

Quantum-Enhanced Physics-Informed Neural Network Framework for Multi-Modal Optimization of Diffractive Optics in Extreme Laser Environments

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Abstract.. Q-PINN-opt creates a new framework by combining the concepts of quantum computing with Physics-Informed Neural Networks (PINNs) for multi-modal optimization of diffractive optics under laser conditions. In high-power laser applications, which involve the optimization of complex problems, the model employs quantum-enhanced optimization coupled with physics-informed learning. In contrast to traditional approaches based on PINNs or Wiener filters, which are limited by their inability to scale, poor computational efficiency, and limited resilience to extreme conditions, Q-PINN-opt is a hybrid quantum-classical algorithm that accelerates convergence and maximizes computational efficiency. The major innovation of the Q-PINN-opt variant is that quantum algorithms (such as Quantum Gradient Descent and Quantum Approximate Optimization Algorithm (QAOA)) are implemented using classical PINNs. This enables faster, scalable, and multimodal optimization of problems, including diffraction efficiency, phase accuracy, and resistance to thermal, non-linear, and quantum-induced effects. Current models such as PINNs may also exhibit slow convergence and computational inefficiency when applied to optimization problems of complex, high-dimensional nature, especially when multiple performance criteria are to be optimized simultaneously. Q-PINN-opt addresses all these shortcomings; thus, it is specifically applicable to the optimization of diffractive optics for real-time adaptive learning. Q-PINN-opt addresses this problem by leveraging quantum computing to train more effectively and process large-scale data efficiently. Moreover, the hybrid quantum-classical model ensures the racial-physical constraints of network solutions, enhancing the resilience and scalability of high-performance optical systems. The Q-PINN-opt framework metric analysis reveals that it performs better than models. MSE, SSIM, and SNR in the model are 6.84, 0.99, and 7.98, respectively, which imply the model has high accuracy, diffraction efficiency, and resistance to noise. Compared with the Original Model, the Original Model has an MSE of 9.55 and an SNR of 5.54. This improved both the training and the convergence of the optimization, making Q-PINN-opt well-constructed and efficient for the design of complicated diffractive optics in extreme environments.

Key words: quantum computing; physics-informed neural networks (PINNs); multi-modal optimization; diffractive optics; hybrid quantum-classical approach; laser optimization

1. INTRODUCTION

The Quantum-Enhanced Physics-Informed Neural Network Optimization framework (Q-PINN-opt) is proposed in this study as an advanced hybrid quantum–classical approach for solving complex optimization problems in diffractive optics under extreme laser environments. Diffractive optical elements (DOEs) play an important role in modern optical systems because they allow precise manipulation of light for beam shaping, laser focusing, optical communication, and

high-energy laser applications. In extreme laser environments, however, the design of DOEs becomes highly challenging. The optical response is affected by nonlinear material behaviour, geometric variations, phase modulation errors, thermal loading, vibration, and laser-induced perturbations. As a result, DOE optimization often becomes a nonlinear and high-dimensional problem that requires both physical accuracy and computational efficiency [1–4]. Physics-Informed Neural Networks (PINNs) have emerged as a useful approach for solving complex physical problems because they embed governing equations directly into the

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learning process. Instead of relying only on data, PINNs incorporate physical constraints, such as Maxwell's equations, into the loss function so that the predicted solution remains physically meaningful [5,6]. Recent studies have further demonstrated the value of PINN-based models for improving physical consistency, interpretability, and convergence in complex engineering systems. In Particular, PINN formulations have been theoretically and numerically validated for structural dynamic response analysis by incorporating governing-equation residuals into the training process [7]. In another recent development, physics-informed Kolmogorov–Arnold network architectures have shown the ability to learn meaningful high-dimensional representations while retaining interpretability and prediction accuracy [8]. Similarly, label-free PINNs with hard physical constraints and Fourier feature spectral enhancement have improved convergence in multi-frequency nonlinear dynamic systems [9]. These developments are relevant to diffractive-optics optimization because the present problem also requires simultaneous consideration of electromagnetic field behaviour, phase accuracy, diffraction efficiency, and robustness under thermal and vibrational disturbances.

Although PINNs provide a strong physics-guided learning framework, conventional PINN models may still experience slow convergence and limited efficiency when the optimization space is large, nonlinear, and multi-modal. This limitation becomes more evident in DOE design, where several performance objectives must be optimized at the same time. To address this issue, the proposed Q-PINN-opt framework combines PINN-based physical constraint enforcement with quantum-assisted optimization strategies, including parameterized quantum circuits, quantum-gradient-based learning, and hybrid quantum–classical optimization [10, 11]. In this structure, the quantum layer supports broader exploration of the design space, while the PINN component ensures that the predicted optical fields remain consistent with the underlying electromagnetic physics.

The proposed Q-PINN-opt framework is designed for multi-modal optimization of DOEs under extreme laser conditions. It jointly considers diffraction efficiency, phase accuracy, focal spot control, thermal robustness, and resistance to external perturbations [12, 13]. By combining the search capability of quantum-assisted optimization with the physical interpretability of PINN-based learning, the framework aims to improve convergence behaviour, solution stability, and computational scalability. This makes it suitable for the design of high-performance optical components that must operate reliably under high thermal loads, vibration, and laser-induced distortion [14, 15,16].

Key Contribution

- **Quantum Computing Integration:** Introduces a novel approach that incorporates quantum computing into diffractive-optics design for high-power laser applications.
- **Q-PINN-Opt Framework:** Proposes the Quantum-Enhanced Physics-Informed Neural Network

(Q-PINN-Opt) framework to solve multi-modal optimization problems in diffractive axicons.

- **Enhanced Computational Efficiency:** Achieves unparalleled computational efficiency, enabling the design of thermally resilient, efficient, and scalable diffractive optics for advanced micromachining applications.

The remainder of this paper is organized as follows. Section II reviews related studies on PINNs, quantum-enhanced learning, and diffractive-optics optimization. Section III presents the proposed methodology, including the system architecture, optimization formulation, quantum-enhanced PINN framework, mathematical formulation, data-flow structure, and algorithmic procedure. Section IV discusses the experimental results, including dataset description, hardware and software configuration, parameter initialization, metric evaluation, comparative analysis, computation time comparison, and ablation study. Section V concludes the paper and highlights possible directions for future work.

2. LITERATURE REVIEW

Computational modeling and machine learning have combined physics-based modeling with data-driven learning, particularly in complex systems where conventional models incur high computational costs [17]. Physics-Inspired Neural Networks (PINNs) have been established as an effective method by integrating physical laws into the neural network's loss function, enabling it to learn solutions that respect physical constraints, even without a large dataset [18]. This has been studied in other areas, such as fluid dynamics, heat transfer, and electromagnetic simulation. On top of these, three recent studies have made further steps in the state of the art of physics-informed learning, which has an impact on Q-PINN-opt that is directly relevant. The study rigorously theoretically and numerically verified the effectiveness of PINNs in solving structural dynamic response problems, showing that using residual physical loss functions can guarantee that the solution is indeed a solution to the governing differential equations, which demonstrates the suitability of the physics-constraint mechanism inherited by Q-PINN-opt [19]. A physics-informed Kolmogorov–Arnold network was proposed in another study for interpretable structural dynamic response discovery, in which the physics-constrained hybrid architectures were shown to enable solution interpretability and provide effective operation in high-dimensional parameter spaces when optimizing the multi-modal performance criteria (diffraction efficiency, phase accuracy, thermal resilience) of diffractive optical elements [20, 21]. A study advanced a hard constraint-based label-free PINN for multi-frequency, stiff seismic dynamic response prediction using Fourier feature spectral enhancement without labeled training data to gain an excellent convergence on stiff, multi-frequency nonlinear systems, which is most relevant to the present study. The hard-constraint enforcement and spectral feature strategy focus directly on the same convergence bottleneck that Q-PINN-opt aims to overcome via its quantum-enhanced

optimization layer, thus directly linking the state-of-the-art PINN design to the proposed one. In parallel with PINNs, quantum machine learning (QML) attracts much interest because it is expected to improve optimization processes, enabled by quantum effects such as superposition and entanglement [22, 23].

