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TOWARDS SPACECRAFT REAL-TIME THERMAL SIMULATION WITH ARTIFICIAL NEURAL NETWORKS

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Abstract. *One of the most complex software developed to support the spacecraft operation phase is the Operational Spacecraft Simulator (OSS). It must provide data in real-time to the spacecraft operators, as if they were transmitted from the real spacecraft, with the best possible fidelity. All spacecraft subsystems are presented in the OSS and their computer models need not only be representative of the real subsystem performance behavior, but also computationally inexpensive, such that real or near real telemetry response simulation is guaranteed. The spacecraft simulation model used for its thermal design is usually computationally expensive for application in OSS, and simplified models must be developed for this purpose. In this work, the use of Artificial Neural Networks (ANN) is investigated as a potential estimator of the spacecraft thermal behavior in orbit. The trained ANNs are used to provide the transient thermal behavior of a simplified model of a hypothetical CubeSat in Earth orbit. Results show that the ANN can reproduce with good fidelity the orbit temperatures generated by a thermal simulation software including points not used for training.*

Keywords: *thermal design; spacecraft; real-time simulation; artificial neural networks*

1. INTRODUCTION

In modern approaches such as Systems Engineering and Model-Based Engineering the use of computational modeling and simulation is practically mandatory. Modeling and simulation can save a significant amount of resources, including material, personnel and time. This is particularly true in the development of complex and unique systems as a spacecraft, which must be extensively tested and evaluated in various scenarios before launch.

Simulations can be applied throughout the entire system life cycle, from mission conception to operation and disposal. Here we are interested in the simulations that support the operations phase of a spacecraft life cycle, performed by a tool here called Operational Spacecraft Simulator (OSS). This simulator can be used before launch to validate the ground segment and to train the flight control teams to respond quickly and correctly in routine or unexpected situations, and for planning orbital maneuvers and rapid assessment and analysis of any abnormal readings, during operation ((Eickhoff, 2009; Ambrosio, *et al.*, 2006).

The OSS must reproduce the spacecraft's function and behavior as if it were actually in space. In this way, the simulator can be integrated with the ground control system to run complete scenarios with such fidelity that its output would show little difference between the simulation and the real spacecraft (Reggestad, *et al.*, 2011). In order to achieve this goal, one of the main requirements of this simulator is to produce data in real-time, which can be challenging, given the complexity of space systems.

The complete simulator is comprised by a set of software building blocks that are developed according to the systems involved (space and ground) and the specific mission it will support. All spacecraft subsystems must be present in the OSS and their computer models need not only to be representative of the real subsystem performance behavior, but also computationally inexpensive, such that real or near real telemetry response simulation is guaranteed.

Among the models that compose the simulator, the thermal model is one of the most challenging to be implemented in real-time. The design of the thermal control subsystem is usually supported by specialized software used for modeling and analysis. In this software the thermal system is discretized into a network of nodes (a few thousands for a medium satellite) and differential heat equations are integrated to compute the temperatures of these nodes for a specific scenario and at a given time. For this reason, high fidelity thermal simulations are computationally very expensive, which makes it difficult to use directly in an OSS. So it is necessary to seek an alternative capable of providing data on the thermal behavior of the spacecraft in real-time without loss of fidelity compared to the real system.

The literature about high fidelity thermal simulation in real-time, as found so far by the authors, is scarce. As stated by Perpiñán (1994), usually there are two approaches to this problem. One is to carry out an interpolation over a finite set of selected typical scenarios for which the thermal behavior is known. The disadvantage is the uncertainty of the output for nonstandard scenarios. Other method is to simplify the thermal model, reducing drastically the number of nodes (to some dozens) and interactions to save CPU time in the integration of the system of differential equations. The drawback is the loss of accuracy, especially for the standard scenarios.

Kang *et al.* (1995) developed a real-time simulator to support ground operations activities of ETRI's (Electronics and Telecommunications Research Institute - Republic of Korea) satellite control system. Applications include: ground system testing, validation of flight control, checking the controls of satellites and ground training of operators. The model simulates the characteristics of a geostationary satellite communications. According to the authors, it is a high-fidelity simulation tool which can be used in low cost desktop computers. The model of the thermal control subsystem simulates the switching state of the heaters and calculates the temperature of satellite nodes in accordance with the angle of the sun. The model export telemetry data to the shared memory. Most thermal commands are in the category of enable/disable heaters and heating control units. The authors do not report details on how the calculation of temperatures is done.

