learning techniques. However, ML techniques offer exciting new possibilities for creating reduced models. ML methods are potentially well suited for the creation of reduced models given that the discovery of the reduced model parameters will come from the inputs and corresponding outputs of the full model for a variety of cases [5-7].

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