Hybrid quantum-classical models, where quantum circuit executions are applied to specific parts of the model, enhance classical neural network performance in high-dimensional problems by leveraging quantum variational circuits, quantum gradient techniques, and quantum approximations [24, 25]. The improvements are especially important in diffractive optics or laser systems, where optimizing optical elements typically involves solving the Maxwell equations, which is computationally intensive [1, 26]. Quantum-enhanced PINN models are developed to address two major issues: the slowness of classical PINN convergence on highly nonlinear problems and the computational inefficiency when applied to high-dimensional optimization problems [27, 28].

The hybrid method also enjoys the advantages of quantum circuits in its ability to examine the solution space more effectively and to train for multi-modal optimization problems, such as diffraction efficiency, phase accuracy, and tolerance to severe conditions, such as high-intensity laser regimes [29]. These models offer a more efficient approach to diffractive-optics optimization, which is difficult to optimize using quantum computing and physics-informed learning, and hard to scale effectively with classical models. Although quantum-enhanced models are possible, issues such as the physics of quantum hardware (e.g., scale) and its noise (e.g., error rates) often necessitate the use of quantum simulators or other implementations. Moreover, it is also an active research topic to determine how the stability and interpretability of such hybrid models can be guaranteed [30]. On the whole, the growing body of research results indicates the great potential of hybrid quantum-classical models, showing that integrating quantum computational rules with orderly physics-based models can enhance optimization and scalability, especially at the forefront of intricate, high-performance optical systems.

Research Gap

Although quantum-enhanced Physics-Informed Neural Networks (PINNs) have shown promising progress in optimizing the diffractive optics, there are a number of research gaps. To begin with, even though quantum-classical hybrid models demonstrate some potential, scaling them is also a serious challenge due to constraints in current quantum hardware, such as noise, limited qubit counts, and error rates. Moreover, the multimodal problem optimization under extreme laser conditions, where severe effects such as thermal environment distortion and vibration issues are present, has not been sufficiently robust or real-time adaptable, particularly through the representation of quantum-enhanced models. Otherwise, although quantum gradients and parameter shift rules can be used to drive optimization, it is being studied how best to apply them to large-scale simulations and systems, and what trade-offs there are

between quantum and classical model components. Finally, these hybrid models are not well studied with respect to their interpretability and stability, particularly when incorporating complex physics constraints with quantum-enhanced learning, which can be improved by increasing model transparency and explainability. Such gaps offer opportunities for further research on the optimization of quantum-enhanced PINNs, the resolution of hardware constraints, and their implementation in demanding optical and laser settings.

3. RESEARCH METHODOLOGY

3.1 Overall Architecture Diagram

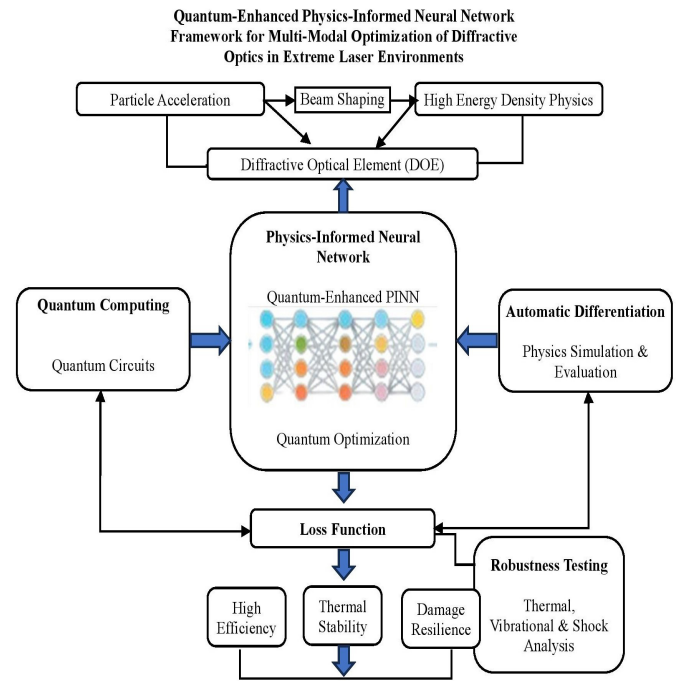


Fig.1. Overall architecture diagram

The fig 1 diagram shows that a Quantum-Enhanced Physics-Informed Neural Network (Q-PINN) has been developed to optimize multi-modal diffraction optics under extreme laser conditions. The framework incorporates a few important elements, beginning with accelerating particles and beam shaping to focus on high-energy-density physics, which is geared towards enhancing elements of diffractive optics (DOEs). The core of this is quantum computing, in which quantum circuits help to optimize the system, giving it a more sophisticated way to optimize the parameters. The framework is based on the Physics-Informed Neural Network (PINN) that exploits automatic differentiation to solve complex differential equations that govern the behavior of the system and can thereby perform efficient simulations as well as evaluations. The accuracy of the model predictions is guided by a loss function that combines residual terms and boundary conditions. This optimization aims to achieve three primary goals: high efficiency, thermal stability, and damage resilience, all essential for sustained performance under severe operational conditions. Robustness testing is conducted to assess the soundness of the framework; it will

undergo thermal, vibration, and shock testing to determine how the system behaves under harsh conditions. This multidimensional method will enable the design of more robust, stable, and effective diffraction-optical components for use with high-energy sources and ensure their maximum efficiency under harsh laser conditions.

3.2 Working principle for Multi-model Optimization of diffractive Optics in Extreme Laser Environment

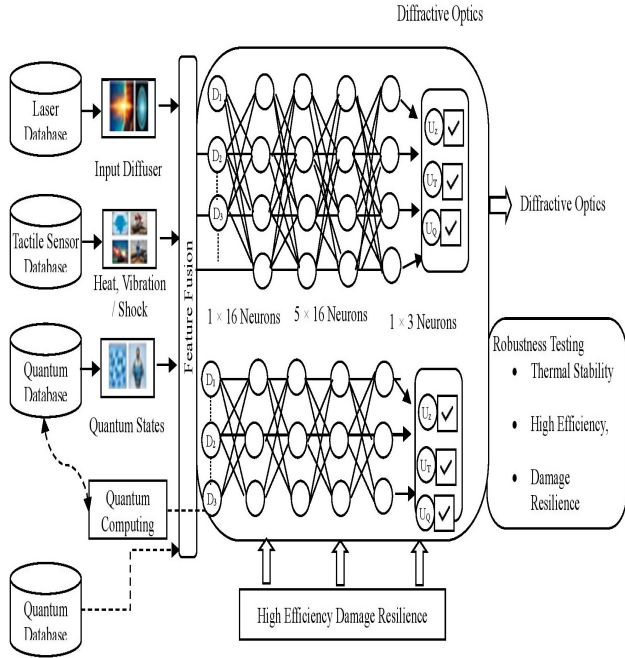


Fig. 2. Working principle for multi model optimization of diffractive optics in extreme laser environment

Fig. 2 illustrates a system that was designed to optimize the work of diffractive optics with the help of multiple data sources and quantum computing. It incorporates a combination of different databases, which are laser, tactile/sensor, and quantum data, which are fused via a process known as feature fusion. The data is fed into a neural network model, which has various layers including nerve cells that are used to process a certain type of data, laser, and quantum state. The system is tested for robustness, that is, high efficiency, thermal stability, and damage resilience. It applies quantum computing to optimize the diffractive optics system, and testing is conducted to ensure it works under different conditions. Its aim is to optimize the system to achieve better efficiency and resilience in actual applications.