More recently, Raif *et al.* (2009) developed a modular dynamic simulation approach, based on SysML to model the design of a small satellite, regarding the system composition and its dynamic behavior. The described method is used to predict the performance of the system in the initial project design phase. So they use simple models to limit complexity. Although the modular method is adaptable and may be used in later stages. The goal is to build a library of modules, from which the satellite design can be assembled and simulated. The thermal behavior describes the temperature distribution inside the satellite. As they wanted to avoid the use of partial differential equations, only a model of lumped parameters was considered in which several isothermal nodes exchange thermal energy by conduction and radiation. The number of nodes was limited to minimize the computational effort. Each node was characterized by its temperature (state) and the thermal capacity.

Martínez-Heras and Donati (2004) investigated the benefits and drawbacks of using data based models, such as neural networks, in support of satellite behavior modeling process. This approach was applied to the ESA CLUSTER mission to retrieve the readings of a simulated faulty temperature sensor. They supposed that one of the thermal sensors failed suddenly, so that their data would no longer be available. The goal then was to reconstruct the values that this sensor would have generated, considering the availability of the previous telemetry data, and using the implicit redundancy of the information generated by the remaining sensors. They also applied neural networks for the ROSETTA mission. The goal was to provide the readings of certain important thermal sensors as a function of distance from the Sun and attitude. In this case, were used the data from the thermal balance/thermal vacuum simulations.

In our literature review, the work of Martínez-Heras and Donati (2004) was the only one we have found that applies ANNs to simulate the thermal behavior of spacecrafts. However their work only addressed the thermal behavior of some specific components, and they did not have the requirement to run the simulations in real-time. In this way, our objective is to investigate the application of ANNs as a potential real-time quantitatively high fidelity estimator of the thermal behavior of a satellite in Earth orbit. To assess this we performed a test case which consists in a simulation of the behavior of a very simplified, thermal model of a hypothetical CubeSat (Woellert, 2011), in an equatorial Low Earth Orbit (LEO). Although not representative of a real satellite, the model can provide indications that the ANNs could reproduce results obtained from more detailed models.

2. SPACECRAFT THERMAL CONTROL

In the design of space systems, thermal control subsystem serves to maintain the temperature of all equipment and components within acceptable ranges for its proper operation during all phases of the mission.

The thermal control of satellites should be planned in such a way that the system is protected from temperature variations in different environments throughout its life cycle (Gilmore, 2002).

The main sources of external heating in orbit are the direct solar radiation, solar radiation reflected by Earth (albedo) and infrared (IR) radiation emitted by Earth. The thermal control of a satellite in orbit is usually accomplished through the balance between the energy emitted by the satellite as IR radiation, the energy dissipated internally by the electrical components and the energy absorbed from the space environment.

Inside the spacecraft, thermal transfers occur mainly by radiation and conduction. Convection only occurs in equipment or components containing fluid or gas, such as heat pipes. The heat produced by the electric equipment dissipation is propagated by means of radiation emission and thermal conduction to the structure, components and other equipment. The excess heat generated internally is conducted away through the satellite radiators.

For the development of thermal design it is important to consider, for each device, its operational and non-operational temperature ranges, if there is a wide variation in the external loads or in the equipment dissipation along the orbit, if the equipment presents high heat dissipation rate, if requires strict temperature control, if thermal insulation is necessary and if the equipment needs to work on cryogenic temperature.

3. ARTIFICIAL NEURAL NETWORKS

In its most general form, an Artificial Neural Network (ANN) is a logical machine designed to model the way in which the brain performs a particular task or function of interest (Haykin, 2009). To achieve this goal, ANNs employ a wide interconnection of simple computational cells, called neurons or processing units. In other words, a neural network is a parallel distributed processor that has a natural tendency for storing experiential knowledge and making it available for use.

A neuron is an information processing unit that is fundamental to the operation of a neural network. Figure 1 shows the model of an artificial neuron.

