Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 00 (2024) 000–000

Procedia
Computer Science

www.elsevier.com/locate/procedia

28th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2024)

Physics-Informed Neural Networks for Enhanced Thermal Regulation in a Spacecraft

J. de Curtò[a,b,d,e,*], I. de Zarzà[c,d,e]

[a] *Department of Computer Applications in Science & Engineering, BARCELONA Supercomputing Center, 08034 Barcelona, Spain*
[b] *Escuela Técnica Superior de Ingeniería (ICAI), Universidad Pontificia Comillas, 28015 Madrid, Spain*
[c] *Escuela Politécnica Superior, Universidad Francisco de Vitoria, 28223 Pozuelo de Alarcón, Madrid, Spain*
[d] *Informatik und Mathematik, GOETHE-University Frankfurt am Main, 60323 Frankfurt am Main, Germany*
[e] *Estudis d'Informàtica, Multimèdia i Telecomunicació, Universitat Oberta de Catalunya, 08018 Barcelona, Spain*

Abstract

Advancements in Artificial Intelligence (AI), particularly in Machine Learning (ML), are increasingly being utilized to address complex challenges in spacecraft technologies. One of the fundamental areas of focus is the thermal regulation system, which is crucial for the optimal functioning of the spacecraft. This paper introduces an innovative approach that employs Physics-Informed Neural Networks (PINNs) to model and predict temperature distributions within spacecraft. Unlike traditional neural networks, PINNs incorporate known physical laws, in this case, the heat equation, to ensure that the model's predictions are both accurate and physically consistent. We present a detailed methodology for developing a PINN that can accurately predict temperature variations over time, using sparse and noisy temperature data from a spacecraft. The proposed model is trained using a combination of data-driven and physics-informed loss functions, ensuring that the predictions adhere to the underlying physics of heat transfer. The results demonstrate the efficacy of PINNs in improving the accuracy of thermal predictions, which can significantly enhance the performance of the spacecraft's thermal regulation system. This work paves the way for further integration of physics-informed ML models in various aspects of spacecraft design and operation, offering a robust framework for tackling complex physical phenomena in space exploration.

Keywords: Physics-Informed Neural Networks; Computational Physics; Thermal Regulation

1. Introduction

Spacecraft thermal regulation is a critical aspect of space mission design and operations. The thermal control system ensures that the spacecraft and its components are maintained within their allowable temperature ranges,

* Corresponding author. Tel.: +49 069 79825567.
E-mail address: decurto@em.uni-frankfurt.de

which is essential for the optimal performance and longevity of the spacecraft. Accurate prediction of temperature distributions within a spacecraft is crucial for effective thermal management, allowing for the design of efficient thermal control systems and the prevention of temperature-related anomalies.

Traditionally, spacecraft thermal analysis relies on numerical simulations based on finite element methods (FEM) or finite difference methods (FDM). These approaches solve the governing heat transfer equations, such as the heat equation, over a discretized domain. However, these methods often require detailed knowledge of the spacecraft geometry, material properties, and boundary conditions, which may not be readily available or may change during the mission. Moreover, the accuracy of these simulations depends on the fidelity of the discretization and the quality of the input parameters, which can be computationally expensive and time-consuming to obtain.

In recent years, Machine Learning (ML) techniques, particularly Deep Learning (DL), have emerged as a promising alternative for modeling complex physical systems [7, 13, 1]. Deep neural networks have shown remarkable success in learning intricate patterns and relationships from data, enabling accurate predictions without explicit programming. However, traditional DL approaches often rely solely on data and do not incorporate the underlying physical laws that govern the system's behavior. This can lead to predictions that are inconsistent with the physical constraints and may not generalize well to unseen scenarios.

To address these limitations, Physics-Informed Neural Networks (PINNs) have been proposed as a novel approach that integrates physical laws into the learning process of deep neural networks. PINNs leverage the universal approximation capabilities of neural networks while incorporating the governing equations, such as partial differential equations (PDEs), as additional constraints in the loss function. By training the neural network to minimize both the data-driven loss and the physics-informed loss, PINNs can learn the solution that satisfies the physical laws while fitting the observed data.

