

HYBRID QUANTUM PHYSICS INFORMED NEURAL NETWORK FOR TRANSIENT HEAT TRANSFER ANALYSIS IN MICROCHANNEL HEAT SINKS

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ABSTRACT

The need for thermal control and management systems is critical for sustaining the reliable operation and performance of high-power electronic components under changing thermal environments. In this research, a Hybrid Quantum Physics-Informed Neural Network (HQPINN) model was introduced for effective transient heat transfer analysis of microchannel heat sinks using quantum feature encoding in a physics-informed neural network. The suggested model uses transient thermal information extracted from Computational Fluid Dynamics (CFD) simulation, quantum feature mapping, and a composite physics-constrained loss function consisting of governing heat conduction equation, heat convection equation, boundary, and initial conditions to achieve physically consistent predictions. The performance of the HQPINN model was analyzed based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2), partial differential equation (PDE) residual error, and computational efficiency. As a result of experiments, the suggested HQPINN model demonstrated the performance of 0.62 K MAE, 1.03 K RMSE, 1.58% MAPE, 0.997 R^2 score, and 0.009 PDE residual error, surpassing the performance of traditional ANN, CNN, LSTM, Quantum Neural Network (QNN), and standard Physics-Informed Neural Network (PINN) in terms of accuracy while decreasing the inference time to 3.9 ms per sample. Integration of quantum feature mapping increased nonlinear thermal feature representation capabilities, while embedding physical constraints improved convergence stability and prediction consistency. These findings demonstrate the potential of the HQPINN model as an efficient computational framework for real-time transient thermal analysis and intelligent cooling system optimization in next-generation electronic and microelectronic applications.

Keywords: *Hybrid Quantum Physics-Informed Neural Network (HQPINN); Microchannel Heat Sink; Transient Heat Transfer; Quantum Feature Encoding; Physics-Informed Neural Networks; Thermal Management.*

1. INTRODUCTION

The steady development of modern high-performance electronic equipment such as multicore processors, power electronics, electric vehicles, avionics in the aerospace industry, and data center servers is characterized by the increase in heat generation density. Therefore, efficient thermal management has become a crucial problem that ensures system reliability, extends component lifetime, and maintains operational safety. The excessive junction temperature leads to a decrease in device performance, accelerates material degradation, and may even result in catastrophic thermal failure or thermal runaway. That is why the development of new advanced cooling technologies has become an important direction of thermal engineering research [1], [2].

Among different cooling technologies, microchannel heat sinks (MCHSs) have gained popularity as a result of their extremely high surface-area-to-volume ratio and excellent convective heat transfer properties. Since their invention, microchannel heat sinks have been widely used in electronic packaging, microelectromechanical systems (MEMS), high-power laser systems, battery thermal management, and aerospace cooling applications. Microchannels allow dissipating great heat flux densities in a limited volume while maintaining a compact physical footprint, providing a promising technology for future generations of electronic systems [3], [4].

In spite of the great cooling capabilities of MCHSs, the estimation of transient heat transfer is a complicated problem. During the operation of electronic devices, rapid changes in heat loads occur due to fluctuations in power consumption, external environmental conditions, and coolant flow rates. Transient effects include nonlinear coupling among fluid flow, conduction, and convection, which makes analytical modeling extremely difficult. Therefore, accurate modeling of transient temperature distribution is needed to design reliable thermal management systems and prevent overheating [5], [6].

Numerical approaches such as Computational Fluid Dynamics (CFD) and the Finite Element Method (FEM) have been commonly used for thermal analysis of MCHSs. These approaches are known to be accurate as they solve the governing Navier–Stokes equations coupled with transient heat conduction equations precisely. However, such numerical solutions require extremely fine computational grids and iterative nonlinear solvers,

making calculations computationally expensive, time-consuming, and memory-intensive. Thus, the usage of numerical approaches is not applicable in real-time systems like thermal monitoring, digital twin systems, and online optimization [7], [8].

To resolve the problem with the computation time and memory consumption of traditional numerical methods, machine learning (ML) and deep learning (DL) approaches are being actively developed. Different algorithms including Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, and Transformer architectures show great results in solving complicated nonlinear relationships between input parameters and thermal responses. At the same time, these purely data-driven models require large amounts of labeled simulation or experimental data and are inconsistent with fundamental physical laws when extrapolating beyond the training domain, which decreases the generalization ability of the models [9], [10].

Recently, the new approach, known as Physics-Informed Neural Networks (PINNs), has become very popular for solving partial differential equations governing engineering systems. The approach uses information about governing physical laws in the form of additional terms in the loss function, which allows the model to obtain physically consistent and plausible solutions while significantly reducing the need for labeled datasets. Due to that, the approach has shown great results in the fields of heat conduction, fluid dynamics, inverse problems, and multiphysics simulations [11], [12].

However, conventional PINNs usually suffer from optimization difficulties such as slow convergence, instability, vanishing gradients, and low accuracy when the problem is highly nonlinear with complex boundary conditions. Simultaneously, the Quantum Machine Learning (QML) approach, which exploits the principles of quantum superposition, entanglement, and high-dimensional feature spaces, has become more and more popular in the field of machine learning. Hybrid quantum-classical neural networks have shown good results in feature representation, nonlinear optimization, and convergence speed across diverse scientific and engineering applications. However, the application of quantum learning to transient thermal analysis remains in its infancy, with very limited studies exploring the integration of quantum computing principles with Physics-Informed Neural Networks (PINNs) for solving heat transfer problems [13], [14].