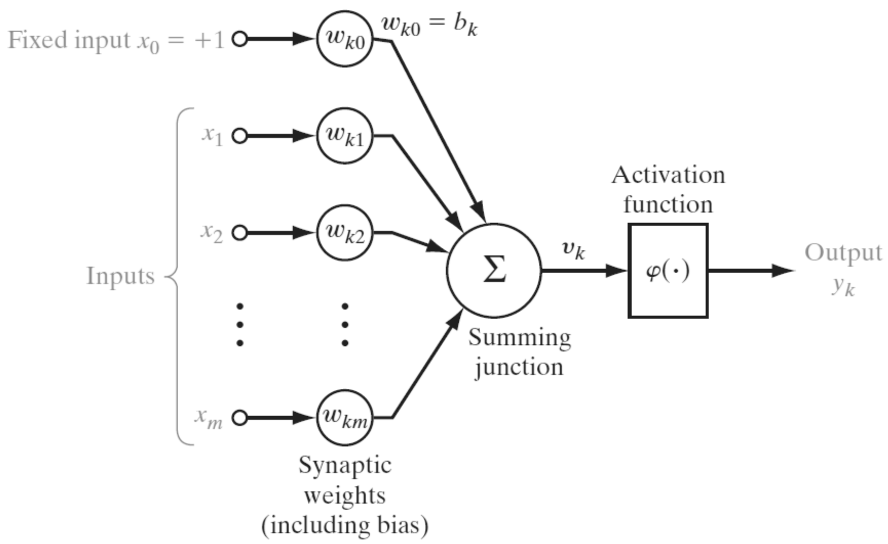

Figure 1. Artificial neuron model (Haykin, 2009).

In this diagram we identify three basic elements of the neuronal model: a set of connecting links, or synapses, each characterized by its own intensity, called the synaptic weight (w); one summing junction, that performs a linear combination of the input signals (x) at the synaptic weights; and an activation function (φ) that restricts the range of neuron output to a finite value.

The activation function (φ) can be any function that limits the output values between 0 and 1 or between -1 and 1, as the threshold function, the sigmoid function and a hyperbolic tangent function. Equations 1 and 2 define how the linear combination at the junction (υ) and the neuron output (y) are calculated:

$$\upsilon_k = \sum_{j=0}^{m} w_{kj} x_j \tag{1}$$

$$y_k = \varphi(\upsilon_k) \tag{2}$$

In general, three different classes of network architectures may be identified: feed forward networks with single layer and with multiple layers, and recurrent networks. Figure 2 shows a network of multiple layers, called Multilayer Perceptron (MLP). MLP networks have one or more inner layers of artificial neurons, called hidden layers as they don't have direct contact with the external environment of the network. The circles represent the artificial neurons.

Knowledge is acquired by the network through a training process, in which a series of data, also called training examples, are presented to the network. These examples can be labeled or unlabeled. In the labeled examples each signal input value is associated with a corresponding desired response. On the other hand, the unlabeled examples consist of different realizations of the input signal all by itself. In any event, a set of examples, labeled or otherwise, represents knowledge about the environment of interest that a neural network can learn through training.

In a simplified way, the process of training a neural network with labeled examples is to feed the network an input value that is transmitted by the neurons by the calculation of Eqs. 1 and 2, to produce an output value. This output value is then compared with the desired response and the associated error is calculated. This error in turn is used to update the synaptic weights of the network such that the output becomes closer to the desired value. Then, the next example is provided and so on, until the last training sample is presented to the network. If the total mean error is greater than a certain tolerance value, then the entire training set is presented again to the network. This procedure repeats until the total mean error is less than the tolerance. At this time, the network is considered trained.

However, to successfully conduct the training process is a complex task, as there are several free parameters such as the number of layers, the number of neurons, the learning rate, which defines the value size that is added or subtracted from the weights, among others.