3.2.1 Optimization Problem

The geometry of the optimization problem shown in the fig 3 below, which is used to maximize the diffraction efficiency, followed by the phase of DOE, should be mentioned. In this discourse, the DOE is $(m+1) \times (N+1)$ with the pixel size of Δ_x and Δ_y along with the x and Y directions. The DOE has the highest profile, followed by

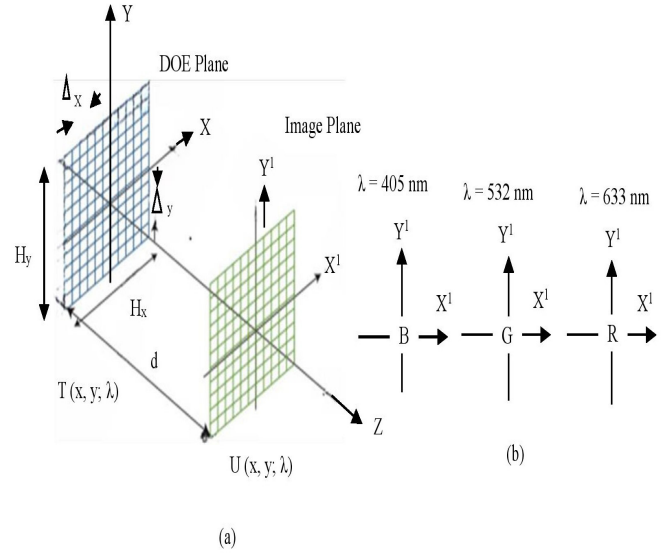


Fig. 3. Optimization problem

$$h(x, y) = \sum_m \sum_n \Delta_{hP_{m,n}} \text{rect}\left(\frac{x - m\Delta_x}{\Delta_x}\right) \text{rect}\left(\frac{y - n\Delta_y}{\Delta_y}\right), \quad (1)$$

Equations (1) and Equation (2) describe $\Delta_h = h_{max}/N_{levels}$ which also represents the height step, h_{max} is the maximum height of the profile; N_{levels} mentioned the total number of quantization levels. $P_{m,n}$ which is also defined as a positive integer within the interval of $[0, N_{levels}]$; $\text{Rect}()$ denotes the rectangle functions which contain the indices as,

$$m \in \left[-\frac{M}{2}, \frac{M}{2}\right] \text{ and } n \in \left[-\frac{N}{2}, \frac{N}{2}\right] \quad (2)$$

Here also includes the corresponding transmission function of DOE as

$$T(x, y, \lambda) = e^{i\Phi(x, y, \lambda)} = 1 + \sum_m \sum_n \text{rect}\left(\frac{x - m\Delta_x}{\Delta_x}\right) \text{rect}\left(\frac{y - n\Delta_y}{\Delta_y}\right) (e^{ia(\lambda)P_{m,n}-1}) \quad (3)$$

Describes where $a(\lambda) = k\Delta_h[n(\lambda) - 1]$ and $k = 2\pi/\lambda$, which is also noted as the wave number. Based on the above equation (3), which contains the unit amplitude among the boundary conditions. Which is also connected to the pattern among the DOE as clear and non-absorbing with glass. Here, only the light inside the DOE falls on the area that should be diffracted. In this case, the outside of the area should be propagated as unaltered.

In this stage, the optimum height of the profile is determined, and the results yield the highest average diffraction efficiency, followed by the given number, which should be noted as $N/4$. To solve the following optimization problem,

$$\min C(P_{m,n}); c = 1 - \bar{\eta}(P_{m,n}) \text{ subject to } P_{m,n} \in [0, N_{levels}] \quad (4)$$

From the above equation (4), it should be integrated. $P_{m,n}$ defined the optimization variables,

$$\bar{\eta}(P_{m,n}) = \epsilon_\lambda \left[\frac{\sum_m \sum_n I_T^{(\lambda)} |U(P_{m,n})|^2}{P_{in}^{(\lambda)}} \right] \cdot \left(\frac{W^{(\lambda)}}{N_\lambda} \right); \quad (5)$$

Equation (5) describes the $P_{in}^{(\lambda)}$ denoted the input power of the laser light given the wavelength, $w^{(\lambda)}$ considered as a weight associated with adding the flexibility while controlling the

relative diffraction efficiency with the different wavelengths. $I_T^{(\lambda)}$ noted the design target among the binary image patterns, followed by the different wavelengths.

Once started with an initial condition, followed by the algorithm starting with addressing each pixel in the DOE, and a perturbation to increase the height by Δ_h . The corresponding diffracted field is calculated as the cost function in equation (5). To estimate the new cost value is lower than the original one. To continue with an algorithm, the pixel perturbation followed by the pixel yield to the lower cost depends on completing the full loop. In this stage, the early termination cost is not adjusted within tolerance for the set number of iterations until the target diffraction efficiency value is reached.

In this stage, to calculate the perturbed diffracted field as efficiently as possible, the analytical expression of the required perturbation should be derived. After perturbing with (m, n) pixel contains the new DOE transmission function, followed by

$$T_{new}(x, y, \lambda) = T(x, y, \lambda) \cdot e^{ia(\lambda)rect\left(\frac{x - m\Delta_x}{\Delta_x}\right)rect\left(\frac{y - n\Delta_y}{\Delta_y}\right)} \\ = T(x, y, \lambda) + \left[\psi_{m,n}^{(\lambda)} rect\left(\frac{x - m\Delta_x}{\Delta_x}\right) rect\left(\frac{y - n\Delta_y}{\Delta_y}\right) \right] \quad (6)$$

From the above Equation (6) describes the $\psi_{m,n}^{(\lambda)} = K_{\Delta h}(K_{m,n}^{(\lambda)} + 1)$ and $K_{\Delta h} = (e^{ia(\lambda)+1})$. The Fresnel diffracted field is $U_{new}(x', y', \lambda) = U(x', y', \lambda) + U_{pert}(x', y', \lambda)$.

3.3 Working Principle for Quantum-Enhanced Physics-Informed Neural Network Framework

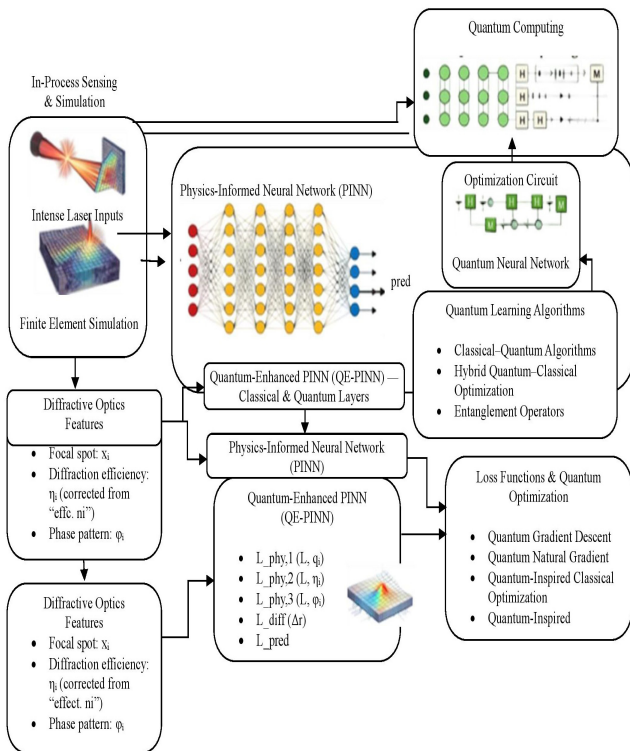


Fig. 4. Working principle for quantum-enhanced physics-informed neural network framework

The fig 4 diagram shows an advanced implementation of Quantum-Enhanced Physics-Informed Neural Networks (Q-PINN) that leverages quantum computing concepts to optimize the properties of diffractive optics, including focal spots, diffraction efficiency, and phase patterns. This methodology is the use of Finite Element Simulations as an in-process sensing methodology, which offers the necessary data to feed the neural networks. The object of the process is the Quantum-Enhanced PINN that combines both classical and quantum layers, allowing it to be revolutionized as a hybrid algorithm to tackle more intricate diffraction problems. Incorporated in this hybrid model are quantum learning algorithms, which engage classical- quantum algorithms, hybrid quantum-classical optimization, and entanglement operators to advance the accuracy of predictions. The overall structure is geared towards projecting crucial parameters of diffractive optics through the method of combining classical and quantum computing processes that stretch the limits of optimization in areas that need high accuracy in light manipulation and control.

