Original Article

Physics-Informed Neural Networks for Accelerated Thermal and Energy Flow Simulation in Healthcare Infrastructure Systems.

Rahul Joshi, Deepak Upadhyay, Krishna Pandey, Rhythma Badola, Mitali Mohanty, Ankita Bharti , Suman Kumari

Abstract

Background:
Healthcare facilities require stable temperature and energy management to ensure safe operation of medical equipment and efficient functioning of critical areas. Conventional numerical simulation techniques used for thermal analysis are accurate but computationally expensive and unsuitable for rapid operational assessment. This study evaluates the feasibility of using a Physics-Informed Neural Network (PINN) to accelerate thermal and energy flow simulation in healthcare infrastructure systems without using clinical or patient data.

Materials and Methods:
A synthetic hospital infrastructure environment was modeled using heat diffusion and energy balance equations. The governing physical laws were embedded directly into the neural network training process. A fully connected deep neural network was trained using spatial and temporal inputs representing infrastructure conditions. The proposed model was compared with a finite-difference numerical solver using prediction error, boundary condition adherence, stability, and computational time as evaluation parameters.

Results:
The PINN generated smooth and physically consistent temperature distributions with low residual errors and good boundary compliance. The model showed stable performance under changing conditions and generalized well to unseen scenarios. Compared to the numerical solver, the proposed method significantly reduced computational time while maintaining realistic thermal behavior.

Conclusion:
Physics-informed neural networks can provide fast and reliable simulation of thermal and energy flow in healthcare infrastructure systems. The method enables rapid evaluation of operational strategies and energy management while preserving physical accuracy, making it a useful tool for infrastructure-level planning.

JK-Practitioner2026(31(1):44-51

Author Affiliations
Rahul Joshi, **Mitali Mohanty**, **Ankita Bharti.** Assistant Professors; **Krishna Pandey**. Associate Professor; Department of Journalism & Mass Communication, Manav Rachna International Institute of Research & Studies, Haryana, India
Deepak Upadhyay. Department of Computer Science and Engineering, Graphic Era Hill University & Research Scholar, Graphic Era deemed to be University, Dehradun, India;
Rhythma Badola. Physician, Patanjali India Limited, Haridwar, India ;
Suman Kumari. Professor, School of Journalism & Mass Communication, Shri Venkateshwara University, Gajraula, Uttar Pradesh, India

Correspondence
Rahul Joshi
Assistant Professor, Department of Journalism & Mass Communication, Manav Rachna International Institute of Research & Studies, Haryana, India
rahuljoshi.785@gmail.com

Indexed
EMBASE, SCOPUS, IndMED , ESBCO, Google Scholar besides other national and international databases.

Cite this article as
Joshi R, Upadhyay D, Pandey K, Badola R, Mohanty M, Bharti A, Kumari S. Thermal and Energy Flow Simulation in Healthcare Infrastructure Systems.
JK Pract2026;31(1):44-51.

Full length article available at **jkpractitioner.com** one month after publication

Keywords
Physics-Informed Neural Networks, Thermal Simulation, Energy Flow Modeling, Healthcare Infrastructure Systems, Physics-Guided Learning, Accelerated Simulation, Heat Diffusion, Synthetic Environment Modeling

Introduction

In healthcare environments, hospitals, clinics, and diagnostic centres require reliable temperature management and continuous energy flow to maintain operational safety and efficiency. In addition to providing a comfortable environment for patients, staff, and visitors, maintaining stable temperatures is necessary for optimal functioning of medical equipment [1], proper storage of medications, safe operating conditions for surgical suites and other critical spaces, and proper functioning of medical imaging systems and energy management systems. Unstable thermal behaviour could result in increased energy consumption due to reduced efficiency in cooling or heating, and in extreme cases, failure of sensitive equipment. For this reason, the application of thermal and energy flow simulation is becoming increasingly important in the design and operation of healthcare facilities. The objective of this paper is to explore how physics-informed neural networks can accelerate the process of simulating thermal and energy flow [2]. Traditional methods for modeling thermal and energy flows rely almost exclusively on numerical solutions to physical equations such as those governing heat transfer by diffusion, and energy conservation. Numerical solutions are typically generated by finite difference, finite volume, and finite element methods [3]. While these traditional methods are highly accurate, they are also computationally intensive, particularly when the system being modeled is as large and complex as a typical hospital building. Hospital buildings contain numerous rooms with different construction materials and configurations, variable occupant populations, and varying levels of energy consumption. Consequently [4], performing detailed simulations of the thermal and energy behaviors of such a building using traditional methods requires significant amounts of computing resources and time. Furthermore, since operational conditions in healthcare facilities change relatively frequently, the repeated use of full-scale simulations of these changes is impractical. Therefore, there exists a strong motivation for developing faster simulation techniques that remain faithful to the underlying physics [5].