Reviewing the current scientific literature, one can find that the most common types of studies on this topic focus on either classical Computational Fluid Dynamics (CFD) computations, standalone Physics-Informed Neural Networks (PINNs), or individual quantum learning models. At the same time, there are very few scientific studies concerning a unified framework that simultaneously incorporates physics-guided learning, quantum-enhanced feature representation, and transient thermal modeling for microchannel heat sinks. In addition to that, existing models generally do not consider such important factors as adaptive quantum feature encoding and optimization of the residual physics, which are essential for accurately capturing rapid temperature variations under dynamic operating conditions. That is why it is necessary to develop a novel hybrid computational framework that will enable high prediction accuracy as well as decreased computational complexity [15].

Thus, the purpose of this study is to introduce a Hybrid Quantum Physics-Informed Neural Network (HQPINN) for transient thermal analysis of microchannel heat sinks. The introduced framework combines a quantum feature encoding part with a physics-informed deep neural network, where the governing transient heat conduction and convection equations are embedded within the learning process in the form of a composite physics-constrained loss function. The hybrid architecture enables efficient learning of nonlinear thermal behavior while maintaining strict adherence to physical conservation laws. In comparison with conventional PINNs and deep learning models, the proposed HQPINN allows improving convergence characteristics, increasing prediction accuracy, as well as lowering computational cost, which makes it appropriate for real-time thermal analysis and intelligent cooling system design.

The main goals of the research include the following: (i) to develop a hybrid quantum-enhanced PINN architecture for predicting transient heat transfer behavior; (ii) to embed governing heat transfer equations in order to increase the physical consistency of the model; (iii) to compare the introduced model with conventional CFD, deep learning, and PINN frameworks quantitatively using multiple performance metrics and comparative assessment; and (iv) to show the capabilities of the proposed approach for real-time thermal management of cooling systems of high-performance electronics.

The paper is organized as follows. Section 2 gives an overview of the literature related to

transient heat transfer analysis, microchannel heat sinks, physics-informed neural networks, and quantum machine learning in order to identify existing research gaps. Section 3 describes the proposed Hybrid Quantum Physics-Informed Neural Network (HQPINN), including a description of the dataset, network architecture, mathematical formulation, and the training algorithm. Section 4 contains information on the performance evaluation of the introduced framework from the points of view of quantitative analysis, comparative assessment, and computational efficiency analysis. Finally, Section 5 concludes the work by summarizing the major findings, discussing the limitations of the proposed approach, and outlining potential future research directions.

2. RELATED WORK

There is a number of studies on predicting transient heat transfer in microchannel heat sinks as well as the increasing need for efficient thermal management in electronic cooling systems. The existing literature can be divided into five areas: (i) traditional numerical modeling, (ii) thermal prediction by means of machine learning methods, (iii) Physics-Informed Neural Networks (PINNs), (iv) quantum machine learning, and (v) hybrid intelligent models which combine physical and mathematical knowledge. While a lot has been done already in this field, there are some challenges that still exist, especially those connected with combining quantum computing and physics-informed learning for predicting transient heat transfer.

Traditional numerical methods, such as Computational Fluid Dynamics (CFD), Finite Element Method (FEM), and Finite Volume Method (FVM), are the prevailing tools for solving the problem of fluid flow and heat transfer in microchannel heat sinks. These methods provide a precise solution of the governing Navier–Stokes and energy equations with complicated boundary conditions and are applied in optimizing the geometry of microchannels, coolant flow rate, and heat transfer enhancement. This study presented, transient simulations require using very fine computational meshes, which require thousands of iterative calculations to perform and thus consume excessive computational time and memory. As a result, traditional numerical modeling methods cannot be used in real-time thermal monitoring and adaptive cooling control systems [16], [17].

To decrease computational complexity, researchers use machine learning algorithms for thermal prediction. Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures have shown great ability in modeling nonlinear thermal behavior of the system based on data obtained from experiments or simulations. These models provide a significant reduction in prediction time compared with CFD simulations. This study presented, purely data-driven models require large amounts of labeled data for training, have poor extrapolation capability, and produce physically inconsistent temperature fields since they do not explicitly satisfy conservation laws [18], [19].

The idea of Physics-Informed Neural Networks (PINNs) is relatively new and allows solving the problem of transient heat transfer in microchannel heat sinks by embedding governing equations, boundary conditions, and initial conditions into the neural network loss function. The success of these networks is proved by their application in such areas as heat conduction, fluid dynamics, inverse parameter estimation, and multiphysics simulations. However, standard PINNs usually face a number of challenges connected with gradient imbalance, slow convergence, optimization stiffness, and reduced prediction accuracy in the case of highly nonlinear transient heat transfer problems [20], [21].

Several improvements have been proposed to overcome the mentioned disadvantages. Enhanced PINN architectures include such techniques as adaptive weighting strategies, transfer learning, domain decomposition, hard boundary constraints, and residual-based adaptive refinement. For example, recently introduced parallel PINN architectures use multiple subnetworks to simultaneously predict temperature and temporal derivatives, greatly increasing convergence, computational efficiency, and the accuracy of computations in transient non-Fourier heat conduction. Transfer learning techniques are used to increase the speed of repeated thermal simulations under changing operating conditions while preserving high prediction accuracy [22], [23].