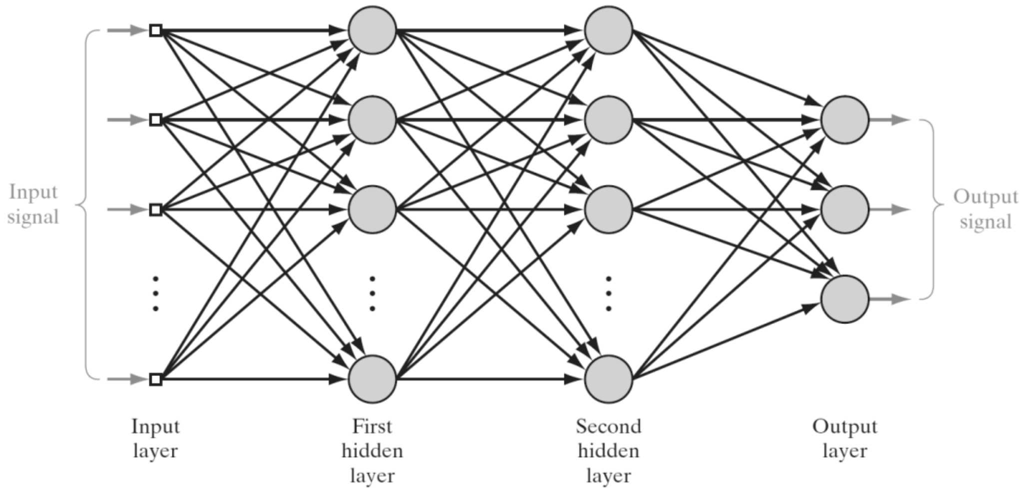

Figure 2. Multilayer Perceptron neural network with two hidden layers (Haykin, 2009).

This learning process allows the network not only to reproduce the acquired knowledge but also to generalize, that is, produce reasonable outputs for inputs not provided during training.

Neural networks also have the advantage of providing results very quickly, considering that after the training process, the knowledge is already stored in their structure and their parameters. However, in practice, the neural network cannot provide the working solution by itself. Instead, they need to be integrated into a consistent systems engineering approach.

4. TEST CASE

A thermal analysis software was used to simulate the temperatures of the CubeSat in a specific scenario and then part of such data was utilized to train the ANN to estimate the thermal behavior.

In order to implement this approach, we have modeled a very simple CubeSat using Thermal Desktop® and SINDA/FLUINT. The thermal CAD model is shown in Fig. 3.

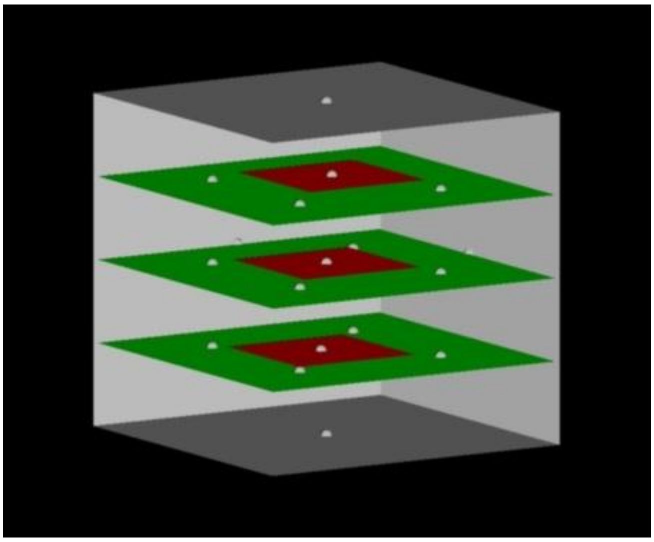

Figure 3. Thermal CAD model of the CubeSat.

The front walls were obscured so that the interior can be seen. This simplified model is comprised of an aluminum box of 10 x 10 x 10 cm, with three printed circuit boards (PCBs; in green) containing one dissipative component each (in red). The power of each component is, from top to bottom: 0.8, 0.4 and 0.6 W.

The orbit used in simulations is equatorial (inclination equal zero) at 500 km of altitude (LEO). This gives a period of 5676.98 s or approximately 94.62 min. The attitude is stabilized in 3-axis with one side always facing the Earth. For the Space Environment it was considered a constant Solar Flux of 1354 W/m^2, Earth Albedo of 35% and Infrared Radiation of 250 K (black body temperature).

The thermo-physical properties can be seen in Tab. 1 and the optical properties in Tab. 2. It was considered that the external surfaces are covered with Solar Cells and the internal surfaces painted with black paint. The dissipative components are composed of Silicon and covered with Graphite Epoxy.

Table 1. Thermo-physical properties (Costa, 2010).

Material	Density (kg/m^3)	Thermal Conductivity (W/m ºC)	Specific Heat (J/kg ºC)
Aluminum Alloy	2710	168.0	963.0
Fiberglass (PCB)	2440	1.1	737.0
Silicon	2320	148.8	712.0

Table 2. Optical properties (Costa, 2010).

