Multi-Parameter modelling of heat transfer in a battery pack using PINNs

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Abstract

Thermal modelling is crucial in analyzing the health and the life of a battery pack. The heat generated in the battery pack is a function of multiple parameters including thermal conductivity of the cell, the connectors, the current passing through the cells, the contact resistance, etc. Traditional battery pack thermal modelling like finite element or finite volume modelling involve modelling the heat transfer for a given set of parameters making the design process rigid as the simulations have to be repeated for various set of parameters. We present a battery pack modelling metododlogy that accelerates the design process using physics informed neural networks, where all the parameters of the guven system are fed in as inputs to the considered architecture. We show that this methodology accelerates the simulation process by 90% comapred to the traditional methods as this aids real-time prediction of the heat transfer characteristics for any combination of parameters once the appropriate model is trained.

1 Introduction

Modeling the thermal behavior of a battery pack is essential for assessing its health and longevity. In electric vehicles, the battery pack is the core energy source. As current flows through the pack, ohmic heating occurs due to the internal resistance of the cells and the contact resistance between the cells and connectors. This heat raises the temperature of both the cells and the connectors. Additionally, the battery pack contains highly conductive thermal pads that transfer the heat generated by the cells to the pack's enclosure. Heat is then dissipated through either forced or natural convection to maintain the battery pack's optimal operating temperature.

Traditional methods like finite element and finite volume analysis have been effective for modeling heat transfer in battery packs. However, these systems involve numerous parameters that influence the governing equation, such as pack current, cell thermal conductivity, internal resistance, connector thermal conductivity, and the convection heat transfer coefficient on the enclosure. Simulating different combinations of these parameters using conventional methods can be computationally expensive and time-consuming. Additionally, meshing a battery pack is a labor-intensive and tedious process, especially due to the presence of varying length scales, which significantly adds to the poor quality of the mesh.

In this work, we employ Physics-Informed Neural Networks (PINNs) to model heat transfer in battery packs, effectively incorporating the key parameters that govern the system. Specifically, we use a Fourier neural network architecture to capture the high-frequency solutions of the heat diffusion equation for materials with properties that differ by up to two orders of magnitude. This approach enables efficient modeling across varying material properties.

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2 Physics-informed neural networks

Any physical phenomenon can be described by a governing differential equation. To solve this equation using Physics-Informed Neural Networks (PINNs), a deep neural network is utilized, with spatial coordinates (and time, if the phenomenon is dynamic) represented as a point cloud serving as the input (Cai et al. [2021]) (Figure 1). The network's outputs correspond to the dependent variables that describe the physical system. The governing differential equation is incorporated into the neural network's loss function, ensuring that for a set of domain points, along with appropriate boundary or initial conditions, the equation is satisfied (Figure 2). Automatic differentiation facilitates efficient and precise computation of gradients for the dependent variables at these points, avoiding any truncation errors.