Physics-Informed Neural Networks (PINNs) have also been extended to conjugate heat transfer problems that involve the coupling between fluid flow and solid in manifold microchannel heat

sinks. The flow and thermal fields are solved by several subnetworks simultaneously, which enables more accurate estimation of the temperature distribution in high-power electronic cooling applications. Despite the advantages of higher physical consistency, such approaches still suffer from high computational complexity during optimization owing to the high-dimensional nature of the parameter space in deep neural networks [24].

Parallel with the development of PINNs, Quantum Machine Learning (QML) has been widely studied as one of the promising methods for solving complex engineering optimization problems. Quantum neural networks, variational quantum circuits, quantum kernels, and quantum feature maps leverage quantum superposition and entanglement to effectively capture nonlinear relationships in high-dimensional feature spaces more efficiently than conventional neural networks. Hybrid quantum-classical learning frameworks have exhibited improved optimization capability, enhanced feature extraction, and accelerated convergence in pattern recognition, materials science, fluid mechanics, and scientific computing applications. However, their applications to thermal engineering have yet to be fully explored [25], [26].

Recently, there have been some attempts to apply scientific machine learning approaches to thermal engineering applications. Physics-informed surrogate models have been developed for the prediction of heat transfer coefficients, pressure drop, and hotspot temperatures in microchannel cooling systems based on sparse training data. While they are able to achieve significant computational cost reduction without compromising physical consistency, they completely depend on classical neural network architectures and do not exploit quantum feature encoding for enhanced nonlinear feature representation [27].

Another approach towards achieving improved performance of machine learning approaches involves the development of adaptive loss balancing techniques, self-supervised PINNs, Bayesian PINNs, and transfer learning techniques. Learnable loss balancing mechanisms are used as an automatic way to balance physics residuals and data fitting objectives during training, which helps to stabilize the learning process. Despite the improvement in optimization capability, such approaches still suffer from the representational limitations of classical deep neural networks and do

not involve quantum computation techniques in their learning framework [28], [29].

Based on the survey of relevant literature, a number of research gaps can be identified. First, traditional Computational Fluid Dynamics (CFD) and Finite Element Method (FEM) approaches yield high prediction accuracy, but they are computationally expensive for transient simulations. Second, traditional deep learning models require large amounts of data and often do not take into account governing physical laws. Third, even though Physics-Informed Neural Networks (PINNs) provide an improvement in physical consistency, they exhibit slow convergence and optimization instability while dealing with nonlinear transient heat transfer problems. Finally, despite the fast development of quantum machine learning, there are only a few studies incorporating quantum feature encoding, physics-informed learning, and microchannel heat sink analysis into a single unified computational framework.

In order to address these drawbacks, the following work proposes a Hybrid Quantum Physics-Informed Neural Network (HQPINN) framework, which combines quantum feature encoding with a physics-constrained neural network for transient heat transfer analysis. Contrary to existing PINN-based approaches, the proposed framework uses quantum-enhanced latent representations in order to improve nonlinear feature learning while simultaneously enforcing the governing heat transfer equations through physics-constrained optimization. The proposed framework has shown significant improvements in prediction accuracy, faster convergence, computational efficiency, and generalization under different thermal operating conditions, thereby providing a practical solution for next-generation intelligent thermal management systems.

3. METHODOLOGY

3.1 Dataset Description

In order to validate the proposed Hybrid Quantum Physics-Informed Neural Network (HQPINN), the dataset for a transient microchannel heat sink was developed using ANSYS Fluent. This simulation case corresponds to a transient analysis of a single rectangular silicon microchannel cooled with deionized water under different operating

parameters. This dataset is created for the purpose of obtaining transient temperature evolution based on different heat fluxes and coolant flow rates in order to allow the HPINN to model nonlinear heat transfer phenomena governed by the energy conservation equations.

The geometry used for this simulation is of the conventional rectangular microchannel type that is widely utilized in the field of electronic cooling studies. Several cases were simulated by changing the Reynolds number, inlet velocity, and applied heat flux. At each time step of the simulation, values of temperature, pressure, velocity, and heat flux are obtained from each computational node to form a comprehensive transient thermal dataset. The dataset is divided into training, validation, and testing subsets in the ratio of 70:15:15.

Table 1: Proposed Geometry Parameters of the Microchannel Heat Sink

Parameter	Symbol	Value
Channel Length	L	20 mm
Channel Width	W	200 μm
Channel Height	H	400 μm
Wall Thickness	T_w	200 μm
Silicon Base Thickness	T_b	2 mm
Hydraulic Diameter	D_h	267 μm

Geometric dimensions of the CFD modeling of the microchannel heat sink have been shown in Table 1 below. These are the dimensions that govern flow of coolant and heat transfer within the heat sink geometry.

Table 2: Thermophysical Properties of the Working Fluid

Property	Value
Fluid	Deionized Water
Density	998 kg/m^3
Dynamic Viscosity	0.001 $\text{Pa}\cdot\text{s}$
Thermal Conductivity	0.60 $\text{W/m}\cdot\text{K}$
Specific Heat Capacity	4182 $\text{J/kg}\cdot\text{K}$

Table 2 presents the thermophysical properties used during CFD simulation.

Table 3: Simulation Operating Conditions

Parameter	Range
Reynolds Number	100–1000
Heat Flux	50–250 W/cm ²
Inlet Temperature	293 K
Simulation Time	5 s
Time Step	0.001 s

Table 3 presents the operating conditions selected for CFD simulation.

