

Deep Learning Based Thermal Stress and Deformation Analysis of Satellites

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Abstract. When analyzing the thermal stress and deformation of satellites in orbit, the traditional numerical methods, such as the finite difference and the finite element, are expensive and time-consuming. To improve computational efficiency, we propose a deep-learning based surrogate to immediately predict the thermal stress and deformation of a satellite with a given temperature field, where the U-Net is employed to learn the end-to-end mapping from the temperature field to the thermal stress and deformation. A data set with less smooth temperature fields is generated to augment the training data, by which the accuracy and generalization performance of the model is significantly improved. Combined with a rapid temperature prediction method, the model predicts the thermal stress and deformation of a satellite motherboard given several heat sources, verifying the feasibility and effectiveness of the proposed method.

Keywords: Deep Learning, thermal stress and deformation, satellites motherboard

1. Introduction

As influential performers of space missions, satellites play an irreplaceable role in communication, remote sensing, navigation, and military reconnaissance [1]. Nevertheless, their reliability and longevity are long-stand challenges. The satellite components will be periodically exposed to alternating high and low temperature fields from outer space during the period of on-orbit. The change of temperature will cause fatigue, delamination, and fracture of satellite components, affecting their operational performance and service life [2]. Besides, the satellite components will inevitably generate immense heat during operation due to high power density, which will lead to a series of problems such as thermal deformation, thermal buckling or thermal vibration [3]. All above will significantly affect the pointing precision of the satellite when performing missions. Therefore, it is essential to analyze the thermal stresses and deformation of the satellite.

At present, there are three primary means to analyze the in-orbit satellites: experimental, simulation and theoretical [4]. For experimental methods, the ground-based simulation test is expensive, and it still cannot measure the parameters directly in a thermal vacuum tank accurately; besides, the increasing size of the satellite structure makes it more challenging to perform ground tests of a full-size model of the satellite.

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Therefore, theoretical analysis and simulation have become the mainstream methods for the in-orbit analysis of satellites [5]. However, these traditional numerical calculation methods, such as finite difference and finite element, often cost much calculation time [6]. It is difficult to provide an immediate response to the thermal stresses and deformation when the temperature field changes. Therefore, it is necessary to develop an efficient surrogate model with high precision that meets the fast calculation requirement.

With the booming development of artificial intelligence, deep learning technology based on Deep Neural Network (DNN) has emerged in many fields, such as computer vision and natural language processing [7]. Due to the universal approximation ability and efficient computation of neural networks [8], the surrogate modeling technique based on deep learning provides a paradigm to construct high-precision models for thermal stress and thermoelastic deformation.

In recent years, many deep learning based surrogate models for regression between high-dimensional variables have emerged in various fields. In thermodynamics, Rishi Sharma et al. [9] solved thermal transport problems by U-Net structure. In aerodynamics, Shen et al. [10] developed a generative deep learning model to generate the numerical solutions for N-S equations. Also, Thuerey et al. [11] investigated the accuracy of deep learning models for the inference of Reynolds-Averaged Navier-Stokes solutions. In addition, Cheng et al. [12] predicted the 2D velocity and pressure fields around arbitrary shapes in laminar flows by deep learning based surrogate model. In optics, Li et al. [13] proposed a deep learning framework for real-time predictions of the scattering from an isolated nano-structure in the neared regime. The literature above has demonstrated the powerful regression capabilities of surrogate models endowed with deep learning techniques.

In the field of elasticity, Saurabh Deshpande et al. [14] predicted the response of super elastomers under load by the U-Net framework. The proposed approach to similar problem motivated us. In this paper, we introduce a deep learning based method to predict thermal stress and deformation of the satellite. We simply the problem as predicting the thermal stress and thermal deformation of a satellite motherboard where some heat sources distribute in. Firstly, to address the point of the problem, we implement the regression task, which maps the temperature field to thermal stress and deformation by U-Net structure. Secondly, to augment the training data, a data set with low smoothness is used for training. In this way, the accuracy and generalization performance of the model is well improved. Experiments show that the U-Net surrogate can effectively return accurate estimates of the thermal stress and deformation. Finally, the surrogate is used to predict the thermal stress and deformation of the satellite motherboard. This new approach can be used in real-time monitoring techniques. Also, it helps to promote the application of deep learning in practical engineering and enrich the solution to engineering problems.