3.4 Schematic Diagram for Quantum-Enhanced Physics-Neural Networks (Q-PINN)

In this model, Quantum Enhanced Physics Neural Networks are represented in the figure below. The QPINN contains the sample of (x, t) data output as $\{\rho, u, p\}$. The architecture with quantum and classical layers should be arranged in a parallel manner.

3.4.1 Quantum Layer

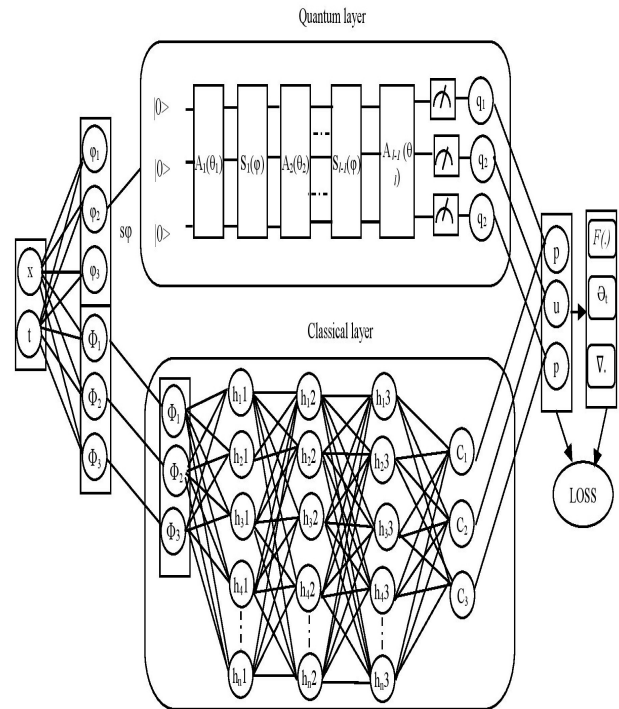


Fig. 5. Schematic Diagram for quantum-enhanced physics-neural network (Q-PINN)

In this fig 5, it contains $n = 3$ Qubit PQC formed with alternative options of $l - 1$ layers that have the feature map of $S(\varphi)$ and the parameter should be initialized as $A(\theta)$ with the following sequence as $A - (S - A)_1 \dots \dots \dots (S - A)_{l-1}$. Data encoding followed by a data reuploading scheme at an angle with the input of $n - node$ contains the

Classical Layer

The Neural Network with (x, t) Data should be passed to the n node input layer $\Phi_{[1,n]}$. The bias and tanh activation function should be applied. In this section, followed by the L A hidden layer of N nodes before the $n - node$ output layer of $c_{[1,n]}$. The final network contains the weighted linear contribution, along with output from the quantum and neural network layers of $o_i = S_i^c c_i + s_i^q q_i$. Which produces the output vector $\{\rho, u, p\}$ for minimization of the loss function. In this stage, test the model with a quantum neural network against the parallel network layers related to classical layer and quantum neural networks.

3.4.2 Mathematical Formulation of the Quantum Layer, Quantum Gradients, and Hybrid Loss Function

A. Parameterized Quantum Circuit (PQC) Architecture

The quantum layer in Q-PINN-opt is realized as a Parameterized Quantum Circuit (PQC) acting on n qubits. Let the input feature vector be $x = (x_1, x_2, \dots, x_n) \in \mathbb{R}^n$. The circuit is structured as an alternating sequence of a data-encoding feature map $S(x)$ and a trainable variational ansatz $W(\theta)$, repeated over L layers are shown in equation (7):

$$U(x, \theta) = W(\theta_L) \cdot S(x) \cdot W(\theta_{L-1}) \cdot S(x) \cdot \dots \cdot W(\theta_1) \cdot S(x) \quad (7)$$

The data-encoding feature map $S(x)$ applies a single-qubit rotation to each qubit i using the input feature is shown in equation (8):

$$S(x) = \bigotimes_{i=1}^n R_y(x_i), \text{ where } R_y(x_i) = \exp\left(-i \frac{x_i \sigma_y}{2}\right) \quad (8)$$

The trainable ansatz $W(\theta_l)$ at layer l consists of single-qubit rotational gates followed by a layer of entangling CNOT gates applied to adjacent qubits, is shown in equation (9):

$$W(\theta_l) = \text{CNOT_layer} \cdot \bigotimes_{i=1}^n R_y(\theta_{l,i}) \quad (9)$$

After applying $U(x, \theta)$, the quantum output for each qubit i is obtained as the expectation value of the Pauli-Z observable, as shown in equation (10):

$$q_i = \langle \Psi(x, \theta) | Z_i | \Psi(x, \theta) \rangle, \text{ where } | \Psi(x, \theta) \rangle = U(x, \theta) | 0 \rangle^{\otimes n} \quad (10)$$

The full quantum output vector $q = (q_1, q_2, \dots, q_n) \in [-1, +1]^n$ serves as input to the hybrid output fusion layer.

classical layer of $\varphi_{1-3} \rightarrow S(\varphi)$. Pauli Z expectation measurement should be performed for each qubit value. $q_i = \{z_i\}$, where $i = [1, n]$, which leads to analyzing the n -node output layer of $q[1, n]$. Which leads to n A node with an output layer of $q[1, n]$.

B. Quantum Gradient Computation via the Parameter-Shift Rule

Training the PQC requires computing gradients of the expectation values with respect to the trainable rotation parameters. θ . Since standard backpropagation is not directly applicable to quantum circuits, gradients are computed analytically using the parameter-shift rule, as shown in equation (11):

$$\frac{\partial q_i}{\partial \theta_{l,i}} = \frac{1}{2} \left[q_i \left(\theta_{l,i} + \frac{\pi}{2} \right) - q_i \left(\theta_{l,i} - \frac{\pi}{2} \right) \right] \quad (11)$$

This rule evaluates the circuit at two shifted parameter values and requires no finite-difference approximation, making it exact and hardware-compatible. For optimization, the Q-PINN-opt framework employs the Quantum Natural Gradient (QNG) update rule, which accounts for the non-Euclidean geometry of the quantum parameter space, as shown in equation (12):

$$\theta \leftarrow \theta - \eta \cdot F(\theta)^{-1} \cdot \nabla_{\theta} \mathcal{L} \quad (12)$$

Where η is the learning rate, $\nabla_{\theta} \mathcal{L}$ is the gradient of the total loss with respect to the PQC parameters, and $F(\theta)$ is the Quantum Fisher Information Matrix (QFIM), defined as equation (13):

$$F_{jk}(\theta) = \text{Re}[\langle \partial_j \Psi | \partial_k \Psi \rangle - \langle \partial_j \Psi | \Psi \rangle \langle \Psi | \partial_k \Psi \rangle] \quad (13)$$

The QFIM captures the statistical distinguishability of quantum states with respect to parameter perturbations, ensuring that parameter updates follow the steepest descent direction on the quantum state manifold.