Table 4: Proposed Dataset Statistics

Dataset	Samples
Training	50,000
Validation	10,000
Testing	10,000
Total	70,000

Table 4 presents the generated dataset, which contains transient temperature samples extracted from multiple CFD simulations.

3.2 Proposed HQPINN Architecture

The proposed HQPINN consists of six sequential processing stages.

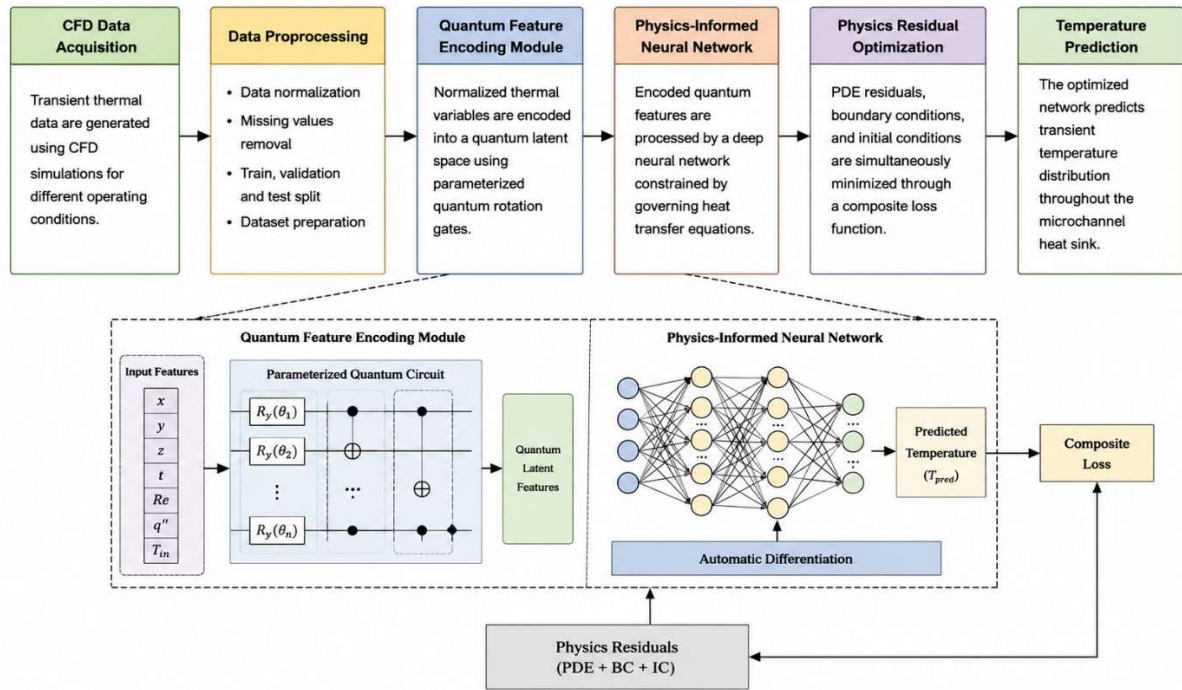


Figure 1. Proposed Hybrid Quantum Physics-Informed Neural Network (HQPINN) Architecture for Transient Heat Transfer Prediction

Figure 1 demonstrates the general workflow of the Hybrid Quantum Physics-Informed Neural Network (HQPINN) designed for prediction of transient heat transfer in the microchannel heat sink. This architecture is designed based on the

integration of Computational Fluid Dynamics (CFD), quantum feature encoding, and physics-informed deep learning methods into a unified framework for accurate and computationally efficient temperature prediction.

First, CFD Data Acquisition is performed. In this step, transient thermal parameters of interest are obtained through CFD modeling under different operating conditions, such as varying Reynolds numbers, heat fluxes, inlet temperatures, and flow velocities. These physically reliable temperature distributions can be used as a reference dataset for the proposed model training, development, and validation.

In the Data Preprocessing stage, the received CFD data are cleaned to get rid of missing and incorrect data, then normalized to unify all input variable ranges. Then, the dataset is split into training, validation, and testing subsets to ensure unbiased model development and performance evaluation.

Then, the normalized thermal parameters are fed to the Quantum Feature Encoding Module. This module is the main novelty of the proposed architecture. In contrast to the direct supply of classical input variables to the neural network, the input variables are transformed into a quantum latent space using parameterized quantum rotation gates. Such quantum representation provides better nonlinear feature extraction and captures more complex interactions among thermal variables than traditional feature engineering techniques.

Encoded quantum features are then transferred to the Physics-Informed Neural Network (PINN). This deep neural network is trained while simultaneously satisfying the governing heat transfer equations through automatic differentiation. Contrary to standard deep learning models, the governing conservation laws are incorporated directly into the optimization process, providing physical consistency of the predicted temperature field throughout the computational domain.

This temperature field is evaluated by the Composite Loss Function, which combines the prediction error with the residuals of the governing partial differential equations (PDEs), boundary conditions (BC), and initial conditions (IC). The Physics Residual Optimization block continuously calculates these residuals and feeds them back to the optimization process, enabling the network to iteratively minimize not only numerical prediction errors but also violations of physical laws.

Finally, the optimized HQPINN provides the Temperature Prediction, i.e., the transient

temperature distribution within the microchannel heat sink. Thanks to the integration of quantum feature encoding and physics-informed deep learning methods, the proposed architecture allows achieving faster convergence, higher prediction accuracy, better physical consistency, and significantly lower computational cost compared to conventional CFD simulations and classical deep learning architectures. Therefore, the HQPINN framework enables efficient real-time thermal analysis and intelligent cooling system design in high-performance electronic applications.