This paper is organized as follows. In section 1, we introduce the background and related works. Section 2 presents the essential mathematical models of the thermal field, thermal stress, and deformation. Section 3 describes the training processes of the planar thermoelastic problem by U-Net. Then section 4 shows the experiment results. In Section 5, the summary of the research is outlined.

2. Mathematical model of thermodynamic coupling problems

This section investigates linear thermoelastic problems driven by thermal properties. The solution of thermodynamic coupling problems is segmented into two processes, heat conduction problem and thermoelastic problem. We discuss the two mathematical models respectively.

2.1. Mathematical model for heat conduction problem

This paper studies the thermal stress and deformation of a satellite motherboard where some heat sources distribute in. Firstly, we need to calculate the temperature field of the motherboard. The thermal layout model of the satellite motherboard was previously defined by Chen et al. [15], which is illustrated in Fig.1. The thermal layout shows a two-dimensional satellite motherboard with partial openings, with three sides of the plate adiabatic and one side with a convective heat transfer coefficient of . FDM method is used to build the dataset, the process of which is indicated by the red arrow. The blue arrow indicates the surrogate model approach. In this way, we can focus our energy on the tricky part.

The steady-state temperature field T , which contains multiple heat sources in the two-dimensional motherboard, can be calculated by the Poisson equation. The partial differential equations are as follows,

$$\frac{\partial}{\partial x} \left(k \frac{\partial T}{\partial x} \right) + \frac{\partial}{\partial y} \left(k \frac{\partial T}{\partial y} \right) + \phi(x, y) = 0, \quad (1)$$

$$\text{Boundary : } T = T_0 \text{ or } k \frac{\partial T}{\partial \mathbf{n}} = 0 \text{ or } k \frac{\partial T}{\partial \mathbf{n}} = h(T - T_0),$$

where k means the thermal conductivity of the layout domain, $\phi(x, y)$ represents the power distribution of heat sources and h means the convective heat transfer coefficient. The following Poisson equation includes three different boundary conditions: Dirichlet (isothermal), Neumann (adiabatic), or Robin (convective). The power distribution function $\phi(x, y)$ is determined by the positions and power of different heat sources, which can be expressed as

$$\phi(x, y) = \begin{cases} \phi_i, (x, y) \in \Gamma_i, \\ 0, (x, y) \notin \cup \{\Gamma_i\}, \end{cases} \quad (2)$$

where ϕ_i means the intensity of one single heat source and Γ_i denotes the area the heat source covered. When the layout and the power of heat sources changes, functions change, so as to influence the steady-state temperature field of the domain.

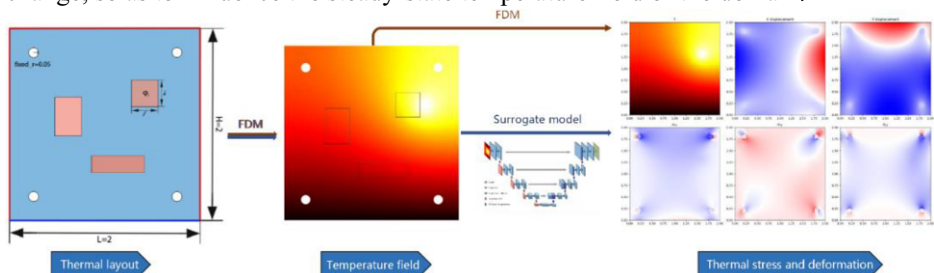


Figure 1. Model definition and calculation process.