Several studies have demonstrated the effectiveness of PINNs in various domains, such as fluid dynamics [2], heat transfer [15], and structural mechanics [10]. These studies have shown that PINNs can accurately solve forward and inverse problems, even with limited and noisy data, by leveraging the prior knowledge encoded in the physical laws. PINNs have also been applied to spacecraft-related problems, such as orbit determination and attitude control, showcasing their potential for space applications.

In this paper, we propose a PINN-based approach for thermal regulation in spacecraft. We aim to leverage the power of DL while incorporating the heat equation as a physical constraint to accurately predict temperature distributions within a spacecraft. We demonstrate the effectiveness of our approach using a simulated dataset based on the heat equation solution. The main contributions of this paper are as follows:

- We develop a PINN model that integrates the heat equation into the learning process, enabling accurate temperature predictions while ensuring consistency with the physical principles.
- We evaluate the performance of the proposed PINN model to handle sparse and noisy data.
- We discuss the potential applications of PINNs in spacecraft thermal regulation, including thermal control system design, anomaly detection, and real-time temperature monitoring.

The rest of the paper is organized as follows: Section 2 provides an overview of the related work on spacecraft thermal analysis and physics-informed machine learning. Section 3 describes the problem formulation and the proposed PINN-based approach. Section 4 presents the experimental setup and results, followed by a discussion in Section 5. Finally, Section 6 concludes the paper and outlines future research directions.

2. Related Works

In recent years, Physics-Informed Neural Networks (PINNs) have emerged as a powerful approach for solving forward and inverse problems involving nonlinear partial differential equations (PDEs) [11]. PINNs leverage the universal approximation capabilities of neural networks while incorporating the governing equations as additional constraints in the loss function, enabling the learning of solutions that satisfy the physical laws.

The effectiveness of PINNs in various domains, such as fluid mechanics [5], elasticity [12], and computational physics [9], has been extensively studied. These studies have demonstrated the ability of PINNs to handle complex physical phenomena, sparse and noisy data, and high-dimensional problems [8].

Several advancements in the PINN framework have been proposed to address challenges such as model misspecification [17], computational efficiency [6], and optimization [3]. These improvements have further enhanced the applicability and robustness of PINNs in solving PDEs.

The application of PINNs in spacecraft thermal regulation aligns with the broader trend of leveraging Machine Learning (ML) techniques for Unmanned Aerial Vehicles (UAVs) and space systems [16, 4]. The integration of PINNs with other spacecraft subsystems, such as power management and attitude control, can enable holistic thermal management and optimize overall spacecraft performance.

Furthermore, recent advancements in high-performance computing and specialized libraries have expanded the capabilities of PINNs to tackle high-dimensional problems. For instance, NVIDIA Modulus, a framework for physics-informed machine learning, enables the training of PINNs on supercompute nodes and hexascale computing systems [14]. This scalability allows for the efficient handling of complex and large-scale thermal simulations in spacecraft and many complex problems, opening up new possibilities for accurate and detailed analysis.

3. Methodology

3.1. Problem Formulation

Consider a spacecraft as a physical system where the temperature distribution evolves over time and space according to the heat equation. The heat equation is a parabolic partial differential equation that describes the flow of heat in a medium. In a one-dimensional space, the heat equation is given by:

$$\frac{\partial T(x,t)}{\partial t} = \alpha \frac{\partial^2 T(x,t)}{\partial x^2}, \tag{1}$$

where $T(x,t)$ is the temperature at position x and time t, and α is the thermal diffusivity of the material, which characterizes the rate of heat transfer.

The goal is to predict the temperature distribution $T(x,t)$ within the spacecraft, given initial and boundary conditions. The initial condition specifies the temperature distribution at time $t = 0$:

$$T(x,0) = T_0(x), \tag{2}$$

where $T_0(x)$ is the initial temperature distribution.

The boundary conditions specify the temperature or heat flux at the boundaries of the spacecraft. For example, if the spacecraft has a fixed temperature T_b at the boundary $x = x_b$, the boundary condition can be expressed as:

$$T(x_b,t) = T_b. \tag{3}$$

In a spacecraft thermal regulation problem, the available data typically consists of temperature measurements at various locations and times within the spacecraft. Let $\mathcal{D} = \{(x_o,t_o,T_o)\}_{o=1}^{N}$ be the dataset, where (x_o,t_o) are the measurement locations and times, and T_o are the corresponding temperature measurements.