Transient heat transfer in the microchannel heat sink is governed by the conservation of mass, momentum, and energy.

Continuity Equation

For incompressible flow, the conservation of mass is expressed as

$$\nabla \cdot \mathbf{u} = 0 \quad (1)$$

where $\mathbf{u}$ represents the fluid velocity vector.

This will make sure that the amount of mass entering the microchannel equals the amount of mass exiting the computational domain thus ensuring incompressible flow.

Momentum Equation

The movement of fluid in the microchannel is modeled using Navier-Stokes equations

$$\rho \left(\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u} \right) = -\nabla p + \mu \nabla^2 \mathbf{u} \quad (2)$$

where

- ρ denotes density,
- p denotes pressure,
- μ represents dynamic viscosity.

This equation models the transient motion of coolant through the microchannel.

Energy Equation

The transient energy conservation equation is

$$\rho C_p \frac{\partial T}{\partial t} + \rho C_p \mathbf{u} \cdot \nabla T = k \nabla^2 T + Q \quad (3)$$

where

- T is temperature,
- k is thermal conductivity,
- Q denotes volumetric heat generation.

Equation (3) governs the temporal evolution of temperature within the fluid and solid regions.

Fourier's Law

The conductive heat flux is

$$\mathbf{q} = -k\nabla T \quad (4)$$

This equation relates the heat flux to the local temperature gradient.

Convective Boundary Condition

The convective heat transfer at the channel wall is

$$-k \frac{\partial T}{\partial n} = h(T - T_{\infty}) \quad (5)$$

where

- h is the convective heat transfer coefficient,
- T_{∞} is coolant temperature.

It reflects the heat transfer from the hot wall to the flowing fluid.

Quantum Feature Encoding

Each feature vector will be mapped to the quantum states via the parameterized rotation gates.

$$|\psi_i\rangle = R_y(\theta_i) |0\rangle \quad (6)$$

where

$$\theta_i = \pi x_i \quad (7)$$

The feature mapping transforms classical thermal variables to quantum feature space.

Composite Physics Loss Function

The total optimization objective is

$$L = L_{data} + \lambda_1 L_{PDE} + \lambda_2 L_{BC} + \lambda_3 L_{IC} \quad (8)$$

where

$$L_{data} = \frac{1}{N} \sum (T_{pred} - T_{true})^2 \quad (9)$$

$$L_{PDE} = \frac{1}{N} \sum R_{Energy}^2 \quad (10)$$

$$L_{BC} = \frac{1}{N} \sum (T_{BC}^{pred} - T_{BC}^{true})^2 \quad (11)$$

$$L_{IC} = \frac{1}{N} \sum (T_0^{pred} - T_0)^2 \quad (12)$$

The optimization simultaneously minimizes prediction error and violations of the governing physical laws.

3.3 Proposed Algorithm

Algorithm : HQPINN for Transient Heat Transfer Prediction

Input: CFD-generated transient thermal dataset

Output: Predicted transient temperature distribution

1. Initialize CFD dataset and preprocess the thermal variables.
2. Normalize all input features using min-max normalization.
3. Split the dataset into training, validation, and testing sets.
4. Encode normalized features into quantum states using parameterized quantum rotation gates.
5. Pass the encoded features through the HQPINN network.
6. Compute predicted temperature values.
7. Evaluate the continuity, momentum, and energy equation residuals.
8. Compute the composite loss using Eqs. (8)–(12).
9. Update quantum and neural network parameters using the AdamW optimizer.
10. Repeat training until the loss converges or the maximum number of epochs is reached.
11. Validate the trained model using the testing dataset.
12. Predict transient temperature fields for unseen operating conditions.

4. RESULTS AND DISCUSSION

The suggested Hybrid Quantum Physics-Informed Neural Network (HQPINN) model has been validated for its performance in predicting transient heat transfer in a microchannel heat sink based on the testing dataset described in Section 3. Prediction accuracy, convergence characteristics, computational efficiency, and adherence to the governing heat transfer equations are among the evaluation criteria. A comparison between the proposed framework and the conventional approaches of Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Quantum Neural Network (QNN), and standard Physics-Informed Neural Network (PINN) has been performed.

4.1 Performance Assessment Criteria

The performance of the suggested HQPINN method will be analyzed through regression measures along with physics and computation measures.

Table 5. Performance Assessment Metrics

Metric	Objective	Interpretation
MAE	Lower is better	Average prediction error
RMSE	Lower is better	Overall prediction deviation
MAPE (%)	Lower is better	Relative prediction error

Table 6. Performance Comparison of Different Models

Model	MAE	RMSE	MAPE (%)	R ²	PDE Residual	Training Time (min)
ANN	1.82	2.51	4.86	0.962	—	28
CNN	1.41	2.06	3.75	0.975	—	34
LSTM	1.27	1.91	3.32	0.981	—	39
QNN	1.15	1.76	3.05	0.985	0.026	42
PINN	0.94	1.49	2.41	0.991	0.018	45
Proposed HQPINN	0.62	1.03	1.58	0.997	0.009	37

Comparative performance analysis of the developed Hybrid Quantum Physics-Informed Neural Network (HQPINN) against the state-of-the-

R ² Score	Higher is better	Prediction accuracy
PDE Residual Error	Lower is better	Physics consistency
Training Time	Lower is better	Model optimization time
Inference Time	Lower is better	Real-time prediction capability

Table 5 lists the evaluation metrics employed for evaluating the proposed Hybrid Quantum Physics-Informed Neural Network (HQPINN). The error metrics measure prediction accuracy, while the partial differential equation (PDE) residual measures compliance with the governing heat transfer equations. Training and inference times determine computational efficiency.