2.2. Mathematical model of thermoelastic problem

In this part, the temperature field is given as an input. It can be obtained as a solution to the steady-state thermal equation (Poisson equation). The linear elasticity coefficient α is assumed to not change with temperature.

As the elastomer is subject to external constraints as well as mutual constraints between parts of the body, when the temperature changes, The motherboard tends to expand, and the constraints on elastomers will cause thermal stress. It would in turn generate new additional strains due to elasticity. The strain components and temperature T satisfy

$$\begin{cases} \sigma_x = \frac{E}{1-\mu^2} \left(\frac{\partial u_x}{\partial x} + \mu \frac{\partial u_y}{\partial y} \right) - \frac{E\alpha T}{1-\mu}, \\ \sigma_y = \frac{E}{1-\mu^2} \left(\frac{\partial u_y}{\partial y} + \mu \frac{\partial u_x}{\partial x} \right) - \frac{E\alpha T}{1-\mu}, \\ \sigma_{xy} = \frac{E}{2(1+\mu)} \left(\frac{\partial u_y}{\partial x} + \frac{\partial u_x}{\partial y} \right). \end{cases} \quad (3)$$

According to the equilibrium differential equation, the thermal displacement components satisfy

$$\begin{cases} \frac{\partial^2 u_x}{\partial x^2} + \frac{1-\mu}{2} \frac{\partial^2 u_x}{\partial y^2} + \frac{1+\mu}{2} \frac{\partial^2 u_y}{\partial x \partial y} - (1+\mu)\alpha \frac{\partial T}{\partial x} = 0, \\ \frac{\partial^2 u_y}{\partial y^2} + \frac{1-\mu}{2} \frac{\partial^2 u_y}{\partial x^2} + \frac{1+\mu}{2} \frac{\partial^2 u_x}{\partial x \partial y} - (1+\mu)\alpha \frac{\partial T}{\partial y} = 0. \end{cases} \quad (4)$$

The stress boundary conditions according to displacement are

$$\begin{cases} l \left(\frac{\partial u_x}{\partial x} + \mu \frac{\partial u_y}{\partial y} \right)_s + m \frac{1-\mu}{2} \left(\frac{\partial u_x}{\partial y} + \frac{\partial u_y}{\partial x} \right)_s = l(1+\mu)\alpha(T)_s, \\ m \left(\frac{\partial u_y}{\partial y} + \mu \frac{\partial u_x}{\partial x} \right)_s + l \frac{1-\mu}{2} \left(\frac{\partial u_y}{\partial x} + \frac{\partial u_x}{\partial y} \right)_s = m(1+\mu)\alpha(T)_s. \end{cases} \quad (5)$$

According to the equations above, the thermal stress and deformation of the satellite motherboard with any heat source layout can be calculated.

3. Surrogate model of thermal stress and deformation based on U-Net structure

This section describes the surrogate model of thermal stress and deformation based on U-Net, which can predict the planar thermoelastic problem when given the temperature field. According to the above mathematical models, the key lies in solving the equations of thermoelastic dynamics. Therefore, we focus on mapping the temperature field to thermal stress and deformation. It is organized as follows. Section 3.1 introduces the U-Net architecture. In Section 3.2, the construction of the data set is described in detail. Section 3.3 presents the training process.

3.1. U-Net architecture

The structure of U-Net is shown in Fig.2. It is a symmetric structure similar to a U-shape, consisting of two main parts, encoder and decoder. The encoder is the feature extraction part, and it is a classical VGG-16 network similar to the coding process, which learns multi-scale features of an image through pooling and convolution operations; The decoder is an up sampling process, which reduces the image size layer by layer through deconvolution operations. U-Net fuses the feature extraction part with same scale, then obtains more features from the lower-level feature maps, effectively preserving the information in the original image and preventing the loss of too much detailed information. In this way, U-Net combines features at different scales and increases the amount of information, and the accuracy of model benefits from this structure. Referring to the above characteristic, the U-Net is well suited for regression tasks between images.