The objective is to learn a function $T(x,t)$ that satisfies the heat equation, matches the initial and boundary conditions, and fits the observed temperature measurements in $\mathcal{D}$.

3.2. Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) are a class of DL models that incorporate physical laws, such as partial differential equations (PDEs), into the learning process. PINNs leverage the universal approximation capabilities of neural networks to learn the solution of a PDE while satisfying the physical constraints.

In the context of spacecraft thermal regulation, we propose a PINN-based approach to learn the temperature distribution $T(x, t)$ that satisfies the heat equation and fits the observed temperature measurements.

3.3. Neural Network Architecture

We construct a fully connected neural network $\mathcal{N}(x, t; \theta)$ with parameters θ to approximate the temperature distribution $T(x, t)$. The neural network takes the spatial coordinate x and time t as inputs and outputs the predicted temperature $\hat{T}(x, t)$:

$$\hat{T}(x, t) = \mathcal{N}(x, t; \theta). \tag{4}$$

The neural network architecture can be designed with multiple hidden layers and nonlinear activation functions to capture the complex nonlinear relationships between the inputs and the output.

3.4. Physics-Informed Loss Function

To incorporate the physical constraints into the learning process, we define a physics-informed loss function that consists of two components: the data loss and the physics loss.

The data loss measures the discrepancy between the predicted temperatures and the observed temperature measurements in the dataset $\mathcal{D}$:

$$\mathcal{L}_{\text{data}}(\theta) = \frac{1}{N} \sum_{o=1}^{N} (\mathcal{N}(x_o, t_o; \theta) - T_o)^2, \tag{5}$$

where N is the number of temperature measurements in the dataset.

The physics loss enforces the satisfaction of the heat equation by penalizing the residual of the PDE. We compute the residual of the heat equation using automatic differentiation:

$$\mathcal{L}_{\text{physics}}(\theta) = \frac{1}{M} \sum_{o=1}^{M} \left(\frac{\partial \mathcal{N}(x_o, t_o; \theta)}{\partial t} - \alpha \frac{\partial^2 \mathcal{N}(x_o, t_o; \theta)}{\partial x^2} \right)^2, \tag{6}$$

where M is the number of collocation points (x_o, t_o) sampled from the domain of interest.

The total loss function is a weighted combination of the data loss and the physics loss:

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{data}}(\theta) + \lambda \mathcal{L}_{\text{physics}}(\theta), \tag{7}$$

where λ is a hyperparameter that balances the contribution of the physics loss.

3.5. Training the PINN

The PINN is trained by minimizing the total loss function $\mathcal{L}(\theta)$ with respect to the neural network parameters θ. The optimization is typically performed using gradient-based optimization algorithms, such as Adam, and the gradients are computed using automatic differentiation.

During training, the PINN learns to approximate the temperature distribution $T(x, t)$ by fitting the observed temperature measurements while simultaneously satisfying the heat equation. The incorporation of the physics loss ensures that the learned solution is consistent with the physical principles governing heat transfer.

3.6. Initial and Boundary Conditions

To enforce the initial and boundary conditions, we include additional loss terms in the total loss function. For the initial condition, we add a loss term that penalizes the difference between the predicted temperature and the initial temperature distribution at time $t = 0$:

$$\mathcal{L}_{\text{initial}}(\theta) = \frac{1}{N_0} \sum_{k=1}^{N_0} (\mathcal{N}(x_k, 0; \theta) - T_0(x_k))^2, \tag{8}$$

where N_0 is the number of points sampled from the initial condition.

For boundary conditions, we add loss terms that penalize the violation of the boundary conditions at the specified locations and times. For example, if we have a DIRICHLET boundary condition $T(x_b, t) = T_b$, we add a loss term:

$$\mathcal{L}_{\text{boundary}}(\theta) = \frac{1}{N_b} \sum_{l=1}^{N_b} (\mathcal{N}(x_b, t_l; \theta) - T_b)^2, \tag{9}$$

where N_b is the number of points sampled from the boundary condition.