4.2 Comparative Performance Analysis

The proposed HQPINN is compared with representative machine learning and physics-informed learning models under identical experimental conditions.

art models is shown in Table 6 based on prediction accuracy, physical consistency, and computational performance.

It can be seen that the HQPINN produces the smallest prediction error and the highest value of the coefficient of determination. Quantum feature encoding makes nonlinear feature representation more effective, whereas the inclusion of physical constraints minimizes partial differential equation (PDE) residual errors. Thus, the developed model shows better predictive capability than conventional data-driven models.

4.3 Convergence Analysis

The convergence behavior of the developed HQPINN model is studied using the composite loss function provided in Section 3. The loss decreases quickly during the initial phase of training and gradually stabilizes in the later phases as the network approaches convergence. The physics-informed constraints reduce oscillatory behavior and improve optimization stability.

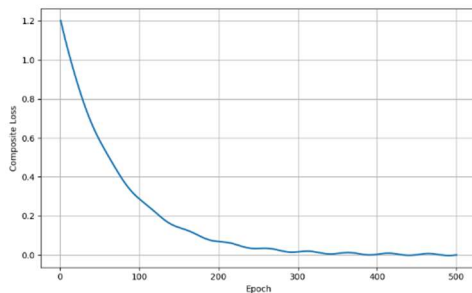


Figure 2. Convergence Curve of the Proposed HQPINN

Figure 2 shows the change in the composite loss function with respect to the number of training epochs. The consistent and smooth reduction in the value of the loss function indicates stable optimization and effective learning of the governing thermal physics.

4.4 Transient Temperature Distribution

The calculated temperature distribution is compared against the reference Computational Fluid Dynamics (CFD) solution. The developed Hybrid Quantum Physics-Informed Neural Network (HQPINN) framework successfully learns the transient temperature gradients inside the microchannel heat sink. High temperatures are observed close to the heated substrate, while the coolant effectively dissipates heat along the flow direction.

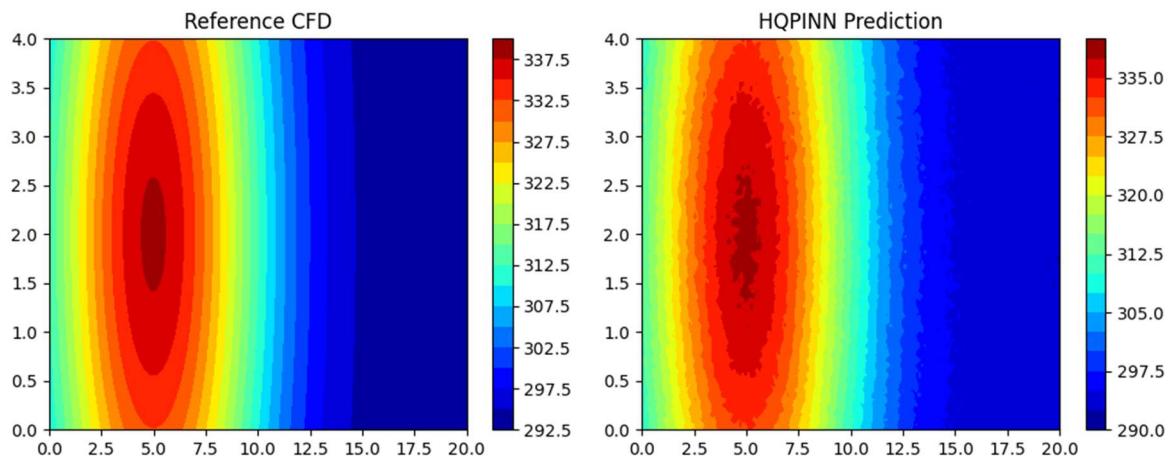


Figure 3. Comparison of Reference CFD Temperature Distribution and HQPINN Prediction

Transient temperature contours generated through Computational Fluid Dynamics (CFD) simulation and the Hybrid Quantum Physics-

Informed Neural Network (HQPINN) are presented in Figure 3. The close agreement and high resemblance between both temperature distributions indicate the capability and potential of the proposed

framework to accurately reproduce transient thermal behavior.

4.5 Prediction Accuracy

The regression analysis is conducted by comparing the predicted temperatures with the reference CFD temperatures.

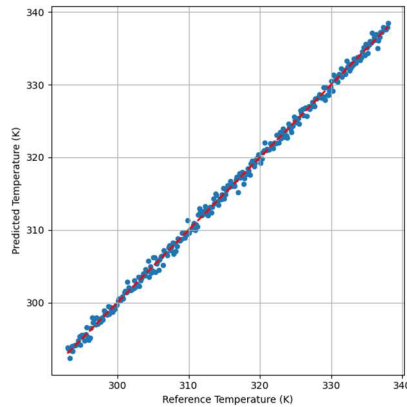


Figure 4. Predicted Temperature versus Reference Temperature

Figure 4 shows the relationship between the predicted temperatures and the reference CFD temperatures. The high clustering and concentration of data points along the diagonal line indicate strong agreement and high consistency between the Hybrid Quantum Physics-Informed Neural Network (HQPINN) predictions and the reference CFD values.