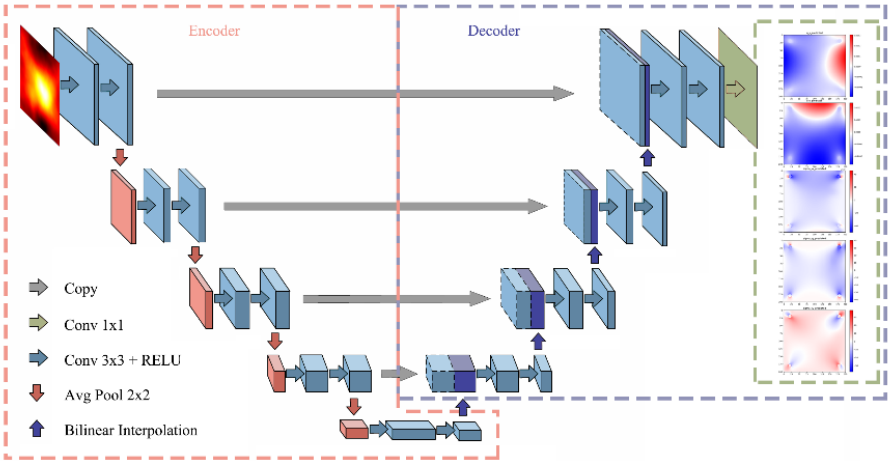


Figure 2. U-Net architecture.

3.2. Data preparation

The specific task problem is shown in Fig.1. We consider a two-dimensional rectangular satellite motherboard with size $L \times H$. The motherboard is not subjected to self-weight loads. It has four circular holes inside, which simulate the screw articulation of an actual engineering component. There is no displacement at the edges of the circular holes. Thermo-elastic properties are assumed to be isotropic and linear. In this model, parameters are the same as those of aluminium and will be considered around a reference temperature $T_0 = 293\text{K}$. Stress and flux-free boundary conditions are applied on the outer boundary of the plate. Detailed parameters are shown in Tab.1.

In the U-Net, the input is a two-dimensional planar temperature field in the form of matrix. The outputs are the corresponding thermal stress matrix and the thermal deformation matrix. The Finite-Difference Method (FDM) [16] was used for the calculation. The computational domain is a 200×200 uniform grid, and the 200×200 temperature field matrix is the input; five 200×200 matrices are outputs, which

represent x-direction displacement(u_x), y-direction displacement(u_y), x-direction thermal stress(σ_{xx}), y-direction thermal stress(σ_{yy}), tangential stress(σ_{xy}) respectively.

Table 1. Parameter list

Option	Symbol	Value	Units
Length of plate	L	20	cm
Height of plate	H	20	cm
Radius of the holes	R	0.5	cm
Thermo-conductivity	k	0.5	W/(m×k)
Linear coefficient expansion	α	$1e-5$	1 / °C
Young's modulus	E	$50e3$	MP
Poisson's ratio	μ	0.2	/

Referring to the solution of Poisson equation, the temperature field of satellite motherboard is very smooth. To augment the training data, two data sets with lower smoothness than actual conditions are used for training. The temperature field is generated by the gaussian random field. When we adjust the standard deviation and mean of the gauss function, the smoothness of temperature changes as well. We generated two training sets, respectively DS and DC (as shown in Fig.3). The DS and DC are two samples in the sample set with a sample size of 10000. DS means relatively smooth temperature and DC means relatively coarse one. However, both of them are more complex than the temperature field of the satellite motherboard.Also, we have 500 general samples as test set TS, and the smoothness level of it is the same as DS. The TS is generated in the same way of training set.