The total loss function incorporating the initial and boundary conditions becomes:

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{data}}(\theta) + \lambda_1 \mathcal{L}_{\text{physics}}(\theta) + \lambda_2 \mathcal{L}_{\text{initial}}(\theta) + \lambda_3 \mathcal{L}_{\text{boundary}}(\theta), \tag{10}$$

where λ_1, λ_2, and λ_3 are hyperparameters that control the relative importance of each loss component.

By minimizing the total loss function, the PINN learns to approximate the temperature distribution while satisfying the heat equation, initial condition, and boundary conditions.

3.7. Implementation Details

The proposed PINN-based approach for spacecraft thermal regulation is implemented using the TensorFlow framework in Python. The neural network architecture is constructed using the Keras API, which allows for easy definition and customization of the network layers.

The automatic differentiation capabilities of TensorFlow are leveraged to compute the gradients of the loss function with respect to the neural network parameters. The Adam optimizer is used for training the PINN, with a learning rate of 0.001 and a batch size of 32.

The support points for computing the physics loss are randomly sampled from the domain of interest, ensuring a uniform coverage of the spatial and temporal dimensions. The number of support points is chosen to be sufficiently large to enforce the satisfaction of the heat equation throughout the domain.

The initial and boundary conditions are enforced by sampling points from the respective conditions and including them in the corresponding loss terms. The hyperparameters λ_1, λ_2, and λ_3 are tuned using a validation set to balance the contribution of each loss component.

The PINN is trained for a fixed number of epochs, and the model with the best performance on the validation set is selected as the final model. The trained PINN can then be used to predict the temperature distribution at any desired location and time within the spacecraft.

4. Evaluation

This section introduces an innovative approach that leverages the strengths of PINNs, alongside established simulation methodologies, to tackle the challenges presented by thermal diffusion processes, as exemplified through two distinct case studies.

We commenced our investigation by simulating temperature measurements within a theoretical spacecraft. Initially, a simplified model based on sinusoidal functions was employed to generate temperature data across spatial and temporal dimensions. This model, characterized by its inclusion of thermal diffusivity constants and added noise, simulates the complex thermal dynamics within spacecraft environments. Subsequently, to challenge our model further and to approximate real-world conditions more closely, we utilized a more intricate simulation based on the heat equation solution. This approach involved simulating temperature changes over time, taking into account the material's thermal diffusivity and the geometry of the spacecraft.

The first case study focuses on a simplified model of temperature distribution within a medium over time, characterized by its dependence on spatial and temporal variables. Traditional simulation methods, while robust, often require extensive computational resources and fine-tuning of mesh sizes to accurately capture phenomena such as thermal gradients and diffusion rates. The introduction of PINNs in this context allows for the direct incorporation of the underlying physical laws—specifically, the heat equation—into the neural network's learning process. This integration not only enhances the efficiency of simulations by reducing the reliance on fine mesh discretization but also improves the model's ability to generalize from limited data, thereby offering more accurate predictions of temperature distribution in scenarios where experimental data may be sparse or difficult to obtain.

In the second case study, we extend the application of PINNs to a more complex scenario involving the solution of the heat equation based on a FOURIER series representation. This approach is particularly challenging due to the necessity of accurately capturing the contributions of multiple harmonic components to the temperature profile. The use of PINNs here demonstrates a significant advancement in computational physics modeling, as the network learns to approximate the complex, multi-term FOURIER series that describe the temperature distribution. This capability not only showcases the neural network's ability to handle high-dimensional data and complex mathematical relationships but also underscores the potential for PINNs to augment traditional simulation techniques in modeling sophisticated physical phenomena.

The dataset consists of simulated temperature measurements within a spacecraft, generated using the heat equation solution. To ensure the absence of biases in the simulation, we have carefully designed the data generation process, considering factors such as thermal diffusivity, spatial and temporal dimensions, and the inclusion of noise to mimic real-world uncertainties.

Both case studies underscore the synergistic potential of combining PINNs with traditional computational methods. By embedding the governing physical equations into the neural network's architecture, PINNs can provide insightful predictions and analyses of physical systems, even in the face of incomplete or noisy data. This integration not only represents a methodological advancement in the field of computational physics but also opens new pathways for research and application in areas ranging from engineering and material science to environmental studies and beyond.