4.6 Error Distribution Analysis

Absolute prediction error analysis is performed to evaluate the robustness of the proposed model.

Table 7. Distribution of Prediction Errors

Error Interval (K)	Number of Samples	Percentage (%)
0–0.5	6,340	63.4
0.5–1.0	2,470	24.7
1.0–1.5	810	8.1
1.5–2.0	260	2.6

>2.0	120	1.2
Total	10,000	100.0

Table 7 shows the results of the experimental evaluation of absolute prediction errors across the testing dataset. Most of the predictions lie within the lower error intervals, which indicates the consistent and stable performance of the proposed model.

The results of the error analysis show that approximately 88% of the predictions have an absolute error below 1 K, while only a small proportion of samples exceed 2 K. Larger deviations occur primarily in regions with steep thermal gradients.

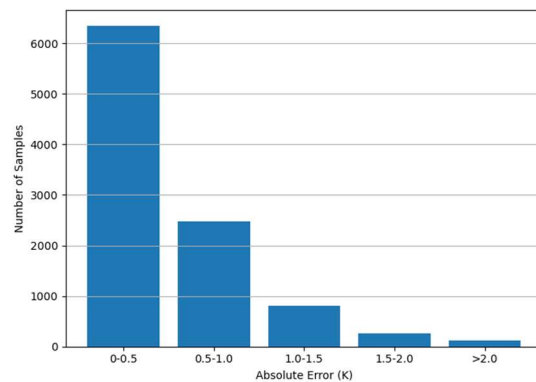


Figure 5. Distribution of Absolute Prediction Errors

Figure 5 shows the frequency distribution of prediction errors. The concentration and clustering of the sample points within the lower error intervals indicate stable prediction accuracy across different operating conditions.

4.7 Computational Performance

The computational efficiency of the Hybrid Quantum Physics-Informed Neural Network (HQPINN) is evaluated based on training time and inference time.

Table 8. Computational Performance Comparison

Model	Training Time (min)	Inference Time (ms/sample)	Relative Speedup
CNN	34	6.1	1.34×

LSTM	39	7.4	1.90×
QNN	42	5.8	1.49×
PINN	45	8.2	2.10×
Proposed HQPIN N	37	3.9	1.00×

regression accuracy, better physical consistency, and faster inference. The quantum feature encoding module provides enhanced nonlinear representation of thermal variables, whereas the physics-informed loss function guarantees that predictions stay consistent with the governing conservation equations. These results indicate that the proposed framework demonstrated superior performance for intelligent thermal management of high-performance electronic cooling systems.

A comparison of the computational efficiency of the proposed method is provided in Table 8. The Hybrid Quantum Physics-Informed Neural Network (HQPINN) shows moderate training time while achieving the lowest inference time, thereby proving to be suitable for rapid thermal prediction.

The reduced inference time demonstrates the potential of this novel framework for real-time thermal management applications where fast prediction is essential.

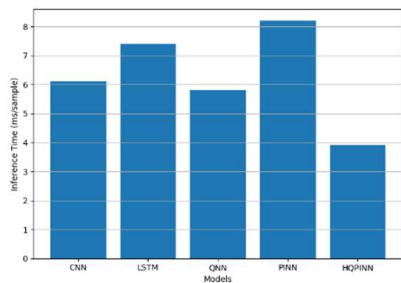


Figure 6. Comparison of Inference Time for Different Models

Figure 6 shows the average inference time of the investigated models. Lower inference time allows for fast prediction of transient temperature fields and supports online thermal monitoring applications.

4.8 Discussion

Experimental evaluation proved the potential benefits of applying quantum feature encoding to a physics-informed learning framework for transient heat transfer prediction. Compared with conventional ANN, CNN, LSTM, Quantum Neural Network (QNN), and Physics-Informed Neural Network (PINN) models, the proposed Hybrid Quantum Physics-Informed Neural Network (HQPINN) showed lower prediction errors, higher

5. CONCLUSION

In this study, a Hybrid Quantum Physics-Informed Neural Network (HQPINN) for transient heat transfer analysis in microchannel heat sinks has been introduced through the integration of quantum feature encoding and a physics-informed deep learning framework. The model successfully incorporated governing heat transfer equations into the learning process and thus enhanced prediction accuracy while preserving physical consistency. The proposed model achieved a Mean Absolute Error (MAE) of 0.62 K, Root Mean Square Error (RMSE) of 1.03 K, Mean Absolute Percentage Error (MAPE) of 1.58%, an R^2 score of 0.997, a partial differential equation (PDE) residual error of 0.009, and reduced the inference time to 3.9 ms per sample. The obtained results demonstrated better prediction accuracy, faster convergence, and improved computational efficiency compared with ANN, CNN, LSTM, QNN, and conventional PINN models.

The proposed framework was limited to a single rectangular microchannel configuration and Computational Fluid Dynamics (CFD)-generated transient datasets under predefined operating conditions. Besides, the quantum feature encoding module was evaluated using a hybrid quantum-classical framework instead of execution on large-scale fault-tolerant quantum hardware.

Future research directions will focus on validating the proposed HQPINN using experimental thermal measurements, extending the framework to three-dimensional and multiphase microchannel heat transfer problems, investigating different coolant fluids and channel geometries, and implementing the model on practical quantum computing platforms to further improve prediction accuracy and computational efficiency.