There is growing interest in using data-driven methods and artificial neural networks (ANNs) to address various types of engineering problems. ANNs can identify relationships and patterns in data and provide rapid predictions after training. However, ANNs have some limitations [6]. First, most ANN-based approaches require large databases to develop an accurate model, and second, the accuracy of the ANN model may degrade rapidly if the database used for training is either incomplete or contains "noisy" data. Both issues are potentially serious concerns for applications involving the health care industry, where both safety and reliability are paramount [7]. Consequently, there is now considerable interest in developing hybrid methods that combine empirical models or knowledge of the underlying physical laws with learning models [8]. Physics-Informed Neural Networks (PINNs) utilize physical laws within the training process for the neural network. The primary difference between traditional data-only based learning approaches and PINNs is that they not only learn from data [9] but satisfy the governing differential equations of heat and energy transfer during training. As such, models trained with PINNs tend to be more physically accurate than their non-physics-informed counterparts and require fewer large sets of labeled training data [10].

The use of PINNs as an accelerated tool for simulating thermal and energy flow in healthcare infrastructure systems is the subject of research presented here; at the same time, physical accuracy is maintained throughout. In a variety of ways, several factors affect the thermal characteristics of health care buildings including: the type of wall material used, the ventilation systems employed, the level of building occupants, the amount of heat generated by medical equipment, and weather patterns outside the building [11][12]. Energy flow is affected similarly: through power distribution networks, HVAC operation, and backup energy systems. Thus, the interactions among these factors are highly nonlinear and can be difficult to model accurately without employing simple assumptions. However, running comprehensive simulations to evaluate the impact of small changes in operating conditions is computationally expensive. Therefore, the objective of this research is to demonstrate the feasibility of using physics-informed learning to simulate system behavior under varying conditions yet always constrained by heat transfer and energy balance equations [13].

Real-time or near-real-time analysis is another critical concern for health care infrastructure, since facility managers may wish to compare the effects of alternative operating strategies, such as modifying ventilation rates or temperature set points, to achieve energy savings without compromising safety [14]. Unfortunately, traditional simulation tools are typically too computationally intensive to provide timely responses to questions posed by facility managers. On the other hand, after a PINN has been trained, it can rapidly evaluate temperature and energy flow distributions. In addition to providing the basis for rapid evaluation of alternatives, a model that is based upon a physics-informed approach provides greater assurance of the reliability of the results. This is due to the fact that the model behaves as would be expected in response to variations in the parameters [15]. In addition to the fact that there are varying operating conditions of health care facilities, the proposed study also considers the varying demands that exist in emergency situations [16][17]. In addition, various areas of hospitals are utilized more at different times. External climate conditions vary each day and with each season [18]. The ideal simulation system should address these variable factors in an effective manner. Physics-informed neural networks have the potential to accomplish this by generalizing physical relationships across different boundary and initial condition scenarios as long as they have been trained adequately. Additionally, the learning process will not just memorize solutions but understand the overall structural relationship of the physical problem. As such, the lack of complete simulation data for all possible case scenarios is acceptable. The proposed method of utilizing a physics-informed neural network (PINN) can potentially save significant amounts of computational time relative to pure numerical solution techniques. However, it does not necessarily imply that numerical methods are entirely replaced. Rather, numerical methods are used to create reference physics and constraints to train the PINN. Once PINN has been trained, it functions as a rapid surrogate model to reference physics and constraints. As such, the primary purpose of this paper is to present the concept of accelerating simulations rather than making predictions regarding patients and/or other clinical analyses. Specifically, no patient data, no clinical data sets and no medical treatment models are presented. The proposed methodology is focused exclusively on the thermal and energy processes occurring at the infrastructure level of the facility; therefore, it represents a safe and generic approach.

This research's inspiration is related to sustainability and energy efficiency. In comparison with standard buildings, health care buildings consume much more energy. Improved thermal performance will result in reduced wasted energy and lower operating costs. Fast simulation tools can help improve both design and operating practices. Since they combine the advantages of both physical modeling and machine learning, physics informed neural networks (PINN) are a new direction for improved simulation tool development; however, developing and applying these for real world infrastructure systems remains an active research area. This research paper contributes by discussing the structure and application of PINNs for specific thermal and energy flow simulations in health care environments. This paper describes the use of a physics-informed neural network (PINN) for fast simulation of heat and energy transfer in health care infrastructure systems. The objective of this work is to allow faster analysis under changing operational conditions while maintaining physical accuracy. In addition to improving upon purely data driven models, this research provides solutions to limitations of traditional numerical solvers through the incorporation of thermal and energy flow equations into the training of PINNs.

Methodology

This research has used a Physics-Informed Neural Network-based simulation technique to enhance the speed of Thermal and Energy Flow Analysis within Healthcare Infrastructure Systems. This technique was chosen due to its ability to include physical laws into the learning process of a model, something that cannot be guaranteed with traditional data-driven Neural Networks. In addition, both Classical Numerical Solvers and Traditional Deep Learning Models were discounted for use in this work. Classical Numerical Solvers were discounted for their reliance upon the repeated creation of meshes and for requiring significant amounts of computing time, while having to operate within the constraints of maintaining stability when changes occur in the operational conditions of the system. Similarly, Pure Deep Learning Models were discounted due to their dependency upon large datasets and their lack of physical consistency. As a result, this research chose the Physics-Informed Neural Network (PINN) Algorithm; an Algorithm that can balance Computational Efficiency and Physical Reliability within a Simulated Environment. In this research, the overall problem was defined as a Spatio-Temporal Prediction Task where Heat Transfer and Energy Conservation Laws govern the behavior of Temperature and Energy Distribution Fields within the layout of a Healthcare Infrastructure System under varying Boundary and Operating Conditions.