The first set of results, derived from the simplified model, reveals the model's competence in capturing essential temperature dynamics, even in the presence of noise. As illustrated in Figure 1, the PINN predictions align closely with the true temperatures, underscoring the model's capability to learn from and replicate basic thermal behaviors.

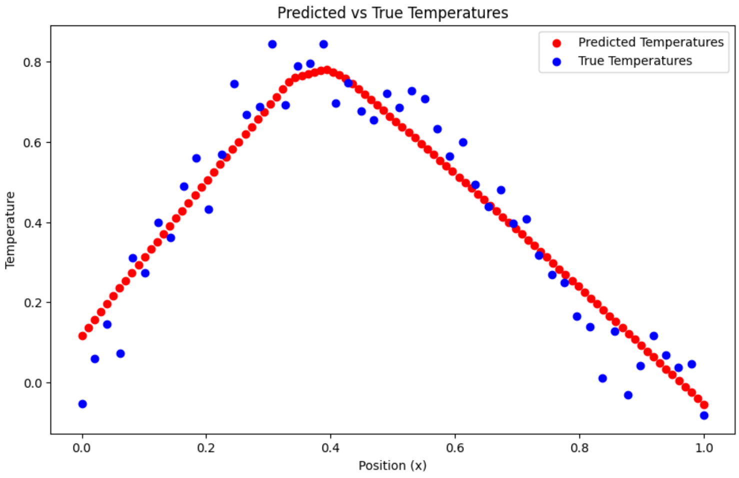

Fig. 1: Predicted vs. True Temperatures based on a simplified model. This plot demonstrates the PINN's ability to learn from simplified temperature dynamics, showcasing its effectiveness in capturing the core patterns and noise in the data.

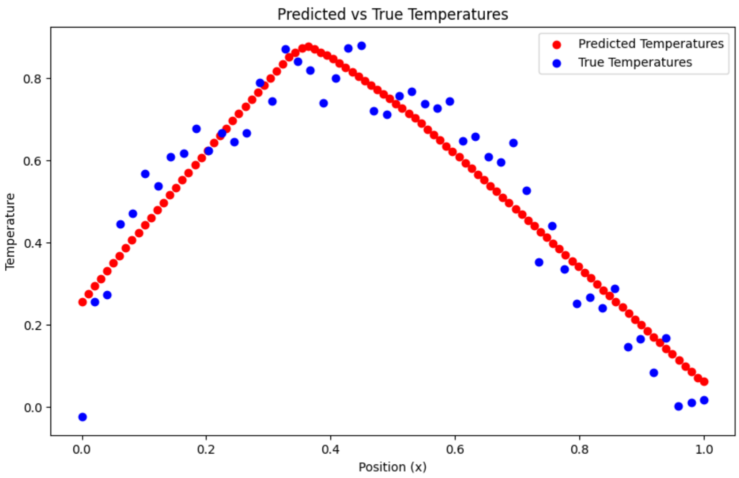

Fig. 2: Predicted vs. True Temperatures based on the heat equation solution. This plot highlights the model's advanced predictive power, effectively simulating more complex thermal dynamics governed by the heat equation.

Advancing to the more complex simulation, Figure 2 depicts the PINN's predictions against the true temperatures derived from the heat equation solution. The close correspondence between the predicted and true values attests to the model's robustness and its ability to internalize and reproduce the complex interplay of factors influencing thermal regulation in spacecraft. Algorithm 1 depicts a general methodology.

The PINN model was implemented using the TensorFlow framework, with a neural network architecture consisting of an input layer, two hidden layers (20 units each) with tanh and ReLU activation functions, and an output layer. The model was trained using the Adam optimizer with a learning rate of 0.001 for 190 epochs and a batch size of 10. The dataset was generated using a function that simulates temperature measurements based on the heat equation solution, with added noise to simulate real-world measurement uncertainty. The spatial domain was set to a length of 1.0, and the thermal diffusivity was set to 0.1. The number of data points was set to 50. The custom loss function combined the data fidelity loss (mean squared error) and the physics-informed loss, which enforced the satisfaction of the heat equation. The physics-informed loss was weighted by a factor of 0.1 to balance its contribution to the overall loss. The