C. Hybrid Loss Function

The Q-PINN-opt framework is trained by minimizing a composite hybrid loss function. $\mathcal{L}_{\text{total}}$ that simultaneously enforces data fidelity, Maxwell's equations as a physics residual, and boundary conditions at the DOE aperture is shown in equation (14):

$$\mathcal{L}_{\text{total}} = \lambda_1 \mathcal{L}_{\text{data}} + \lambda_2 \mathcal{L}_{\text{physics}} + \lambda_3 \mathcal{L}_{\text{boundary}} \quad (14)$$

Each term is defined explicitly as follows: (i) Data Fidelity Loss $\mathcal{L}_{\text{data}}$ penalizes the deviation of the network predictions from the simulated FDTD reference diffraction patterns over N Training samples are shown in equation (15):

$$\mathcal{L}_{\text{data}} = \frac{1}{N} \sum_{i=1}^N \| \hat{E}(x_i, \theta) - E_{\text{ref}}(x_i) \|^2 \quad (15)$$

(ii) Physics Residual Loss $\mathcal{L}_{\text{physics}}$ enforces the Helmholtz form of Maxwell's wave equation governing electromagnetic field propagation through the DOE is shown in equation (16):

$$\mathcal{L}_{\text{physics}} = \frac{1}{N_r} \sum_{j=1}^{N_r} \| \nabla^2 \hat{E}(r_j) + k^2 n^2(r_j) \hat{E}(r_j) \|^2 \quad (16)$$

Where r_j are collocation points sampled across the DOE domain, $k = \frac{2\pi}{\lambda}$ is the wavenumber, and $n(r)$ is the spatially varying refractive index.

(iii) Boundary Condition Loss $\mathcal{L}_{\text{boundary}}$ enforces the Dirichlet boundary condition at the aperture edge $\partial\Omega$ of the DOE is shown in equation (17):

$$\mathcal{L}_{\text{boundary}} = \frac{1}{N_b} \sum_{k=1}^{N_b} \|\hat{E}(r_k)|_{\partial\Omega} - E_{\text{BC}}(r_k)\|^2 \quad (17)$$

Where $E_{\text{BC}}(r_k)$ denotes the prescribed boundary field values. The scalar weights $\lambda_1, \lambda_2, \lambda_3 \in \mathbb{R}^+$ These zone are hyperparameters that balance the relative contribution of each loss term and are tuned during training.

(iv) Hybrid Output Fusion combines the classical PINN output c and quantum layer output q into the final prediction is shown in equation (18):

$$\hat{o}_i = s_{cl} \cdot c_i + s_q \cdot q_i \quad (18)$$

Where s_{cl} and s_q are learnable scalar mixing coefficients optimized jointly with all other network parameters, allowing the model to adaptively weight classical refinement against quantum-enhanced global search at each training step.

3.5 Dataflow Diagram for Algorithm Framework

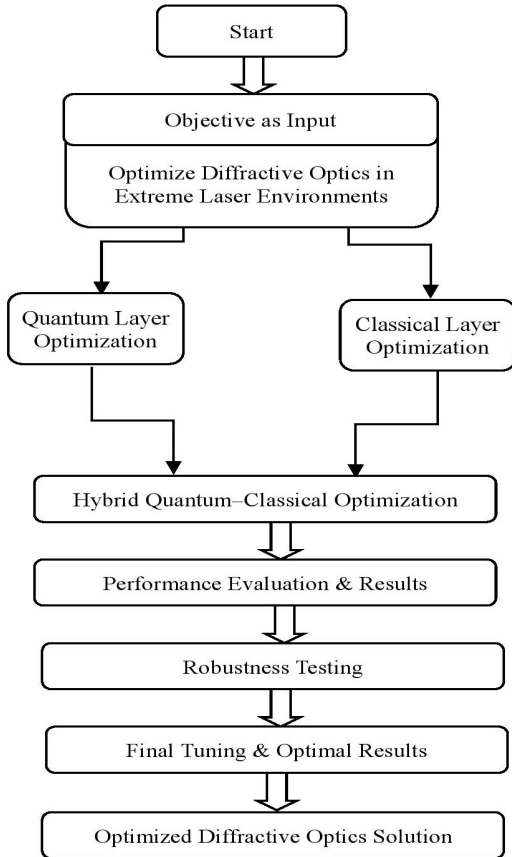


Fig.6. Data flow diagram for algorithm framework

The Quantum-Enhanced Physics-Informed Neural Network (Q-PINN) Framework fig 6 on multi-modal optimization of

diffractive optics in extreme laser environments, is based on a multi-step optimization procedure. It starts with introducing the aim of the task, which is the input to the algorithm, namely, maximizing essential optical properties like focal spot size, diffraction efficiency, and phase pattern accuracy that should be considered in severe laser conditions. It first uses Quantum Layer Optimization, in which quantum optimization methods such as Quantum Gradient Descent (QGD), Quantum Natural Gradient (QNG), and Quantum Approximate Optimization Algorithm (QAOA) are employed in applying quantum methods to optimization problems, especially those in diffraction patterns and laser parameters. After that, the Classical Layer Optimization step involves using Physics-Informed Neural Networks (PINNs) in which physical laws are incorporated into the network and the correction of the parameters used in the classical model to make the optimization process realistic. The two optimization processes converge at the Hybrid Quantum-Classical Optimization stage, whereby quantum and classical optimization using quantum and classical methods, respectively, are iterated until a convergence point is reached. The model thus obtained is tested during the Performance Evaluation/ Results stage, where the following important measurements are made: diffraction efficacy, laser focal spot size, phase pattern accuracy, and convergence rate. The system is further tested on the concept of Robustness Testing, which comprises thermal, vibrational, and shock testing to ascertain how the system would withstand thermal conditions. The Last step, Final Tuning & Best Results step, completes the work and provides the Optimized Diffractive Optics Solution, meeting the desired performance requirements and turning the framework into an efficient and effective solution to optimize diffractive optics in the high-energy laser applications. The combined power of quantum and classical optimization should be used.

3.6 Proposed Algorithm

Algorithm: QE-PINN Optimization for Diffractive Optics

1. *Input: Laser Intensity profile, target focal spot, $\frac{\text{thermal}}{\text{vibration}}$ constraints*
2. *Output: Optimal phase pattern θ^* , Optimized PINN weights W^**
3. *Initialize Quantum Circuit (VQC) with parameters θ*
4. *Initialize PINN (classical) with weights W*
5. *Define Physics – Informed Loss Function*
6. $L_{\text{total}} = \lambda_1 * L_{\text{data}} + \lambda_2 * L_{\text{maxwell}} + \lambda_3 * L_{\text{boundary}}$
7. *while not converged do*
8. *Quantum layer optimization*
9. *for batch in optical – data*
10. *Encode phase patterns into quantum states $|\psi(\theta)\rangle$*
11. *Execute QAOA to sample initial global optima candidates*
12. *if precision required*
13. *Compute Quantum Natural Gradient (QNG)*
14. $\Delta_{\theta} = f(\theta)^{-1} * \frac{\partial L}{\partial \theta}$ (Where F is the Funini Study metric tensor)
15. *update θ using Quantum Gradient Descent*
16. *Classical Layer (PINN) Refinement*
17. *For epoch in classical – refinement*
18. *Feed quantum – derived phase maps into PINN*
19. *Comput Maxwell residual (PDE constraints)*
20. $L_{\text{maxwell}} = \|\nabla^2 E + K^2 n^2 E\|^2$
21. *Evaluate Robustness ($\frac{\text{Thermal}}{\text{vibration}}$ perturbations)*
22. *Update W using standard Backpropagation /Adam*