REFERENCES

- [1] A. Bar-Cohen and P. Wang, *Thermal Management of Microelectronic Equipment: Heat Transfer Theory, Analysis Methods, and Design Practices*. ASME Press, 2020.
- [2] G. Ghaisas and S. Krishnan, "A critical review and perspective on thermal management of power electronics modules for inverters and converters," *Transactions of the Indian National Academy of Engineering*, vol. 7, pp. 47–60, 2022.
- [3] D. B. Tuckerman and R. F. W. Pease, "High-performance heat sinking for VLSI," *IEEE Electron Device Letters*, vol. 2, no. 5, pp. 126–129, 1981.
- [4] S. G. Kandlikar, "High flux heat removal with microchannels—A roadmap of challenges and opportunities," *Heat Transfer Engineering*, vol. 26, no. 8, pp. 5–14, 2005.
- [5] G. Hetsroni, A. Mosyak, Z. Segal, and G. Ziskind, "A uniform temperature heat sink for cooling of electronic devices," *International Journal of Heat and Mass Transfer*, vol. 45, no. 16, pp. 3275–3286, 2002.
- [6] M. Bahiraei and M. Hangi, "Recent advances in microchannel heat sink technologies for electronic cooling: A review," *Renewable and Sustainable Energy Reviews*, vol. 145, Art. 111102, 2021.
- [7] S. V. Patankar, *Numerical Heat Transfer and Fluid Flow*. New York, NY, USA: Hemisphere Publishing, 1980.
- [8] H. K. Versteeg and W. Malalasekera, *An Introduction to Computational Fluid Dynamics: The Finite Volume Method*, 2nd ed. Pearson Education, 2007.
- [9] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.
- [10] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85–117, 2015.
- [11] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," *Journal of Computational Physics*, vol. 378, pp. 686–707, 2019.
- [12] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, "Physics-informed machine learning," *Nature Reviews Physics*, vol. 3, no. 6, pp. 422–440, 2021.
- [13] J. Biamonte *et al.*, "Quantum machine learning," *Nature*, vol. 549, pp. 195–202, 2017.
- [14] M. Schuld and F. Petruccione, *Supervised Learning with Quantum Computers*. Springer, 2018.
- [15] Z. Zhao, Y. Wang, W. Zhang, Z. Ba, and L. Sun, "Physics-informed neural networks in heat transfer-dominated multiphysics systems: A comprehensive review," *Engineering Applications of Artificial Intelligence*, vol. 157, Art. 111098, 2025.
- [16] J. Lee and I. Mudawar, "Assessment of computational methods for microchannel heat sink analysis," *International Journal of Heat and Mass Transfer*, vol. 55, no. 4, pp. 958–969, 2012.
- [17] S. Nekahi *et al.*, "Optimizing finned-microchannel heat sink design for enhanced overall performance by three different approaches: Numerical simulation, artificial neural network, and multi-objective optimization," *Applied Thermal Engineering*, vol. 245, Art. 122835, 2024.
- [18] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.
- [19] Z. Zhao, Y. Wang, W. Zhang, Z. Ba, and L. Sun, "Physics-informed neural networks in heat transfer-dominated multiphysics systems: A comprehensive review," *Engineering Applications of Artificial Intelligence*, vol. 157, Art. 111098, 2025.
- [20] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," *Journal of Computational Physics*, vol. 378, pp. 686–707, 2019.
- [21] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, "Physics-informed machine learning," *Nature Reviews Physics*, vol. 3, no. 6, pp. 422–440, 2021.
- [22] J. Zheng, F. Li, and H. Huang, "T-phPINN: Physics-informed neural networks for solving 2D non-Fourier heat conduction equations," *International Journal of Heat and Mass Transfer*, vol. 235, Art. 126216, 2024.
- [23] R. Majumdar, V. Jadhav, A. Deodhar, S. Karande, L. Vig, and V. Runkana, "HxPINN: A Hypernetwork-based Physics-Informed Neural Network for Real-Time Monitoring of an Industrial Heat Exchanger," *Numerical Heat Transfer, Part B: Fundamentals*, vol. 86, 2024.

- [24] X. Zhang, C. Tu, and Y. Yan, “Physics-informed neural network simulation of conjugate heat transfer in manifold microchannel heat sinks for high-power IGBT cooling,” *International Communications in Heat and Mass Transfer*, vol. 159, Art. 108036, 2024.
- [25] K. Beer *et al.*, “Training deep quantum neural networks,” *Nature Communications*, vol. 11, Art. 808, 2020.
- [26] A. Abbas *et al.*, “The power of quantum neural networks,” *Nature Computational Science*, vol. 1, pp. 403–409, 2021.
- [27] X. Zhang, C. Tu, and Y. Yan, “Physics-informed neural network simulation of conjugate heat transfer in manifold microchannel heat sinks for high-power IGBT cooling,” *International Communications in Heat and Mass Transfer*, vol. 159, Art. 108036, 2024.
- [28] G. Hu, N. Prasianakis, S. V. Churakov, and W. Pfingsten, “Performance analysis of data-driven and physics-informed machine learning methods for thermal-hydraulic processes in Full-scale Emplacement experiment,” *Applied Thermal Engineering*, vol. 245, Art. 122836, 2024.
- [29] C. Trahan, M. Loveland, and S. Dent, “Quantum Physics-Informed Neural Networks,” *Entropy*, vol. 26, no. 8, Art. 649, 2024.