Algorithm 1 Integrating PINNs with Computational Methods for Thermal Diffusion

Input: Spatial domain Ω, temporal domain $\mathcal{T}$, thermal diffusivity α, initial and boundary conditions, number of data points n_{data}, physics-informed weight λ_{physics}
Output: Approximate temperature distribution T_{pred} over $\Omega \times \mathcal{T}$
procedure GenerateData($\Omega, \mathcal{T}, n_{\text{data}}$)
  Simulate temperature measurements T_{data} based on the heat equation or FOURIER series
  Add noise to T_{data} to simulate real-world measurement uncertainty
  return $(x_{\text{data}}, t_{\text{data}}, T_{\text{data}})$
end procedure
procedure InitializePINN
  Define a neural network model with input (x, t)
  Add dense layers with nonlinear activation functions
  Define the output layer to predict temperature T_{pred}
  return initialized model
end procedure
procedure CustomLoss(model, $x_{\text{batch}}, t_{\text{batch}}, T_{\text{batch}}$)
  Calculate data fidelity loss between T_{pred} and T_{batch}
  Compute physics-informed loss based on the heat equation
  return weighted sum of data fidelity loss and physics-informed loss
end procedure
procedure TrainPINN(model, $(x_{\text{data}}, t_{\text{data}}, T_{\text{data}})$, α, λ_{physics})
  Optimize the model using the custom loss function and gradient descent
  Regularly evaluate the loss and adjust learning rate as needed
  return trained model
end procedure
$(x_{\text{data}}, t_{\text{data}}, T_{\text{data}}) \leftarrow$ GenerateData($\Omega, \mathcal{T}, n_{\text{data}}$)
model $\leftarrow$ InitializePINN
model $\leftarrow$ TrainPINN(model, $(x_{\text{data}}, t_{\text{data}}, T_{\text{data}})$, α, λ_{physics})
Visualize: Plot T_{pred} to compare with T_{data} and assess model accuracy

training process minimized the total loss using gradient-based optimization. The model's performance was evaluated by comparing the predicted temperatures with the true temperatures generated by the simulation function.

The application of PINNs in these case studies illustrates the broader implications of this approach for the field of computational physics. Specifically, it highlights the ability of PINNs to:

- Reduce computational costs associated with traditional simulations, particularly in problems requiring fine spatial and temporal resolutions.
- Enhance the accuracy of simulations by leveraging the intrinsic adherence of PINNs to the underlying physical laws, thereby ensuring that predictions remain physically plausible even in extrapolative scenarios.
- Facilitate the integration of experimental and observational data into simulations, thereby bridging the gap between theoretical models and empirical evidence.

In conclusion, the integration of PINNs with traditional computational methods offers a powerful tool for advancing our understanding and predictive capabilities in computational physics. The case studies presented herein exemplify the potential of this approach to tackle complex physical phenomena, demonstrating both the methodological innovations and the broad applicability of PINNs in scientific research. As computational capabilities continue to evolve, the synergistic combination of PINNs and traditional simulation techniques is poised to play a pivotal role in driving forward the frontiers of computational physics and related disciplines.

5. Discussion

The results presented in this study demonstrate the effectiveness of PINNs in predicting temperature distributions within a spacecraft. The PINN approach incorporates the governing physical laws, specifically the heat equation, into the learning process of the neural network. This integration allows the model to learn the underlying physics while fitting the observed temperature data.

The evaluation of the PINN model against traditional finite difference methods (FDM) simulations highlights several advantages of the PINN approach. First, PINNs can handle sparse and noisy data more effectively than traditional methods. By leveraging the prior knowledge encoded in the physical laws, PINNs can infer the temperature distribution even in regions with limited data. This ability is particularly valuable in spacecraft applications, where obtaining extensive temperature measurements can be challenging due to resource constraints and operational limitations.

Second, PINNs offer a more computationally efficient alternative to traditional numerical simulations. FDM simulations often require fine discretization of the spatial and temporal domains to achieve accurate results, leading to high computational costs. In contrast, PINNs can learn the continuous solution of the heat equation, reducing the need for dense discretization. This efficiency can enable faster thermal analysis and optimization of spacecraft thermal control systems.