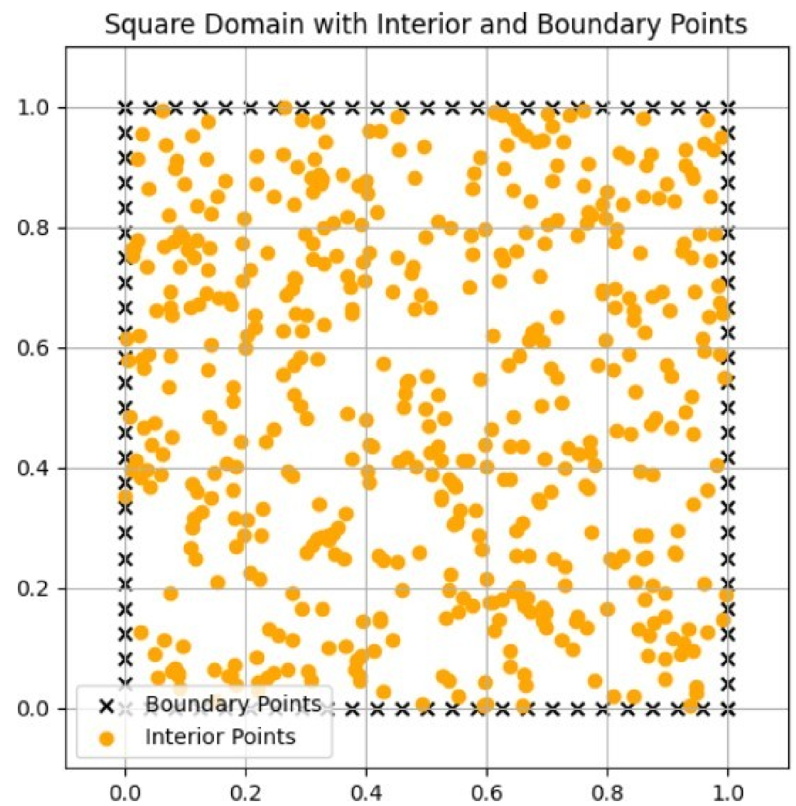

Figure 1: Square Domain with Interior and Boundary Points

One of the primary benefits of using Physics-Informed Neural Networks (PINNs) to solve differential equations is their ability to incorporate multiple input nodes into the deep neural network. This allows the trained model to encompass a broader spectrum of system parameters within the design space. For example, when modeling fluid flow with PINNs, including an input node for fluid viscosity permits the training of a model that accommodates a range of viscosity values. Consequently, once the model is trained, it can predict flow solutions in real time for various viscosity values, significantly reducing the computational time needed to develop models across a wide array of system parameters. Therefore, PINNs facilitate faster predictions in engineering applications and eliminate the need for the intricate meshing process, which can be time-consuming in complex geometries.

However, one limitation of utilizing fully connected deep neural network architectures for PINNs is their tendency to effectively approximate low-frequency functions, a phenomenon referred to as spectral bias. To address the challenges posed by complex geometries that produce sharp gradients, Fourier neural networks are often employed. In this architecture, the inputs are transformed into a higher-dimensional feature space using high-frequency functions (Rahaman et al. [2019]). In this work, we consider a battery pack that comprise of different domains including cels, connectors, thermal pads, In this work we consider a set of 64 frequencies to represent the input parameters in a

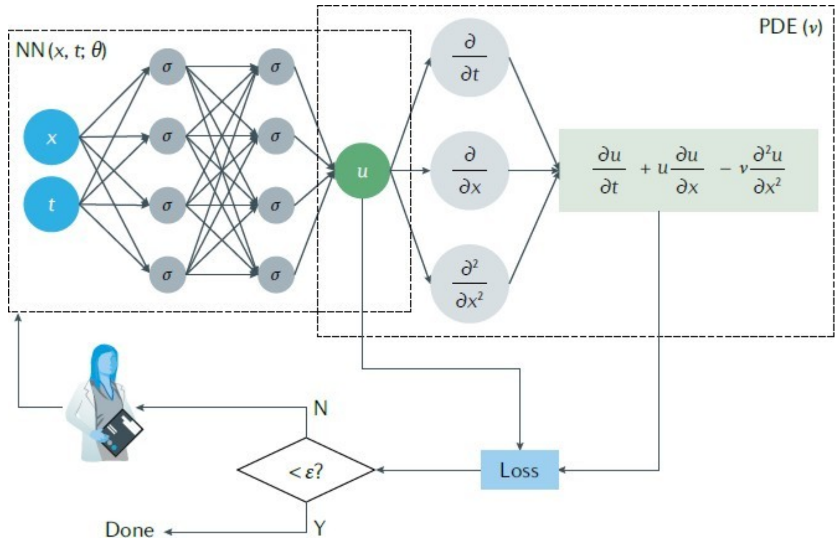

Figure 2: A sample PINNs architecture

higher dimension latent space. All the domains in the battery pack are represented by a feed forward neural network with 512 hidden units with 6 layers which are acted upon by SiLU activation function.

