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Multiphysics optimization framework for high-power fiber amplifiers

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Abstract: The interplay of nonlinear and thermal dynamics fundamentally constrains the power scalability of fiber lasers. Conventional development cycles rely on heuristic iterations between modeling and experiment, inevitably leading to extensive resource consumption and suboptimal architectures. In this work, we demonstrate a predictive in silico design paradigm for high-power fiber amplifiers by integrating a coupled multiphysics model with a physics-informed, surrogate-assisted optimization algorithm. This framework enables the efficient co-optimization of macroscopic configurations and internal waveguide parameters, thereby directly identifying the system-level optimum under rigorous physical constraints. Computationally directed by this method, we designed an optimal gain fiber featuring a numerical aperture of 0.0585 and a centrally depressed refractive index profile. Upon physical fabrication and integration into a 0.5-nm-linewidth setup, the amplifier delivered an output power of 7.68 kW with high optical-to-optical efficiency (84%) and excellent beam quality ($M^2 < 1.5$), setting a new power record for sub-nanometer-linewidth fiber lasers. This generalizable framework paves the way to unlock previously inaccessible performance regimes in high-power lasers and accelerate the realization of fully functional digital twins for next-generation photonic systems.

Keywords: optimization framework; multiphysics model; physics-informed algorithm

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1 Introduction

The generation and control of coherent light at extreme power densities are central pursuits in modern science, unlocking new frontiers from fundamental physics to advanced manufacturing^{1,2}. However, success in this regime is ultimately constrained by severe material degradation that emerges when gain media are pushed to their thermal and nonlinear limits. High-power fiber lasers have historically circumvented these constraints because the optical fiber acts as both a distributed gain medium and a robust waveguide^{3–5}. Broadly, with optical waveguides serving as fundamental carriers, significant breakthroughs have been achieved in creating compact, smart, and multifunctional light sources, which currently represent a pivotal developmental trend in modern photonics^{6–8}. Although this dual functionality has driven remarkable power scaling over the past

decades, the field is now colliding with an intrinsic physical barrier^{9–15}. Under extreme thermal loads and optical densities, the internal dynamics of the fiber transcend isolated mechanisms and evolve into a strongly coupled multiphysics regime. Specifically, the interplay between nonlinear and thermal effects imposes intricate trade-offs that dictate the ultimate performance of these systems^{16,17}. Consequently, the evolution of high-power fiber lasers has reached a critical juncture: the bottleneck has shifted from raw material manufacturing to the global architectural design of the entire system. Breaking through this ceiling necessitates a paradigm shift from piecemeal optimization to a holistic co-design methodology.

Resolving these competing multiphysics constraints transforms optical system design into a challenging inverse problem¹⁸. Under extreme operational regimes, the mapping between structural parameters and system performance

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becomes so convoluted that optimizing for one metric often inadvertently compromises another^{19,20}. Consequently, the underlying parameter space is high-dimensional, non-convex, and riddled with local optima. Conventional heuristic and empirical approaches are not only prohibitively resource-intensive but also inherently incapable of uncovering the global optimum. Conversely, purely computational optimization remains hampered by the high computational cost of high-fidelity forward-simulation sweeps; the need to repeatedly solve complex coupled partial differential equations renders global search algorithms practically infeasible. This dual physical and mathematical bottleneck becomes particularly pronounced in high-power sub-nanometer-linewidth fiber lasers. In this regime, intensified nonlinear and thermal interactions further compress the available operational window^{21–23}, making such systems a rigorous testbed for exploring advanced methodologies. Overcoming these limitations requires a methodological leap: the development of extreme-performance light sources must transition from heuristic experimental iterations to a predictive computational framework.

Here, we present a multiphysics optimization framework that redefines high-power fiber amplifier design as a predictive *in silico* process. By integrating a rigorous coupled multiphysics model with a physics-informed, surrogate-assisted optimization algorithm, our framework bridges the fundamental gap between simulation accuracy and computational tractability, autonomously reconciling the intertwined physical constraints inherent to power scaling. We experimentally validate this design methodology by fabricating a computationally customized gain fiber and integrating it into a macroscopic system. This co-optimized amplifier achieved a record-breaking output power of 7.68 kW in a 0.5-nm linewidth fiber amplifier while maintaining high optical efficiency (84%) and excellent beam quality ($M^2 < 1.5$). This work demonstrates the feasibility of shifting the immense burden of complex engineering design to a high-fidelity computational domain.