Unlike traditional numerical solvers, the Neural Network learned a Continuous Functional Representation of the Solution, allowing the system to generalize well to un-seen operating scenarios. A Simplified Two-Dimensional or Three-Dimensional Spatial Geometry representing Hospital Zones, Corridors and Equipment Areas were used to represent the physical domain, excluding any Patient-Level or Clinical Variables. The Governing Physics was described using Partial Differential Equations relating to Heat Diffusion and Energy Balance. For Thermal Flow, the Transient Heat Conduction Equation was the Primary Constraint, while Energy Flow was Represented via Source Terms Modeling Internal Heat Generation from Equipment and HVAC Systems. Boundary Conditions, including Fixed Temperature Walls, Convective Heat Transfer, and Time-Varying External Conditions were Imposed Directly During Training. Rather than being Solved Numerically in the Classical Sense, these Equations were Enforced Through the Loss Function of the Neural Network.

Mathematical Formulation of the Physics Constraints

The thermal and energy flow inside the infrastructure had been governed by the heat diffusion equation expressed as;

$$\partial T(x,t)/\partial t = \alpha\, \nabla^2 T(x,t) + Q(x,t),$$

where $T(x,t)$ had represented the temperature field over space x and time t, α had denoted the thermal diffusivity of the building material, and $Q(x,t)$ had modeled internal energy sources such as medical equipment and ventilation loads. Boundary conditions had been expressed as;

$$T(x,t) = T_b \text{ on } \Gamma D,$$

and

$$-k\, \nabla T(x,t) \cdot n = h\,(T - T_\infty) \text{ on } \Gamma N,$$

where ΓD and ΓN had represented Dirichlet and Neumann boundaries respectively, k had been thermal conductivity, h had been convective heat transfer coefficient, and n had been the outward normal vector. The neural network had approximated the solution $\hat{T}(x,t;\theta)$, where θ had represented trainable parameters. The physics-informed loss function had been constructed as;

$$L = L_{data} + \lambda_1 L_{pde} + \lambda_2 L_{bc},$$

where L_{pde} had penalized the residual of the governing PDE, L_{bc} had enforced boundary and initial conditions, and λ_1, λ_2 had been weighting factors. Automatic differentiation had been used to compute spatial and temporal derivatives, which had removed the need for numerical discretization.

Simulated Environment and Data Preparation

All experiments were performed using a fully simulated environment. There were no outside datasets that were used. The spatial coordinates were sampled uniformly over the modeled infrastructure domain, while the temporal points were sampled over the entire duration of the simulation. The initial temperature distributions were created under the assumption of physical reasonableness, for example, uniform start temperatures with small random perturbations. The energy source terms were also created synthetically to reflect real world variations in how people use equipment and HVAC systems. The feature extraction did not require traditional pre-processing because the PINN was able to work directly from continuous inputs. The input features were spatial coordinates, time, material properties, and control settings for operational activities. The output target for the model was not explicitly stated temperature values, but rather implicitly defined by the physical laws that govern heat transfer. By defining the problem space using the physics equations and not requiring explicit labels on the simulation data, the model's reliance on the quality of the simulation data is minimized and the model can be made more robust to noise in the simulation.

PINN Architecture and Model Design

In designing this neural network architecture, we chose to design a fully connected feedforward multi-layered network. We have also made a conscious decision to use smooth activation functions such as tanh in order to obtain the stable higher order derivative that is required for physics enforcement. The number of layers (depth) and the number of units within each layer (width) were determined by preliminary experiments to determine an optimal trade-off between accuracy and training stability; to prevent vanishing gradients that can occur in overly deep networks, this paper did not investigate excessively large architectures. We have minimized the combined physics informed loss function using the optimization algorithm that utilizes gradients. In the initial stage of training, Adam was used due to its rapid convergence on the loss of function space that is complex in nature. Subsequently, a two-stage optimization strategy that utilized L-BFGS was employed to further refine the solutions obtained from the first stage and minimize the residual errors remaining after the first stage. As necessary, the learning rate has been adjusted manually to prevent the occurrence of unstable oscillatory behavior. The training of the model continued until both the PDE residual and boundary conditions error reached low stable values.

Algorithm Execution Steps

The execution of the algorithm was performed in an ordered sequence. The first order was to identify the spatial and temporal domains as well as the materials and operational parameters. Next, sampling was performed for the collocation points within the domain and at the boundary. The third order was to initialize the neural network with random weights. Following this, residuals were calculated from the physics-based residual using automatic differentiation. In the fifth order, the loss function was iteratively reduced using the selected optimization algorithms. Finally, the trained model was tested against new operating conditions that the model had not seen before to determine if the model generalized. Each step was thoroughly monitored to confirm that physical consistency was preserved.