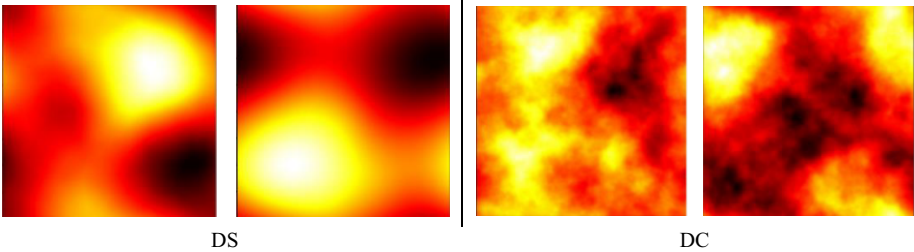


Figure 3. Training set comparison.

3.3. Data preparation

Given an arbitrary temperature field T , we can obtain the outputs from the neural network surrogate model, i.e., the predicted thermal stress and deformation. The training objective of the U-Net model is to minimize the difference between the predicted outcome \hat{Y} and the label Y , so that the surrogate model can fit the labels. Once the model is trained, it can be applied in inference to the thermal stress and deformation corresponding to any temperature field. This task has five predicting targets, and if they were trained individually in a single-channel manner, it would be time-consuming. To solve this problem, this paper adopts multi-task training method.

In this regression task between images, the loss function is defined by

$$Loss_i = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2. \quad (6)$$

The dimensions between different tasks are different. To ensure the balance of training accuracy as well as training speed between different tasks, the normalized operation is applied, and the loss function is weighted according to the task characteristics just as

$$Loss = \sum_{i=1}^m w_i \times Loss_i, \quad (7)$$

where m means the number of tasks, and w_i is the weighted value determined by loss of different tasks. In this way, we map the thermal field to thermal stress and deformation.

4. Experiment results

In this section, the experiment results are discussed. AdamDelda [17] is chosen as the optimization. The U-Net model is implemented by PyTorch 1.8. For training, we set the epoch to 500 and the batch size to 64.

4.1. Performance of U-Net

The predictions of the surrogate model after 500 epochs are shown in Fig.4. It shows the label of a randomly chosen temperature field in TS, along with the output of the trained neural network and the absolute error.

The mean relative error(MRE) in the pixel-by-pixel output is only 2.13%. Average per-pixel error is computed relative to “ground truth”, which is determined by running finite difference to very high precision. Through such a deep learning surrogate model, the computation time is reduced from 2min to 0.23s, effectively saving cost of time. This demonstrates the feasibility of using the U-Net model for regression between ultra-high dimensional variables. It also illustrates the effectiveness of the deep learning based surrogate model of thermal stress and deformation.

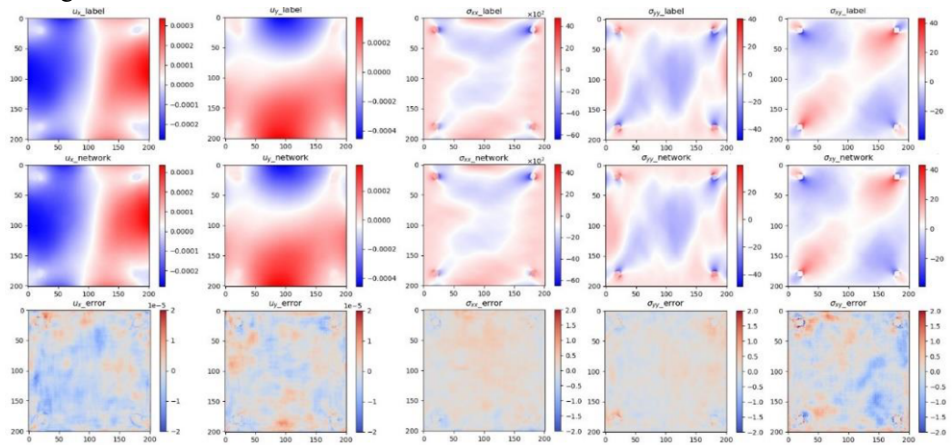


Figure 4. Comparison between ground truth and network result(TS).