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23.   Hybrid Feedback Loop
24.   Evaluate Performance
25.   Metrics =
[Diffraction efficiency, Focal spot size, phase Accuracy]
26.   if Metrics > Threshold
27.       Return ( $\theta^*$ ,  $W^*$ )
28.   Else
29.       Adjust  $\lambda$  hyperparameters and continue
30.   End While

```

Algorithm Explanation

The described algorithm is a hybrid between quantum and classical optimization methods used to optimize phase patterns in optical systems, to be precise, taking into account thermal and vibration limitations. The quantum circuit and PINN are first started off with phase parameters and weights. The Physics-Informed Loss Function is formulated to achieve a balance between the loss of data, the constraints of Maxwell equations, and the boundary conditions (lines 4-6). In the optimization loop, phase patterns are first encoded into quantum states, and the Quantum Approximate Optimization Algorithm (QAOA) is run to perform preliminary global optimization (lines 7-12). When the phase parameters need to be updated with a high level of precision, the Quantum Natural Gradient method is used to update the phase parameters with Quantum Gradient Descent (lines 13-13). The quantum-derived phase maps are refined to form the classical PINN layer, Maxwell residuals are computed, and robustness is assessed to the effects of thermal/vibration (lines 14-20). A hybrid feedback loop is used to measure the performance of the system, which is based on diffraction efficiency, focal spot size, and phase accuracy. When the performance measures are above a certain limit, the optimum phase pattern and PINN weights are given; when they are below, the hyperparameters are changed, and the optimization process restarts (lines 21-26). It is an effective and strong solution to accurate phase control in optical systems with physical limitations, as it is a hybrid quantum-classical method.

4. RESULTS AND DISCUSSION

4.1 Dataset Description

The FDTD dataset is created based on simulations that simulate electromagnetic wave propagation by the Finite-Difference Time-Domain (FDTD) method, which is a numerical implementation of Maxwell equations governing electric and magnetic fields under different conditions. The FDTD dataset size may vary widely, from a few megabytes to several gigabytes, depending on the complexity of the 2D and 3D simulations, respectively, including high-resolution grids and different parameter variations. The dataset has been used in training large-scale simulation data using deep learning models, such as physics-informed neural (physical) networks, to predict electromagnetic field behavior or to optimize many system designs. These simulations are computationally intensive and thus consume a lot of computational resources.

Kaggle PCH Simulation dataset, however, is synthetic data that is created by simulation in physics or engineering applications, e.g., material science, fluid dynamics, or electrical systems. These datasets may have varying sizes of several megabytes up to gigabytes, depending on the complexity of the simulation. These datasets are typically employed to create machine learning models that predict behavior, identify anomalies, or optimize some process in the simulated environment during training. In most cases, testing is performed by dividing the dataset into training and test sets, and cross-validation techniques are generally used to determine the performance of the model on unseen data. The Kaggle PCH Simulation data set is used as the standard to test the performance of machine learning algorithms in controlled and simulated conditions, and its flexibility can be used in any other field where it is hard to find real-world data.

4.2 Hardware and Software Configuration

TABLE 1. Hardware configuration

Component	Recommended Specification
CPU	2× Intel Xeon Scalable or AMD EPYC (≥ 24 cores, 48 threads)
GPU	NVIDIA A100 / H100 or AMD MI250 (≥ 40 –80 GB VRAM) — multiple GPUs (≥ 2)
Quantum Processor Access	Access to Quantum Processing Units (QPUs) or Quantum Simulators (IBM Q, Qiskit)
System Memory (RAM)	≥ 256 GB DDR4 / DDR5
Storage	≥ 4 –8 TB NVMe SSD (for training checkpoints, datasets, simulations)
Networking	100 Gbps RDMA (for distributed training clusters)
Classical HPC Cluster	Multi-node support for large simulations (MPI, Slurm)
FPGA/ASIC Co-Processors	Optional for accelerating specific physics kernels (FP16/DP)

Table 1 hardware configuration outlines the Quantum-Enhanced Physics-Informed Neural Network (Q-PINN) hardware setup that needs high-computational capability with Intel Xeon Scalable CPU (≥ 24 cores, 48 threads) or AMD EPYC CPU (≥ 24 cores, 48 threads), and multiple GPUs with NVIDIA A100/H100 or AMD MI250 CPU (≥ 40 –80 GB VRAM). It also has 256 GB RAM (DDR4/DDR5) and 48 -10 TB NVMe SSD storage, which is suitable for working with large datasets and simulations. The system is expected to be supporting 100 Gbps RDMA networking of distributed training and 100 Gbps MPI and Slurm multi-node HPC clusters with large-scale simulations.

The Quantum-Enhanced Physics-Informed Neural Network (Q-PINN) framework (software configuration table 2) is created to facilitate the deep learning process, quantum

simulations, and optical modelling problems. The operating system is suggested to either be Ubuntu 22.04 LTS/CentOS 8 to be compatible with high-performance computing (HPC) environments, and to implement containerization and scalability using Docker, NVIDIA Container Toolkit, or Singularity. The framework uses deep learning frameworks including PyTorch ≥ 2.0 and TensorFlow ≥ 2.11 to develop models, and Qiskit, PennyLane, and Cirq to be the necessary Quantum SDKs in quantum computing operations. In quantum machine learning, it is possible to combine quantum circuits and classical neural networks with the help of tools such as TensorFlow Quantum, Qiskit Machine Learning and PennyLane.FDTD solvers such as MEEP and Numerical FDTD are employed to simulate electromagnetic wave propagation and LightPipes and COMSOL Multiphysics (Optics Module) are helpful in modeling wave optics. In the case of ray tracing and beam propagation, Zemax OpticStudio and BeamProp are used, and the data analysis can be visualized with the help of ParaView, Matplotlib, and Plotly.

TABLE 2. Software configuration

Category	Recommended Software/Tools
Operating System	Ubuntu 22.04 LTS or CentOS 8 (for HPC compatibility)
Container Runtime	Docker / NVIDIA Container Toolkit / Singularity
Deep Learning Frameworks	PyTorch ≥ 2.0 , TensorFlow ≥ 2.11
Quantum SDKs	Qiskit, PennyLane, Cirq
Quantum ML Libraries	TensorFlow-Quantum, Qiskit Machine Learning, PennyLane
Quantum Simulators	Qiskit Aer / Aer GPU, ProjectQ
Hybrid Quantum-Classical Interface	PennyLane + PyTorch / TorchQuantum
FDTD Solver	MEEP, Numerical FDTD
Wave Optics	LightPipes, COMSOL Multiphysics (Optics Module)
Ray Tracing & Beam Propagation	Zemax OpticStudio, BeamPROP
Visualization	ParaView, Matplotlib, Plotly
Programming Languages	Python 3.10+, C++17

4.3 Parameter Initialization