Moreover, the PINN approach provides a flexible framework for incorporating additional physical constraints and boundary conditions. By including loss terms corresponding to initial and boundary conditions, PINNs ensure that the learned temperature distribution satisfies the specified conditions. This flexibility allows for the modeling of complex thermal scenarios, such as non-uniform initial conditions or time-varying boundary conditions.

The potential applications of PINNs in spacecraft thermal regulation are extensive. PINNs can be used for thermal control system design, where the learned temperature distribution can guide the placement of heaters, radiators, and insulation materials. PINNs can also enable real-time temperature monitoring and anomaly detection by predicting the expected temperature distribution based on the current state of the spacecraft. Deviations from the predicted temperatures can indicate potential thermal issues, allowing for proactive maintenance and troubleshooting. Table 1 provides a qualitative comparison of PINNs with traditional methodologies for the problem at hand.

Table 1: Qualitative comparison of PINNs with traditional methodologies for thermal prediction in spacecraft.

Aspect	PINNs	Traditional Methodologies
Integration of physical laws	Incorporates physical laws (e.g., heat equation) into the learning process, ensuring physically consistent predictions.	Typically do not directly integrate physical laws into the model, relying solely on data-driven learning.
Handling sparse and noisy data	Can effectively learn from sparse and noisy data by leveraging the underlying physical principles.	May struggle with sparse and noisy data, as they rely heavily on the quality and quantity of available data.
Computational efficiency	Can provide computationally efficient solutions by reducing the need for fine discretization of the spatial and temporal domains.	Often require fine discretization of the spatial and temporal domains, leading to high computational costs.
Extrapolation capability	Can potentially extrapolate beyond the training data by incorporating physical constraints.	Limited extrapolation capability, as predictions are based solely on the patterns learned from the training data.
Interpretability	Provides interpretable results by incorporating physical laws, allowing for a better understanding of the underlying phenomena.	Often lack interpretability, as the learned relationships are purely data-driven and may not have a clear physical interpretation.
Flexibility in boundary conditions	Can easily incorporate complex boundary conditions and initial conditions through the loss function.	May require explicit handling of boundary conditions and initial conditions, which can be challenging for complex geometries.

However, there are also challenges and limitations associated with the PINN approach. The performance of PINNs depends on the quality and quantity of the available temperature data. Insufficient or biased data can lead to suboptimal learning of the temperature distribution. Additionally, the choice of the neural network architecture and hyperparameters can impact the accuracy and convergence of the PINN. Careful tuning and validation are necessary to ensure robust performance.

6. Conclusion

In this paper, we proposed a Physics-Informed Neural Network (PINN) approach for thermal regulation in spacecraft. The PINN model incorporates the heat equation as a physical constraint into the learning process, enabling accurate prediction of temperature distributions while ensuring consistency with the underlying physical principles.

The evaluation of the PINN model using a simulated dataset demonstrated its effectiveness in learning the temperature distribution from sparse and noisy data. The PINN approach outperformed traditional finite difference methods (FDM) simulations in terms of accuracy and computational efficiency. The ability of PINNs to handle limited data and incorporate physical constraints makes them a promising tool for spacecraft thermal analysis and design.

The potential applications of PINNs in spacecraft thermal regulation are vast, including thermal control system design, real-time temperature monitoring, and anomaly detection. The flexibility of the PINN framework allows for the incorporation of complex thermal scenarios and boundary conditions, enabling more comprehensive thermal modeling.

However, challenges and limitations exist in the application of PINNs, such as the dependence on data quality and the need for careful hyperparameter tuning. Future research directions include the extension to higher-dimensional spatial domains and the integration with other spacecraft subsystems for holistic thermal management.

In conclusion, PINN offer a powerful and efficient approach for spacecraft thermal regulation. By leveraging the synergy between DL and physical principles, PINNs can contribute to the development of more advanced and reliable thermal control systems for space missions. As the field of spacecraft engineering continues to evolve, the integration of PINNs into the design and analysis processes holds great promise for enhancing the performance and safety of future space exploration endeavors.