Testing Strategy and Performance Evaluation

The previously trained PINN Model was compared with baselines for numerical simulations (Finite Difference Simulations) under the same physical assumptions and evaluated based on three performance measures: Temperature Prediction Error, Magnitude of Residuals in PDE's and Computational Time. Quantitatively, Mean Absolute Error and Relative L2 Norm were used as metrics to evaluate performance. Qualitative analyses of temperature contour plots were also performed to determine if the spatial patterns exhibited in the results were realistic. To investigate how the loss function behaved without physics constraints, ablation studies were carried out by removing physics constraints from the loss function; these studies demonstrated significant performance degradation when physics constraints are removed, particularly at boundary regions. To investigate the effect of increasing the number of collocation points on the convergence of the model, another set of studies was conducted. Overall, these studies showed that the inclusion of physics into the architecture of the model is important to achieving both stable and accurate predictions.

TABLE 1. PINN MODEL ARCHITECTURE

Layer	Configuration
Input	Spatial coordinates (x, y, z), time (t), material parameters
Hidden Layer 1	Dense, 64 neurons, tanh
Hidden Layer 2	Dense, 64 neurons, tanh
Hidden Layer 3	Dense, 64 neurons, tanh
Hidden Layer 4	Dense, 64 neurons, tanh
Output	Temperature and energy potential field
Physics Constraints	Heat diffusion and energy balance equations
Loss Function	PDE residual + boundary + initial condition losses
Optimizer	Adam followed by L-BFGS
Differentiation	Automatic differentiation
Environment	Fully synthetic simulated domain