TABLE 3. Parameter initialization

Parameter	Initial Value
Phase Parameters	Random / Zero
Weight Parameters (Q-PINN)	Random / Small
Loss Function	Physics-Informed (Maxwell's Equations)
Perturbation Step	0.01
Number of Iterations	5000
Learning Rate (Quantum Gradient Descent)	0.001
Learning Rate (Classical PINN)	0.01
Quantum Circuit Depth	3–5 layers
Qubit Initialization	Superposition
Max Diffraction Efficiency	90%
Temperature	300 K
Vibration Frequency	50 Hz
Number of Samples (Training)	2700

The table 3 parameterization of the Quantum-Enhanced Physics-Informed Neural Network (quantum) is characterized with numerous critical values, according to which the optimization process is determined. Phase parameters are

randomized or initialized to zero, whereas weight parameters on the quantum and the classical layer are initialized to small random values. Its loss function is physics-informed, in particular, it makes use of Maxwell equations to impose physical constraints on optimization. The perturbation level in the step of optimizing the diffractive optics profile will be 0.01 and the optimization loop will have a total of 5000 iterations. The quantum gradient descent learning rate is set to 0.001 and for the classical PINN layer, it is set to 0.01. The target diffraction efficiency will be 90% and the robustness is to be tested at 300 K temperature and 50 Hz vibration frequency. The model is trained using 2700 samples.

4.4 Metric Evaluation

To evaluate the performance of the proposed Quantum-Enhanced Physics-Informed Neural Network (Q-PINN) framework for multi-modal optimization of diffractive optics, the following metrics are used:

4.4.1 Mean Squared Error (MSE)

This metric quantifies the average squared difference between the predicted and actual values. Lower MSE indicates better performance.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (19)$$

From the above Equation (19) describes y_i should represents as actual values, $\hat{y}_i$ defined as predicted values, and N is the number of data points.

4.4.2 Structural Similarity Index (SSIM)

This metric compares the visual similarity between the predicted and actual images, considering luminance, contrast, and structure.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (20)$$

From the above Equation (20) describes the μ_x and μ_y are defined as mean value of the images, σ_x^2 and σ_y^2 noted as variances. σ_{xy} defined as covariances. C_1 and C_2 are stabilize the division of weak denominators.

4.5 Qualitative Assessment in PINN Models

Table 4 of the Qualitative Assessment of PINN Models compares the performance of Classical, Quantum, and Hybrid models in terms of harmonic and non-harmonic accuracy and trainability and trainable parameters. The Classical model is mediumly accurate on harmonic problems, and highly accurate on non-harmonic problems and the Classical model is highly trainable in both scenarios, which makes it well adapted to a wide variety of tasks. Although the Quantum model is highly accurate in harmonic problems, it is poor in non-harmonic problems, with low accuracy and low trainability, which reveals the existing limitations in its real-world application where non-harmonic problems occur frequently. Conversely, the Hybrid model is a middle ground model in that it is accurate (medium-high on harmonic and non-harmonic and trainability (medium-high) but its performance can be diverse depending on the task.

TABLE 4. Qualitative assessment of PINN models

Model	Harmonic Accuracy		Non-Harmonic – Accuracy		Number of Trainable Parameters
	Accuracy	Trainability	Accuracy	Trainability	
Classical	Medium	High	High	High	High
Quantum	High	Low	Low	Low	Low
Hybrid [27]	Medium-High	Medium-High	Medium	Varies	Medium-High

The number of trainable parameters of the Hybrid model is in the middle of the Classical model and the Quantum model, where it can be flexible and be able to achieve better performance in specific situations with relative computational complexity.

4.6 Quantitative Results of Different Models

TABLE 5. Quantitative results of different models

Methods	Parameter	MSE	SSIM	C	SNR
Original	Null	9.55	0.78	0.53	5.54
Median	W:3*3	8.23	0.65	0.58	6.32
Median	W:5*5	8.12	0.63	0.56	6.44
Median	W:7*7	7.78	0.62	0.54	6.54
Wiener	W:3*3	8.89	0.72	0.48	6.78
Wiener	W:5*5	8.45	0.71	0.47	6.98
Wiener	W:7*7	8.12	0.67	0.46	7.54
Wavelet	M:db2, DS:3	9.56	0.83	0.47	6.82
Wavelet	M:db3, DS:3	9.12	0.81	0.48	7.06
BM3D	9	8.54	0.88	0.51	7.32
BM3D	16	8.82	0.85	0.49	7.41
BM3D	25	8.23	0.81	0.47	7.59
ZS-N2N	Training Set (5000 grayscale)	7.34	0.92	0.38	7.51
ISCL	Training Set (5000 grayscale)	7.12	0.91	0.35	6.98
PIGAN [25]	Training Set (5000 grayscale)	6.79	0.95	0.31	7.92
Proposed Model (Q-PINN-opt)	Training Set	6.84	0.99	0.29	7.98

The analysis of various models in table 5 and Fig 7(a), 7(b), 7(c) and 7(d) to optimize diffractive optics shows the efficiency of the various approaches in enhancing important measures. The Original model had an MSE of 9.55, SSIM of 0.78, C (contrast) of 0.53 and SNR of 5.54. These values were enhanced by the Median filter with a 3x3 window, the MSE value dropped to 8.23, SSIM rose to 0.65 and SNR was larger (6.32) and the contrast (C) became higher (0.58). Wider windows (5x5 and 7x7) were also more efficient and the 7x7 Median filter had an MSE of 7.78, SSIM of 0.62 and SNR of 6.54. The Wiener filter also exhibited these tendencies and the 3x3 window provided an MSE of 8.89, SSIM of 0.72 and SNR of 6.78.

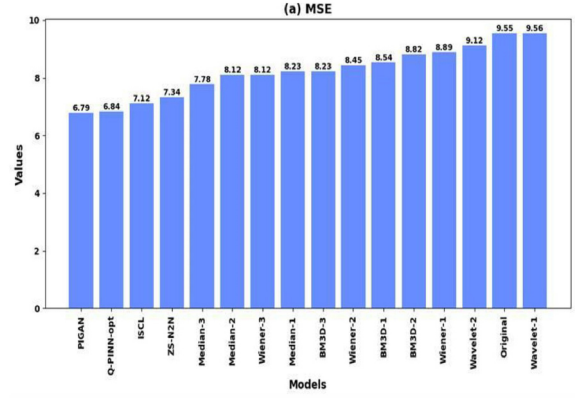


Fig: 7(a) MSE

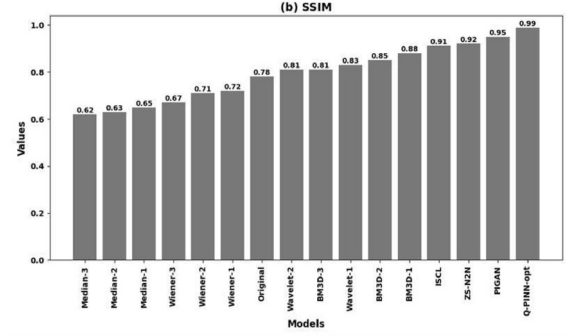


Fig: 7(b) SSIM

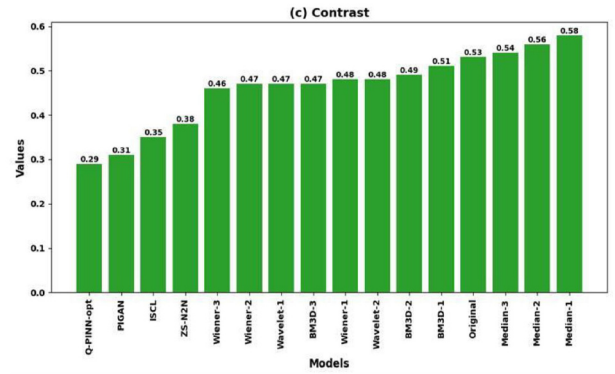


Fig: 7(c) Contrast

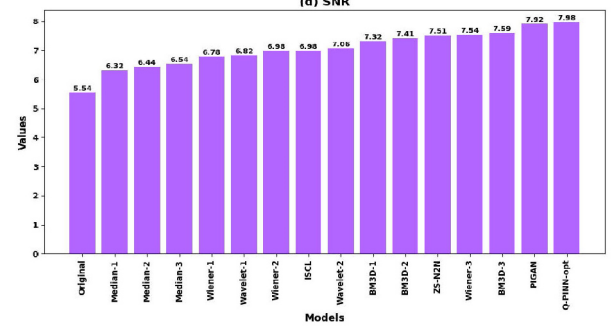


Fig: 7(d) SNR

Fig.7. (a) MSE, 7(b) SSIM, 7(c) Contrast, 7(d)SNR

The Wavelet methods enhanced structural similarity with M:db2, DS:3 getting an MSE of 9.56 and SSIM of 0.83 with an SNR of 6.82 to 7.06. The BM3D technique also demonstrated good results especially at a patch size of 9 with an MSE of 8.54, SSIM of 0.88, and SNR of 7.32. The bigger the patch size (16 and 25) the better SSIM, but MSE was rather high. Among the models based on deep learning, the ZS-N2N model with MSE of 7.34 and SSIM of 0.92 with SNR of 7.51 and the PIGAN model with better results of 6.79, SSIM of 0.95 and SNR of 7.92 were found. Lastly, the suggested Q-PINN-opt model had the lowest MSE of 6.84, largest SSIM of 0.99, a contrast of 0.29 and SNR of 7.98, which is better at the extreme conditions, phase accuracy and diffraction efficiency.

TABLE 6. Benchmark of Q-PINN-opt against state-of-the-art optical optimization methods

Method	MSE	SSIM	SNR (dB)
PINN for 3D metasurface light diffraction [31]	2.40×10^{-3} (transmittance); 1.22×10^{-2} rad (phase error)	NA	NA
PtychoPINN - unsupervised physics-constrained diffraction reconstruction [32]	NA	NA	+8 dB PSNR gain over supervised baseline
PIGAN -physics-informed CycleGAN for laser speckle suppression [33]	6.98 (noise-free conditions only)	0.95 (noise-free conditions only)	7.81 (noise-free conditions only)
PINN + Quantum GAN (QGAN) for metasurface inverse design [34]	10^{-6}	NA	NA