2 Results

2.1 Multiphysics optimization framework

Fiber amplifiers based on the master oscillator power amplifier (MOPA) architecture are the dominant approach for scaling the output power of fiber lasers. These amplifiers function by converting low-brightness pump light into high-brightness signal light in the gain fiber (Fig. 1(a)). Currently, further power scaling of such systems is primarily limited by three key factors: pump brightness, stimulated Raman scattering (SRS), and transverse mode instability (TMI), with the latter two being the most critical. As shown in Fig. 1(b), SRS is a nonlinear optical process that scatters signal light into frequency-shifted Raman Stokes light via optical phonons²⁴. Meanwhile, TMI manifests as a thermally

induced nonlinear phenomenon (Fig. 1(c)), in which the thermo-optic effect converts the modal interference pattern into a dynamic refractive index grating within the fiber core²⁵. The resulting phase shift between this grating and the interference pattern drives dynamic energy coupling between the fundamental mode (FM) and higher-order modes (HOMs). Because the onset of either SRS or TMI abruptly terminates further amplification, their thresholds determine the physical boundaries of achievable output power. Consequently, the design of high-power fiber amplifiers requires a systematic search for global optima within a high-dimensional parameter space where these divergent constraints are precisely reconciled.

To address this multiphysics challenge, we frame the global design of high-power fiber amplifiers as a constrained optimization problem. The primary objective is to maximize the output power of the signal laser, while strictly ensuring operation below SRS and TMI thresholds:

$$\max_{\mathbf{x}} P_{\text{out}}(\mathbf{x}) \quad \text{s.t.} \quad P_{\text{out}} < \min(P_{\text{SRS}}, P_{\text{TMI}}), \quad (1)$$

where P_{out} is the output power of the signal laser, $\mathbf{x}$ is the parameter vector of design variables, and P_{SRS} and P_{TMI} are the SRS and TMI thresholds, respectively.

Figure 2 highlights the paradigm shift from conventional heuristic processes to our multiphysics optimization framework. As shown in Fig. 2(a), conventional workflows rely on iterative feedback between the virtual (computational) and physical (experimental) domains. These methods typically initiate with forward evaluations based on empirical models or sweep simulations, followed by experimental integration and testing. However, such direct assessments frequently fail to capture the high-dimensional interdependencies, while physical implementations are resource-intensive. Consequently, the empirical tuning is biased by initial guesses and prone to converging on local optima. To overcome these limitations, we propose a multiphysics optimization framework (Fig. 2(b)) that shifts the iterative design burden entirely into the computational domain. By integrating a coupled multiphysics model with a physics-informed optimization algorithm, the framework autonomously identifies the system-level optimum, enabling a highly predictive physical realization after training.

The coupling between nonlinear and thermal effects in high-power fiber amplifiers primarily manifests through signal degradation and perturbations to the fiber waveguide. To maximize output power while ensuring operation within stable physical regimes, our model refocuses from tracing signal degradation to characterizing the environment-sensitive properties of the gain fiber. Notably, the transverse mode parameters, particularly the mode field area (MFA) of FM and bending losses of HOMs, govern the SRS and TMI thresholds. These attributes are intricately linked to the localized coiling and thermal states in such systems. Consequently, bridging SRS and TMI effects requires a comprehensive analysis of state-dependent waveguide dynamics.