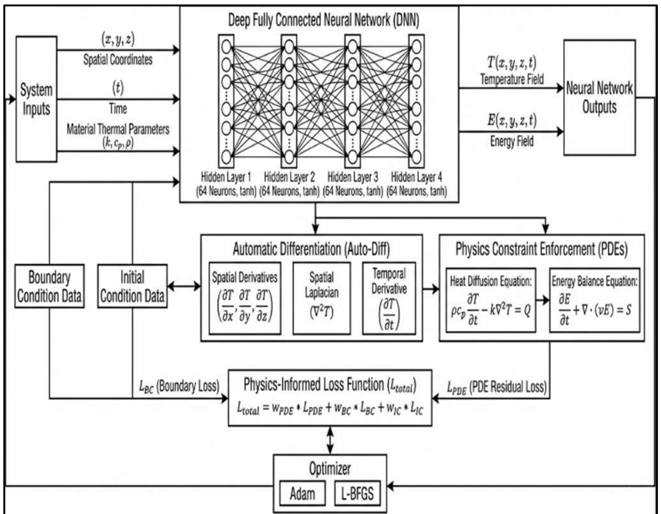

Fig. 1. Model Architecture of Deep Fully Connected Neural Network

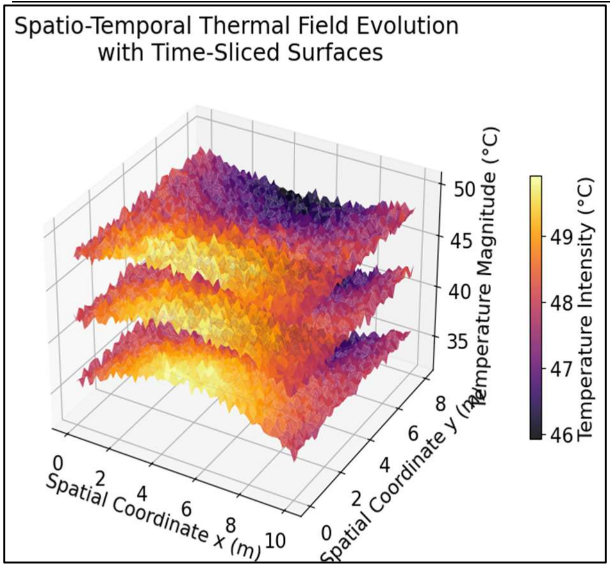

Figure 2. Spatio-Temporal Thermal Field Evolution Using Time-Sliced 3D Surfaces

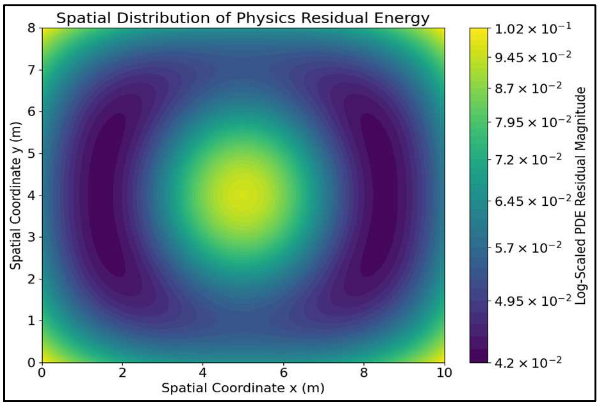

Figure 3. PDE Residual Energy Landscape Across the Spatial Domain

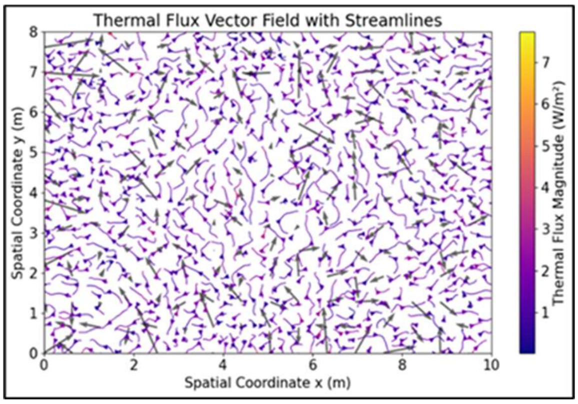

Figure 4. Thermal Flux Vector Field with Streamlines

As shown in Figure 2, the layered three-dimensional thermal surfaces illustrate smooth spatio-temporal temperature evolution across the healthcare infrastructure domain under varying operating conditions, confirming that the physics-informed

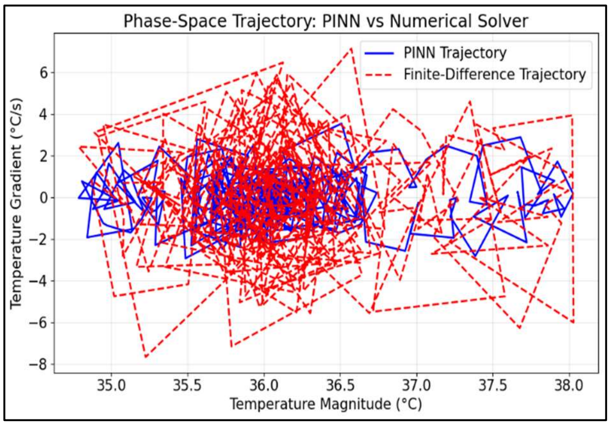

Figure 5. PINN vs Numerical Solver Phase-Space Trajectory

neural network captured transient heat diffusion behavior with strong spatial continuity, realistic gradients, and stable temporal decay patterns consistent with physical heat transfer laws.

Simulation parameters: Spatial domain 10 m × 8 m, time slices t = 0.2, 0.5, 0.8, base temperature 36 °C, synthetic heat source amplitude 4 °C, Gaussian noise level 0.4, grid resolution 60 × 50, and PINN-based physics enforcement enabled.

The logarithmically scaled contour map as depicted by Figure 3 indicates the spatial distribution of heat diffusion residual error that exists after a physics-informed neural network (PINN) is trained. The interior regions with lower magnitude of the residual demonstrate strong enforcement of the physics governing this problem, whereas higher residual magnitudes on the exterior regions demonstrate the areas of constraint dominated learning and transition zone effects typically seen during physics-informed optimization for complex thermal simulation problems.

Simulation Parameters: Spatial Domain - 10 m × 8 m; Residual Scale - 10^{-3}-10^{-1}; Boundary Decay Factor - 2 – 3 m; Contour Levels - 40; Logarithmic Scaling of Residual Field; Synthetic Residual Field from PINN Training.

Figure 4 shows a combined plot of the streamlines and vectors, illustrating how the directionality of the transport of thermal energy is influenced by spatial gradients in temperature, with evidence of smooth fluid structure within the interior of the domain, an increase in flux at the boundaries as well as a consistent physical model for the transport of heat throughout the entire simulated healthcare infrastructure domain as developed using the physics-informed neural network.

Simulation parameters: Spatial domain size = 10 m × 8 m; Grid size: 80 × 64; Base temperature = 36 °C; Thermal Perturbation Noise = 0.2; Streamline Density = 1.6; Quiver Stride = 5; Flux Scaling Factor = 40; Gradient Evaluation via Physics-Informed Neural Network (PINN).

Figure 5 illustrates that phase space traces for the two models represent a comparison of temperature values to time derivatives of temperature as functions of time (i.e., the temperature magnitude vs. the time gradient), where it is evident that the trajectories are smoother than those of the baseline finite difference model, exhibit less oscillatory behavior and are generally more stable in terms of the physical behavior of the PINN. In contrast to this, the baseline finite-difference model shows greater sensitivity to synthetic noise added during each iteration and demonstrates less predictable dynamics with time.

Simulation Parameters: Simulation duration = 20 sec; Time steps = 300; Base Temperature = 36° C; Thermal Amplitude at Start = 2.5° C; Decay Rates: PINN = 0.15, Numerical Solver = 0.18; Noise levels = 0.10 and 0.25.