Material	Absorptivity (α)	Emissivity (ε)	α/ε
Fiberglass (PCB)	0.75	0.89	0.843
Graphite Epoxy	0.93	0.85	1.094
Black Paint	0.95	0.87	1.092
Solar Cells	0.90	0.80	1.125

The temperatures were calculated using the SINDA/FLUINT software, which is a tool for heat transfer design and fluid flow modeling of complex systems. First the steady state was calculated and then the transient temperatures were stabilized for 10 orbits. Afterwards the data from the last orbit were extracted to train the ANNs. Besides the data provided by the thermal analysis software, the same method can be applied to train ANNs with data from the thermal tests and from the telemetry of the spacecraft after launch.

The thermal model contains a total of 21 nodes, but only the data of 9 nodes was used in training. The remaining nodes (PCB's nodes) are important in the computation of the temperature distribution in the satellite, but they are not needed in the OSS, since the satellite telemetry normally does not contain such information.

To perform this work, it was utilized a Multilayer Perceptron ANN with supervised training (Haykin, 2009). The parameters used for training were: two hidden layers, with 40 neurons each; learning rate of 0.01; momentum constant of 0.5; error tolerance of 0.0001; and, in case of non-convergence, the execution was interrupted after 10^6 epochs (complete training iterations).

These data extracted from SINDA/FLUINT are plotted in Fig. 4. The curves represent the temperature variation of the 6 external surfaces (blue squares) and the 3 internal components (red circles) along one orbital period. In this case, the lines are just guides to the eye.

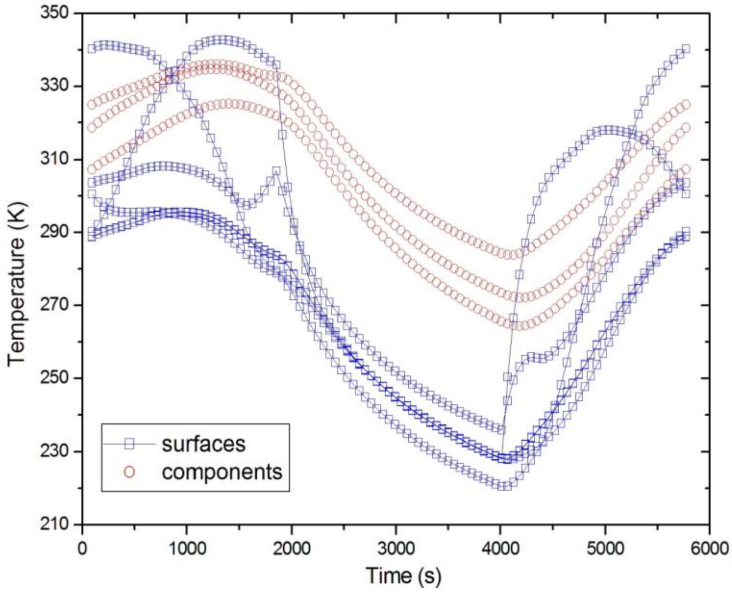

Figure 4. Temperature versus time generated using SINDA.

From the data shown in Fig. 4, twenty points were selected from each curve to train the ANN. The training process was performed so that the ANN could reproduce these 20 values of temperature versus time for each of the 9 curves within the specified tolerance.

After successful training, the ANN was used to build the temperature curves, based on the knowledge acquired. These curves are shown in Fig. 5 (continuous blue lines), along with the points used in training (red circles).

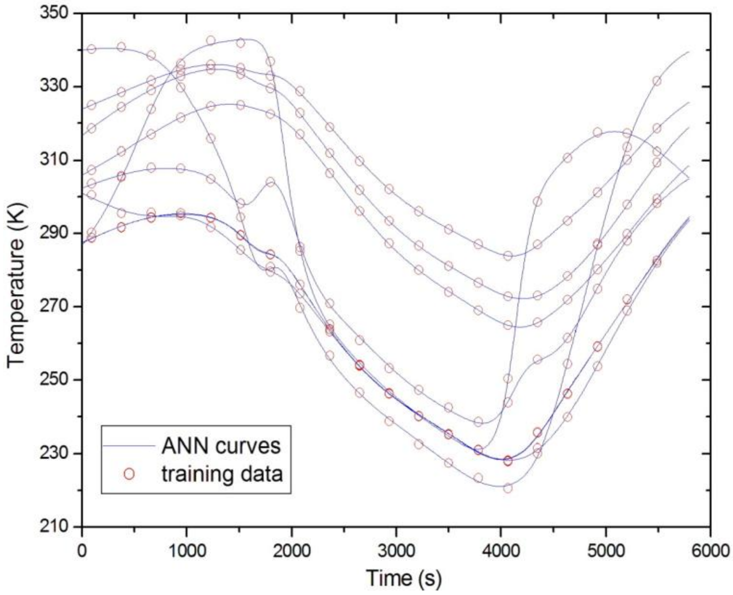

Figure 5. Temperature curves generated by the ANN and the points used for training.