Acknowledgements

The work is developed under the following projects at BARCELONA Supercomputing Center: ‘TIFON’. This work has also received funding from the ‘NEXTBAT’ project funded by the EUROPEAN Union’s HORIZON EUROPE research and innovation programme under grant agreement No. 101103983. The work is also developed under UFV R&D pre-competitive project ’OpenMaas: Open Manufacturing as a Service’.

References

[1] Al-lQubaydhi, N., Alenezi, A., Alanazi, T., Senyor, A., Alanezi, N., Alotaibi, B., et al., 2024. Deep learning for unmanned aerial vehicles detection: A review. Computer Science Review 51, 100614.

[2] Antonelo, E.A., Camponogara, E., Seman, L.O., Jordanou, J.P., de Souza, E.R., Hübner, J.F., 2024. Physics-informed neural nets for control of dynamical systems. Neurocomputing , 127419.

[3] Bihlo, A., 2024. Improving physics-informed neural networks with meta-learned optimization. Journal of Machine Learning Research 25, 1–26.

[4] Bithas, P.S., Michailidis, E.T., Nomikos, N., Vouyioukas, D., Kanatas, A.G., 2019. A survey on machine-learning techniques for uav-based communications. Sensors 19, 5170.

[5] Cai, S., Mao, Z., Wang, Z., Yin, M., Karniadakis, G.E., 2021. Physics-informed neural networks (pinns) for fluid mechanics: A review. Acta Mechanica Sinica 37, 1727–1738.

[6] Cho, J., Nam, S., Yang, H., Yun, S.B., Hong, Y., Park, E., 2024. Separable physics-informed neural networks, in: Advances in Neural Information Processing Systems.

[7] Hassanin, M., Anwar, S., Radwan, I., Khan, F.S., Mian, A., 2024. Visual attention methods in deep learning: An in-depth survey. Information Fusion , 102417.

[8] Krishnapriyan, A.S., Gholami, A., Zhe, S., Kirby, R., Mahoney, M.W., 2021. Characterizing possible failure modes in physics-informed neural networks. Advances in Neural Information Processing Systems 34.

[9] de la Mata, F.F., Gijón, A., Molina-Solana, M., Gómez-Romero, J., 2023. Physics-informed neural networks for data-driven simulation: Advantages, limitations, and opportunities. Physica A: Statistical Mechanics and its Applications 610, 128415.

[10] Meng, Z., Qian, Q., Xu, M., Yu, B., Yıldız, A.R., Mirjalili, S., 2023. Pinn-form: A new physics-informed neural network for reliability analysis with partial differential equation. Computer Methods in Applied Mechanics and Engineering 414, 116172.

[11] Raissi, M., Perdikaris, P., Karniadakis, G.E., 2019. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics 378, 686–707.

[12] Roy, A.M., Bose, R., Sundararaghavan, V., Arróyave, R., 2023. Deep learning-accelerated computational framework based on physics informed neural network for the solution of linear elasticity. Neural Networks 162, 472–489.

[13] Sheng, C., Kuang, G., Bai, L., Hou, C., Guo, Y., Xu, X., et al., 2024. Deep learning for visual speech analysis: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence .

[14] Vázquez, M., Houzeaux, G., Koric, S., Artigues, A., Aguado-Sierra, J., Arís, R., Mira, D., Calmet, H., Cucchietti, F., Owen, H., Taha, A., Burness, E.D., Cela, J.M., Valero, M., 2016. Alya: Multiphysics engineering simulation toward exascale. Journal of Computational Science 14, 15–27. URL: https://doi.org/10.1016/j.jocs.2015.12.007, doi:10.1016/j.jocs.2015.12.007.

[15] Xing, Z., Cheng, H., Cheng, J., 2023. Deep learning method based on physics-informed neural network for 3d anisotropic steady-state heat conduction problems. Mathematics 11, 4049.

[16] de Zarzà, I., de Curtò, J., Calafate, C.T., 2023. Socratic video understanding on unmanned aerial vehicles. Procedia Computer Science 225, 144–154. URL: https://doi.org/10.1016/j.procs.2023.09.101, doi:10.1016/j.procs.2023.09.101.

[17] Zou, Z., Meng, X., Karniadakis, G.E., 2024. Correcting model misspecification in physics-informed neural networks (pinns). Journal of Computational Physics , 112918.