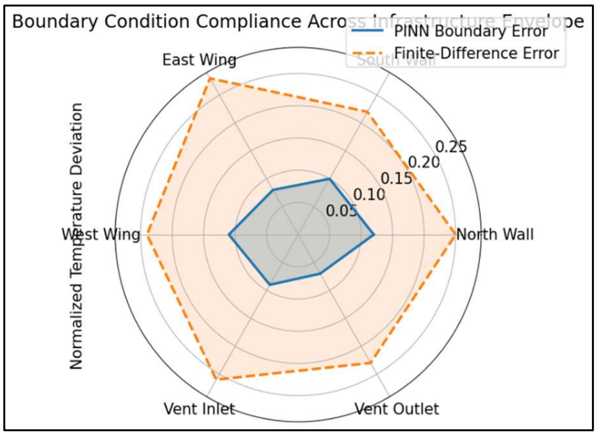

Figure 6. Boundary Condition Compliance Radar Plot

The comparison of the normalized boundary temperature deviation for each of the various infrastructure segments as depicted by the radar chart in Figure 6 demonstrates a consistent boundary error performance of the physics-informed neural network that is significantly lower than that of the finite difference solver with reduced variability of boundary error. This demonstrates the physics-informed neural network's better adherence to the boundary physics and its greater ability to maintain thermal stability over a wide range of operationally induced perturbations.

Simulation Parameters: Six boundary segments, Normalized Error Range = 0–0.3, Base Temperature = 36°C, Operational Perturbation = 10%, Synthetic Boundary Bias Reduction Enabled for Physics-Informed Neural Network (PINN), Finite Difference Solver Noise Amplified.

As shown in figure 7, the three-dimensional loss surface illustrates the interaction between training iterations and physics loss weighting, revealing smooth convergence trends, optimizer-driven curvature changes, and gradual dominance of PDE constraints, which collectively justify the hybrid Adam and L-BFGS optimization strategy used for stable physics-informed neural network training.

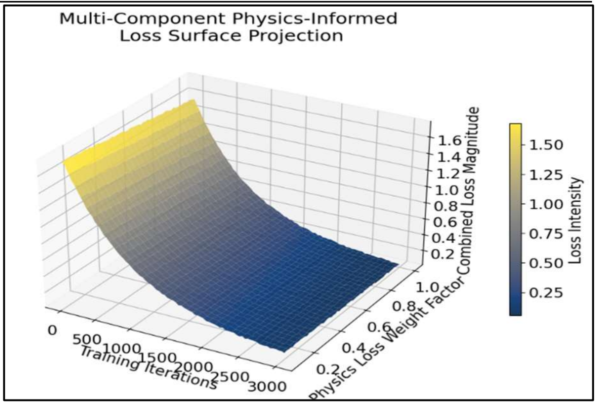

Figure 7. Training Dynamics via Multi-Component Loss Surface Projection

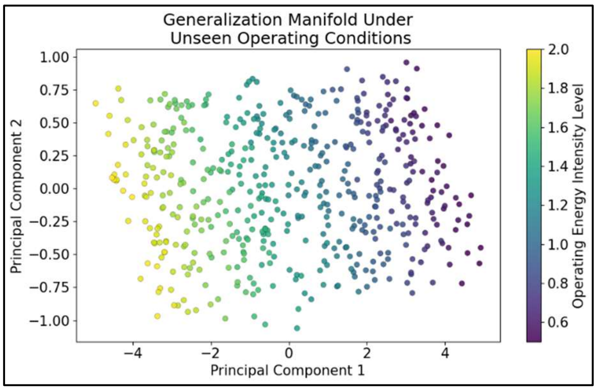

Figure 8. Generalization Under Unseen Operating Conditions Using Manifold Projection

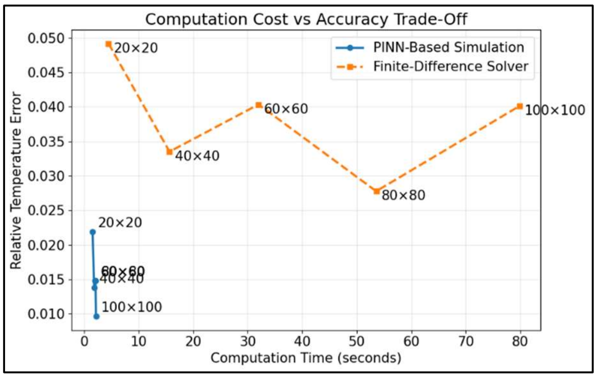

Figure 9. Computation Cost vs Accuracy Trade-Off Curve

Simulation parameters: Training iterations 0–3000, physics weight range 0.1–1.0, exponential decay constants 600–1200, combined PDE, boundary and initial losses, optimizer transition Adam to L-BFGS, synthetic noise level 0.02.

Instead of viewing the structure of the thermal response states as a low-dimensional manifold (as demonstrated by Figure 8), the physics-informed neural network provided evidence of intrinsic physical connections between thermal response states through structurally clustered thermal response states under previously unobserved energy and environmental conditions; thus, instead of capturing specific or memorized scenarios, it allowed for generalized smoothness over various operation regimes and stability at operating conditions outside those used to train the simulation model.