Equation 1 describes the transient diffusion equation that governs the pack temperature in different materials:

$$\frac{\partial T}{\partial t} = D\,\Delta^2 T + I^2 R \tag{1}$$

where:

- T : Temperature (dependent variable).
- t: Time.
- D : Thermal diffusivity (a constant).
- $\nabla^2 T$: Laplacian operator applied to the temperature, representing spatial diffusion.
- I: Current.
- R: Cell internal resistance (for the cell domain)

The problem under consideration is a transient heat transfer problem (Equation 1) where we analyze the evolution of pack temperature over a time period of 1000 seconds. To train the neural networks over this duration of time, we employ the approach of training models in different time windows each of size 500 seconds. This is a standard approach to tackle transient simulations using PINNs (Wight and Zhao [2020]). To implement this, we used the NVIDIA modulus sym (Modulus Contributors [2023]) package that enables implementation of PINNs using Fourier neural networks across multiple domains. This also provides custom functions for efficient application of temperature and flux continuity condition across all the interfaces. We implemented custom governing equations in the package to include multiple parameters to the training model. An illustration of the list of some parameters that we considerd for this work is shown in Figure 3.

3 Results and conclusion

Figure 4 shows the solution of the transient diffusion equation solved in the battery pack using Fourier neural networks. We were able to capture the variation in pack temperature at different time instances and for different combinations of system parameters such as current through the

Name	Input	Min	Max
t	750	0 s	999 s
R	0.04	0.02 Ω	0.06 Ω
d_c	0.9	0.6 mm	1.5 mm
R_c	0.41	0.41 mΩ	0.72 mΩ
k	200	200 W/mK	600 W/mK
I	30	20 A	60 A
h	10	1.5 W/m^{2}K	10 W/m^{2}K

Figure 3: System parameters with minimum and maximum values in the training model

pack, internal resistance of the cells and thermal conductivity of the connectors etc. This method as explained greatly eases the design process of the battery packs by reducing the problem to training a single model for different system parameters. Since the model needs point cloud data as the input, the time for meshing the geometry is greatly reduced. The training process required 1e5 iterations per window to reach a loss error of approximately 1e-6.

Although this method looks promising on multiple accounts, some of the challenges solving these problems include, convergence of the training model across all the domain geometries. Although Fourier nets capture sharp gradients well, a well defined scaling process for the inputs and the loss function is yet to be understood. A well defined scaling process makes the coefficients of the gradients in the loss function consistent that eventually accelerates the convergence.

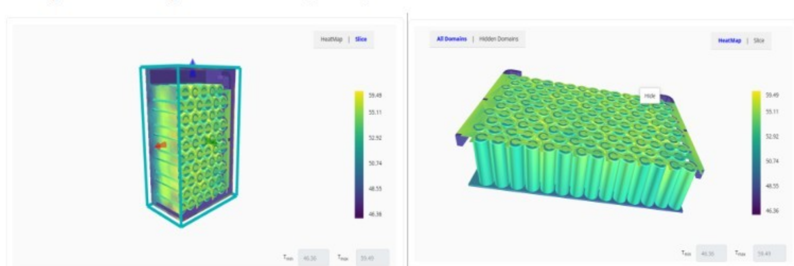

Figure 4: Variation of temperature inside the pack solved using PINNs with Fourier neural nets

References

References follow the acknowledgments in the camera-ready paper. Use unnumbered first-level heading for the references. Any choice of citation style is acceptable as long as you are consistent. It is permissible to reduce the font size to small (9 point) when listing the references. Note that the Reference section does not count towards the page limit.

References

Shengze Cai, Zhiping Mao, Zhicheng Wang, Minglang Yin, and George Em Karniadakis. Physics-informed neural networks (pinns) for fluid mechanics: a review. *Acta Mechanica Sinica*, 37(12):1727–1738, Dec 2021. ISSN 1614-3116. doi: 10.1007/s10409-021-01148-1. URL https://doi.org/10.1007/s10409-021-01148-1.

Modulus Contributors. Nvidia modulus: An open-source framework for physics-based deep learning in science and engineering. https://github.com/NVIDIA/modulus, 2023. URL https://github.com/NVIDIA/ modulus. Released on 2023-02-24.

Nasim Rahaman, Aristide Baratin, Devansh Arpit, Felix Draxler, Min Lin, Fred Hamprecht, Yoshua Bengio, and Aaron Courville. On the spectral bias of neural networks. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 5301–5310. PMLR, 09–15 Jun 2019. URL https://proceedings. mlr.press/v97/rahaman19a.html.

Colby L. Wight and Jia Zhao. Solving allen-cahn and cahn-hilliard equations using the adaptive physics informed neural networks, 2020. URL https://arxiv.org/abs/2007.04542.