The curves produced by the ANN show good agreement with the data used for training. On the other hand, since the ANN only had 20 points per curve to learn the temperature variation over the entire orbit, it is important to compare these curves with the data provided by SINDA and not used in training. Figure 6 illustrates this comparison in which only 3 nodes were selected for better visualization.

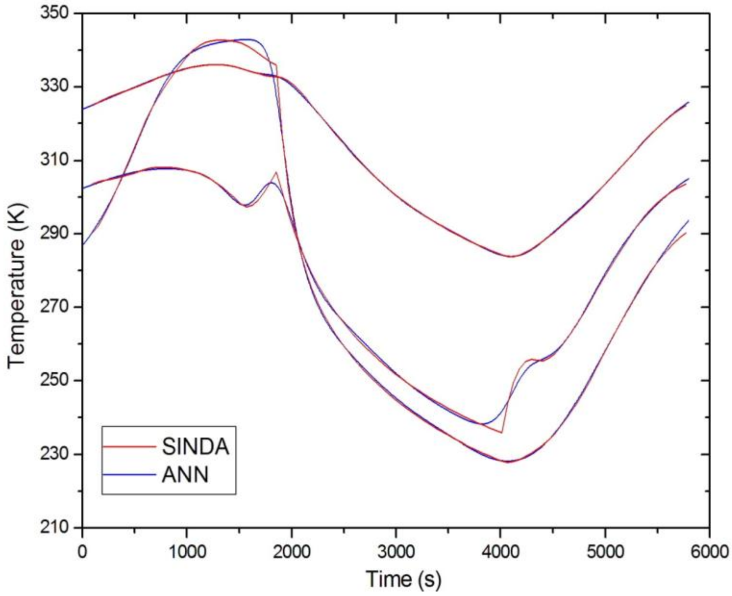

Figure 6. Comparison between the ANN and the SINDA data.

The results produced by the ANN (in blue) feature an extensive overlap with those generated by SINDA (in red). However, in some places the difference becomes greater, especially in the more irregular places. The maximum difference observed was about 13.3 K. As only twenty points per curve were used for training, some sections did not ended up being as well represented. This could be overcome by using a larger amount of points. But, in this way, we can observe the generalization capability of the ANNs.

Table 3 shows the mean error calculated for all the nodes, in Kelvin and percentage.

Table 3. Mean error of the ANN results compared with SINDA.

Node	Mean Error in K	Mean Error in %
Surface 1	0.5957	0.22
Surface 2	0.6142	0.23
Surface 3	0.4430	0.17
Surface 4	0.6654	0.23
Surface 5	0.4166	0.16
Surface 6	0.7723	0.29
Component 1	0.1450	0.05
Component 2	0.1389	0.05
Component 3	0.1345	0.04

The mean error is less than 1 K and less than 0.3% for all the nodes. It is even smaller for the internal components, since these curves are smoother, as the internal components are shielded to some degree from the Space Environment.

5. CONCLUSIONS AND FUTURE WORK

The results indicate that the ANN can learn the thermal behavior of a simplified small satellite into Earth orbit with great accuracy. Moreover, the ANN is able to estimate the temperature at any point in its orbit, although it has been trained with a limited number of points. Whereas the project is still at an early stage, the results obtained so far are very promising.

There are still important steps to achieve our goal, which is to develop a real-time OSS of the thermal behavior of a satellite using ANNs. An important question is whether the ANN will show the same capacity and precision with increasing scale and complexity of the satellite. In addition, we must also test the ability of ANNs to learn the thermal behavior in different scenarios, such as different modes of operation and changes in the space environment over a year.

In this way, the next step will be to conduct training with some different combinations of operating states of the internal components and verify if this can be done by a single ANN.

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7. RESPONSIBILITY NOTICE