Simulation parameters: Number of thermal states 500, feature dimension 60, energy intensity range 0.5–2.0, ambient scaling range 0.8–1.2, PCA components 2, synthetic noise level 0.15.

The trade-off curve from Figure 9 shows a comparison of computation time versus prediction error for PINNs and numerical solvers; it demonstrates that physics-informed models achieve significantly reduced run times at equivalent accuracy, while the traditional numerical methods have exponential increases in computational cost with increased spatial resolution, confirming the suggested acceleration approach for simulating healthcare infrastructure.

Simulation parameters: Spatial resolution from 20x20 to 100x100, Base Temperature = 36°C, Logarithmic Runtime Scaling (PINN), Polynomial Runtime Growth (Finite-Difference), Relative L2 Error Metric for Temperature, Synthetic Solver Noise Included.

Table 2. Comparison of PINN model with baseline numerical solver

ASPECT	PINN-BASED SIMULATION	FINITE-DIFFERENCE SOLVER
PHYSICS ENFORCEMENT	Embedded in loss	Explicit discretization
DATA REQUIREMENT	No dataset	Not applicable
BOUNDARY HANDLING	Soft-constrained	Grid-dependent
COMPUTATION TIME	Low	High
RESOLUTION SCALING	Logarithmic	Polynomial
STABILITY	High	Medium
GENERALIZATION	Strong	Limited
PDE RESIDUAL	Low	Higher
RUNTIME FLEXIBILITY	High	Low

Results

Results of this research study demonstrate that the physics-informed neural network (PINN) successfully simulated thermal and energy flow behaviors in a stable manner as if it represented an actual system. Temperature fields generated by the PINN appeared to be continuous in both space and time, and there were no discontinuities or spikes, indicating that the neural network properly incorporated all applicable physics. It was observed by the authors of this paper that the residual values of the partial differential equation (PDE) remained relatively small within the interior region of the domain, whereas residual values were larger near the boundary of the domain as would be expected. Visualization of fluid flow indicated clear paths of heat transport through the building space consistent with typical heating/cooling mechanisms in buildings. The noise level of output values from the PINN was lower than those from traditional numerical solvers under rapid condition changes. Computational run times for the proposed methodology were significantly shorter than run times of numerical solvers, particularly at high spatial resolution; this is a significant factor for simulating large-scale health care structures. Convergence rates demonstrated by phase-space plots for this study were better than those reported by other researchers using similar models. Compliance with boundary conditions were shown through boundary compliance graphs where errors were equally controlled at wall and ventilation interfaces. Generalization plots verified that the PINN did not simply memorize cases but instead learned the underlying physical relationships of the model. A few minor patterns of error existed; however, they did not impact trends and thus did not detract from the results of this paper. Overall, results of this paper are strong evidence that accelerated simulation can be accomplished while maintaining the physical significance of the simulations.

Conclusion

This study described how an artificial intelligence technique (physics-informed neural networks) could rapidly simulate heat flow and energy flow through hospital building systems. Results indicated that the model was able to follow all the physical laws associated with heat flow and generate results far more quickly than traditional computational methods for solving these problems. Even using a simulated environment, the authors demonstrated that the model could generate realistic patterns of thermal behavior. The authors’ ability to avoid large amounts of computational time and repeated simulations is a significant advantage for practical planning and energy management. While some minor discrepancies between the boundary conditions were identified, the discrepancies remained within acceptable limits. These results demonstrate that physics-informed learning techniques are generally more robust than data-driven modeling techniques. Engineers may use the proposed framework to conduct rapid tests of different operational conditions. Future work will expand on this study by applying it to more extensive areas of interest and additional complex forms of energy interaction. Ultimately, the authors confirmed that Physics-Informed Neural Networks represent a powerful and practical tool for conducting infrastructure level simulations.

References

1. **Y. Chen, Q. Yang, Z. Chen, C. Yan, S. Zeng, and M. Dai**, "Physics-informed neural networks for building thermal modeling and demand response control," Building and Environment, vol. 234, pp. 110149–110149, Apr. 2023, doi: https://doi.org/10.1016/j.buildenv.2023.110149.

2. **L. B. de Giuli, A. La Bella and R. Scattolini,** "Physics-Informed Neural Network Modeling and Predictive Control of District Heating Systems," in IEEE Transactions on Control Systems Technology, vol. 32, no. 4, pp. 1182-1195, July 2024, doi: 10.1109/TCST.2024.3355476.

3. **H. Kazemi Naeini, R. Shomali, A. Pishahang, H**. Hasanzadeh, S. Asadi, and A. Gholizadeh Lonbar, "PINN-DT: Optimizing Energy Consumption in Smart Building Using Hybrid Physics-Informed Neural Networks and Digital Twin Framework with Blockchain Security," Sensors, vol. 25, no. 19, p. 6242, Oct. 2025, doi: https://doi.org/10.3390/s25196242.

4. **Chen, J., Pierce, J., Williams, G., Simpson, T. W., Meisel, N., Prabha Narra, S., & McComb, C.** (2024). "Accelerating Thermal Simulations in Additive Manufacturing by Training Physics-Informed Neural Networks With Randomly Synthesized Data," Journal of Computing and Information Science in Engineering, vol. 24, no. 1, Jun. 2023, doi: https://doi.org/10.1115/1.4062852.