4.2. The performance of data augmentation on the generalization of prediction results

We compared the performance of the surrogate on different training sets after 240 epochs. U-Net was trained on DS and DC respectively (Fig.3), then they were both tested on the TS.

The results are shown in Tab.2. It can be seen that the surrogate models trained on both data sets exhibit good performance. However, the MRE of DC is obviously less than that of DS, even though DS is as smooth as TS. It can be explained as data augmentation. The more complex data set (DC) increase the diversity of the data set, which improves the accuracy and generalization of the surrogate model.

Table 2. Performances on the TS for different data sets

Option	MRE/%	
	DS	DC
u_x	3.32	2.61
u_y	3.47	2.37
σ_{xx}	3.92	2.16
σ_{xy}	3.92	2.32
σ_{yy}	3.22	2.19

4.3. Application: Thermal stress and deformation analysis of the satellite motherboard

When given the heat source layout of a satellite motherboard, the temperature field of it is calculated by finite difference. Then the surrogate, which maps temperature to thermal stress and deformation, is applied. Fig.1 shows a randomly generated heat source layout and the corresponding temperature field of the satellite motherboard. Fig.5 shows the corresponding thermal stress and deformation calculated entirely by the finite differences(label), the output of the trained neural network and its absolute error. The MRE in the pixel-by-pixel output is only 1.76%. It is less than that on TS. This phenomenon also benefits from the data augmentation by DC. This demonstrates that the deep learning-based surrogate model is effective in solving complex thermodynamic coupling problems such as satellite thermal stress and deformation.

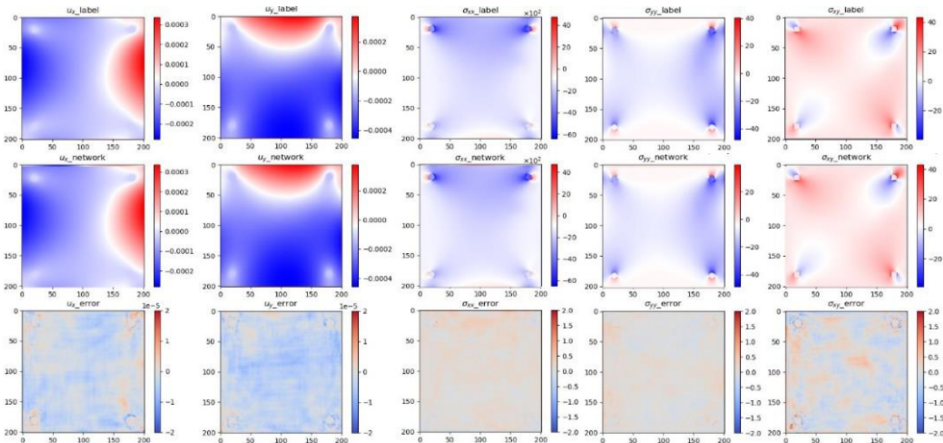


Figure 5. Comparison between ground truth and network result(Satellite motherboard).

5. Conclusions

This paper presents an end-to-end deep learning based surrogate modeling method for predicting the thermal stress and deformation of satellites. The neural network is used to construct surrogate models for fast simulating complex thermodynamic coupling problems, where traditional numerical methods often cost much calculation time and resources.

The prediction problem is simplified as predicting the thermal stress and thermal deformation of a satellite motherboard where some heat sources distributed in. We build a surrogate model which maps the temperature field to the thermal stress and deformation, and then make some data augment strategies to improve the accuracy and generalization performance of the model. The surrogate model later is used to predict the thermal stress and deformation of the satellite motherboard with some heat sources. This case verifies the feasibility and effectiveness of our deep learning surrogate model.

The results demonstrate that this deep learning-based surrogate model method is effective in solving complex thermodynamic coupling problems such as thermal stress and deformation of satellites.

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