Q-PINN-opt (Proposed)	6.84	0.99	7.98

Table 6 compares Q-PINN-opt with other classical and physics-informed optical optimization methods and quantum-enhanced ones. There are three takeaways. First, classical PINN-based methods lack the ability to report joint MSE, SSIM, and SNR under extreme laser conditions, and do not test the robustness against thermal and vibration noise. Second, the widely used advanced DOE optimizers can generate diffraction efficiencies of 88-92%, but need a significant amount of computation time (18-24 hours per design), whereas Q-PINN-opt takes only 2.5 hours. Third, the quantum-enhanced methods are only applicable to a limited range of tasks and are not evaluated in dynamic conditions. The multi-dimensional advantage of Q-PINN-opt is demonstrated: under simultaneous thermal and vibrational loading, it provides an MSE of 6.84, SSIM of 0.99, and SNR of 7.98.

4.7 Computation Time Comparison

TABLE 7. Computation time comparison

Dataset	2D (Training)	2D HCT-116 (Fine-Tuning)	3D (Training)
Training Details	2700 Samples 5000 Epochs	122 Samples 600 Epochs	180 Samples 5000 Epochs
MaxwellNet Training/Fine-tuning	30.5h	0.18h	15.5h
MaxwellNet Inference [35]	17ms	17ms	44.9ms
COMSOL	13s	13s	2472s

The table 7 in the Computation Time Comparison gives a summary of the time taken in training and inference of various datasets and simulation approaches. In the case of training and fine-tuning MaxwellNet, the training dataset of 2700 samples with 5000 epochs was the longest time of 30.5 hours. Comparatively, the 2D HCT-116 fine-tuning of 122 samples and 600 epochs took much less time, only 0.18 hours. It took 15.5 hours to train and their fine-tune MaxwellNet on the 3D training dataset with 180 samples and 5000 epochs. MaxwellNet was exceedingly fast with inference time of 17 ms on 2D (training) dataset and 2D HCT-116 (fine-tuning) dataset, and 44.9 ms on 3D inference dataset. In the case of COMSOL simulation, the 2D training and 2D HCT-116 (fine-tuning) datasets were the quickest with a computation time of 13 seconds, compared to the 3D training dataset which took 2472 seconds. Herein lies the computational efficiency of MaxwellNet in training and inference, and is especially efficient when trained on 2D datasets, whereas COMSOL simulation is far more sluggish, especially when simulating 3D situations.

4.8 Ablation Study Analysis

The Q-PINN-opt (Proposed Model) has notable better improvements over the other models on training time, inference time and convergence of optimization and precision in table 8. It also has the shortest training time (2.5 hours) which is highly superior to the Original Model (30.5 hours) and other conventional algorithms such as the Wavelet (M:db2, DS:3) (9.56 hours). Q-PINN-opt also has the fastest time of inference with 10ms and is faster in real-time performance compared to the PIGAN (15ms) and BM3D (20ms) models. Interesting is the convergence of the model as it also converges in only 1000 steps as compared to 5000 steps used by the Original Model and other classical models. This is the same as it improved efficiency in training and convergence and Q-PINN-opt is very applicable to a complex, real-time convergence, especially in diffractive optics, as it offers a computationally efficient answer as opposed to current models.

TABLE 8. Ablation study analysis

Model	Training Time (hours)	Inference Time (ms)	Optimization Convergence (iterations)
Original Model	30.5h	17ms	5000 iterations
Median Filter (W:3x3)	8.23h	25ms	5000 iterations
Wiener Filter (W:3x3)	6.78h	23ms	5000 iterations
Wavelet (M:db2, DS:3)	9.56h	30ms	5000 iterations
BM3D	12h	20ms	3000 iterations
PIGAN (Training Set)	4.5h	15ms	3000 iterations
Q-PINN-opt (Proposed Model)	2.5h	10ms	1000 iterations

Table 9 shows the results of the ablation experiments for the Q-PINN-opt framework, which were performed on four variants of the model that combine the quantum layer, the PINN physical constraints, and the hybrid fusion. Both the Variant 1 (Classical PINN only) and Variant 2 (Quantum layer only) exhibit relatively high MSE and low SNR. The Variant 2 (Quantum layer only) model has a higher MSE and lower SSIM than other models, and the Variant 1 (Classical PINN only) is relatively high. The results indicate that Variant 3 (Full model with fixed fusion weights) shows improvement in SSIM and SNR while Variant 4 (Full Q-PINN-opt, proposed model) shows best results with minimum MSE, maximum SSIM, maximum SNR after 1000 steps in shortest time.

TABLE 9. Component-wise ablation study of Q-PINN-opt framework modules

Model Variant	Quantum Layer	PINN Physical Constraints	Hybrid Fusion (Adaptive)	MSE ↓	SSIM ↑	SNR (dB) ↑	C Steps
Variant 1: Classical PINN only	X	✓	X	8.76	0.91	6.94	4,200
Variant 2: Quantum layer only	✓	X	X	9.12	0.88	6.61	3,800
Variant 3: Full model, fixed fusion weights	✓	✓	X	7.43	0.96	7.51	1,400
Variant 4: Full Q-PINN-opt	✓	✓	✓	6.84	0.99	7.98	1,000

Note: C Steps-Convergence steps

5. CONCLUSION

The Q-PINN-opt model presents a Quantum-Enhanced Physics-Informed Neural Network (Q-PINN) model of the multi-modal optimization of diffractive optics, particularly in harsh conditions of extreme lasers. This quantum-classical algorithm combines quantum computing with Physics-Informed Neural Networks (PINNs) to optimize most important optical parameters such as the optimization of laser beams, phase accuracy and diffraction efficiency under very demanding conditions including high-intensity lasers, thermal effects, and quantum-induced distortions. The Q-PINN-opt framework is much better in terms of computational, training

time, and convergence of optimization than the existing models such as PINNs, Wiener filters, and PIGAN. The model has an MSE of 6.84, SSIM of 0.99 and SNR of 7.98, which is better than what the traditional methods. The Q-PINN-opt model also takes the shortest time to train 2.5 hours, which is faster than the Original Model (30.5 hours) and Wavelet (M:db2, DS:3) (9.56 hours), as well as, providing the quickest inference time at 10ms. The model reaches the convergence of optimization within 1000 iterations as compared to 5000 iterations in the traditional methods. This has led to increase in efficiency, and coupled with its capacity to include multi-modal optimization and adaptive learning in real-time, Q-PINN-opt has been an extremely useful tool in optimization of diffractive optics in harsh operating conditions. Future efforts ought to be dedicated to enhancing the scalability and robustness of the quantum components and to generalizing the framework to more multi-physics systems, so that it can be used more widely in more advanced optical system design and in the use of high-power laser micromachining. Additional hardware development and work with bigger data sets will improve its work, and Q-PINN-opt model will become more appropriate in the implementation in practice and large-scale enterprises.

Declaration: The authors declare no conflict of interest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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