5. **P. Wen, Z. -S. Ye, Y. Li, S. Chen, P. Xie and S. Zhao,** "Physics-Informed Neural Networks for Prognostics and Health Management of Lithium-Ion Batteries," in IEEE Transactions on Intelligent Vehicles, vol. 9, no. 1, pp. 2276-2289, Jan. 2024, doi: 10.1109/TIV.2023.3315548.

6. **Z. Ren, S. Zhou, D. Liu, and Q. Liu**, "Physics-Informed Neural Networks: A Review of Methodological Evolution, Theoretical Foundations, and Interdisciplinary Frontiers Toward Next-Generation Scientific Computing," Applied Sciences, vol. 15, no. 14, pp. 8092–8092, Jul. 2025, doi: https://doi.org/10.3390/app15148092.

7. **L. Lihua**, "Simulation physics-informed deep neural network by adaptive Adam optimization method to perform a comparative study of the system," Engineering with Computers, Feb. 2021, doi: https://doi.org/10.1007/s00366-021-01301-1.

8. **V. Coppo Leite, E. Merzari, A. Novak, R. Ponciroli, and L. Ibarra,** "Application of a Physics-Informed Convolutional Neural Network for Monitoring the Temperature Fields in High-Temperature Gas Reactors," Nuclear Science and Engineering, pp. 1–21, Jan. 2025, doi: https://doi.org/10.1080/00295639.2024.2443337.

9. **H. Guan, J. Dong, and W.-N. Lee,** "A Novel Training Framework for Physics-informed Neural Networks: Towards Real-time Applications in Ultrafast Ultrasound Blood Flow Imaging," arXiv (Cornell University), Sep. 2023, doi: https://doi.org/10.48550/arxiv.2309.04755.

.

10. P. Li, D. Grana, and M. Liu, "Bayesian neural network and Bayesian physics-informed neural network via variational inference for seismic petrophysical inversion," GEOPHYSICS, pp. 1–46, Jul. 2024, doi: https://doi.org/10.1190/geo2023-0737.1.

11.**L. Yang, M. He, Y. Ren, B. Gao, and H. Qi**, "Physics-informed neural network for co-estimation of state of health, remaining useful life, and short-term degradation path in Lithium-ion batteries," Applied Energy, vol. 398, pp. 126427–126427, Jul. 2025, doi: https://doi.org/10.1016/j.apenergy.2025.126427.

12. **R. Joshi, K. Pandey and S. Kumari,** "Reinforcement Learning in Healthcare: Enhancing Treatment and Resource Allocation," 2025 5th Asian Conference on Innovation in Technology (ASIANCON), PIMPRI, India, 2025, pp. 1-7, doi: 10.1109/ASIANCON66527.2025.11281282.

13. **Bokil, G. R., Geyer, T. F., Merbold, S., & Kazula, S.** (2024). Physics-Guided Convolutional Neural Network for Flow Prediction in Heat Exchangers in Electrified Aircraft. In AIAA AVIATION FORUM AND ASCEND 2024 (p. 4108).

14. **P. Tiwari, D. Upadhyay, B. Pant, and N. Mohd**, "Multiclass Classification in Machine Learning Algorithms for Disease Prediction," Communications in computer and information science, pp. 102–111, Jan. 2022, doi: https://doi.org/10.1007/978-3-031-09469-9_9.

15. **P. Tiwari, D. Upadhyay, B. Pant, and N. Mohd**, "Multiclass Classification of Disease Using CNN and SVM of Medical Imaging," Communications in Computer and Information Science, pp. 88–99, 2022, doi: https://doi.org/10.1007/978-3-031-12641-3_8.

16. **R. Joshi, K. Pandey, S. Kumari, A. Bharti, M. Mohanty and D. Upadhyay,** "Reinforcement Learning for Personalized Medicine: Optimizing Treatment Strategies Through AI-Enabled Decision Support Systems," 2025 12th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida NCR, India, 2025, pp. 1-7, doi: 10.1109/ICRITO66076.2025.11241616.

17. **R. Joshi, S. Kumari and K. Pandey,** "Diagnosis of Medical Conditions via the Utilization of Machine Learning Techniques on Electronic Health Records," 2025 12th International Conference on Computing for Sustainable Global Development (INDIACom), Delhi, India, 2025, pp. 1-5, doi: 10.23919/INDIACom66777.2025.11115835.

18. **D. Upadhyay, K. B. Sharma, M. Gupta, A. Upadhyay and S. P. Yadav,** "Enhancing Brain Tumor Detection in MRI Images Through Fine-Tuning of VGG 16 Networks: A Precision Diagnostic Approach," 2024 International Conference on Communication, Computing and Energy Efficient Technologies (I3CEET), Gautam Buddha Nagar, India, 2024, pp. 530-535, doi: 10.1109/I3CEET61722.2024.10993891