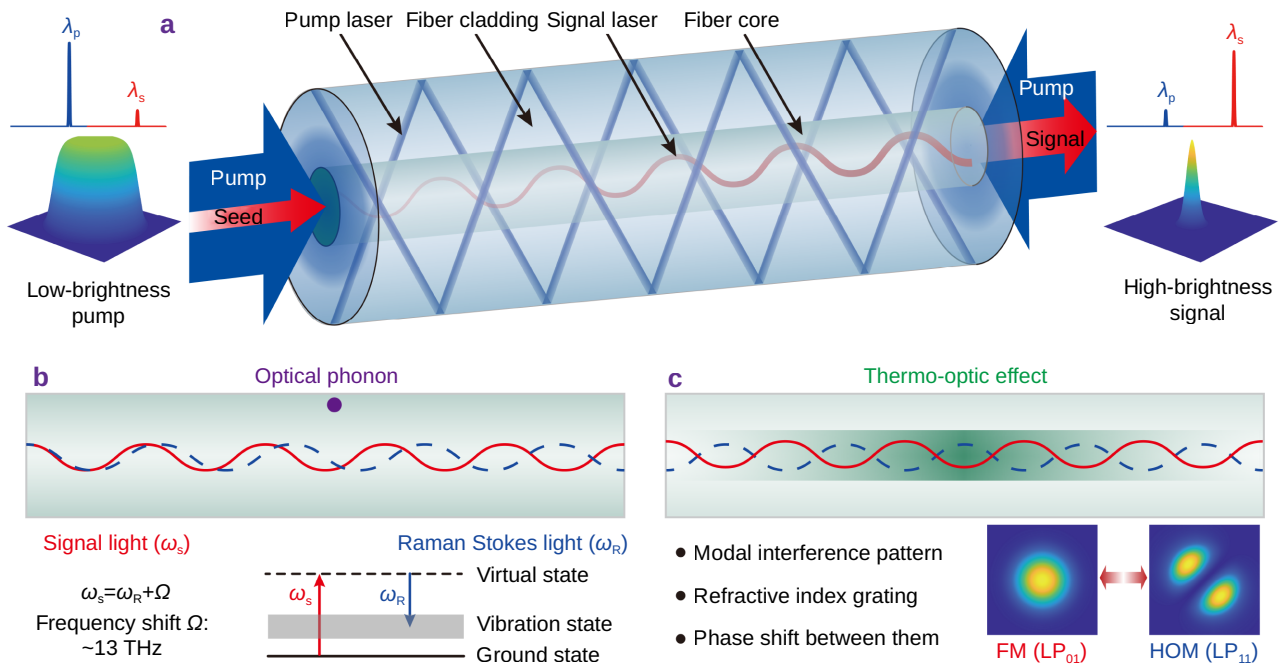


Fig. 1 | Principles and limitations of high-power fiber amplifiers. (a) Schematic of a MOPA-based fiber amplifier. Low-brightness pump light (λ_p , guided in the cladding) is absorbed and converted into a high-brightness signal light (λ_s , amplified in the core), as illustrated by the corresponding 3D beam profiles. (b) Physical mechanism of SRS. Signal light (ω_s) is scattered into lower-frequency Raman Stokes light (ω_R) mediated by optical phonons, resulting in a typical frequency shift Ω of approximately 13 THz in silica fibers. (c) Illustration of the TMI process. A thermally induced refractive index grating (green shading) and its phase shift relative to the modal interference (solid and dashed lines) drive dynamic energy transfer from the FM (LP_{01} mode) to HOMs (typically the LP_{11} mode).

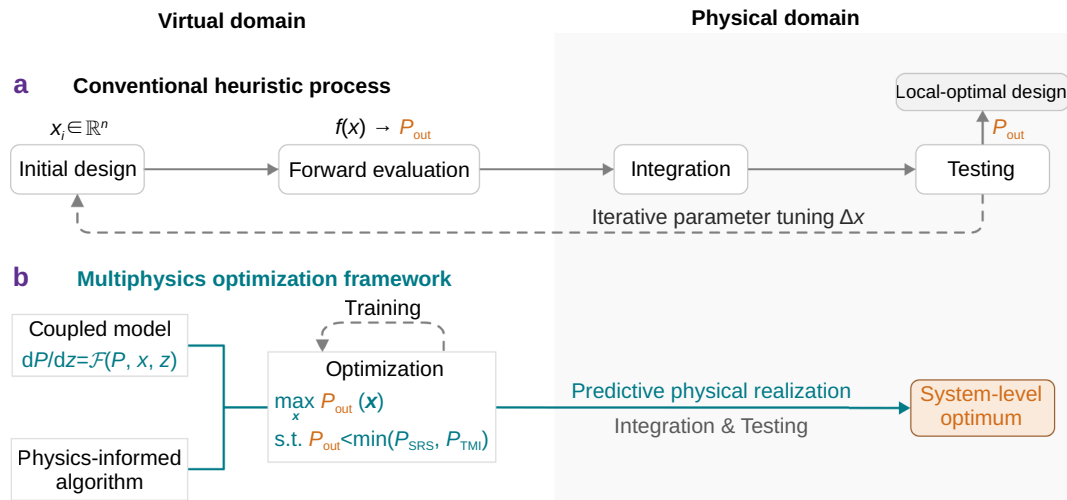


Fig. 2 | Schematic comparison of design methodologies for high-power fiber amplifiers. (a) Conventional heuristic process. It relies on costly iterative parameter tuning (Δx), often resulting in suboptimal designs. $f(x)$ represents the traditional forward evaluation function. (b) Proposed multiphysics optimization framework. By integrating the coupled model ($dP/dz = \mathcal{F}(P, x, z)$) and the physics-informed algorithm into a computational optimization loop, the framework autonomously identifies the system-level optimum for predictive physical realization after training.

Specifically, by employing the finite element method (FEM) to analyze the equivalent refractive index profile (RIP) derived from the initial state (Fig. 3(a)), the transverse mode parameters under specific thermal and coiling conditions can be quantified via the electric field distributions and

effective refractive indices (See Methods). To circumvent step-by-step iterations, we construct a comprehensive modal dataset via parameter sweeps of coiling radii and thermal loads (Fig. 3(b)). This pre-computed foundation enables the subsequent surrogate-assisted strategy to explore the

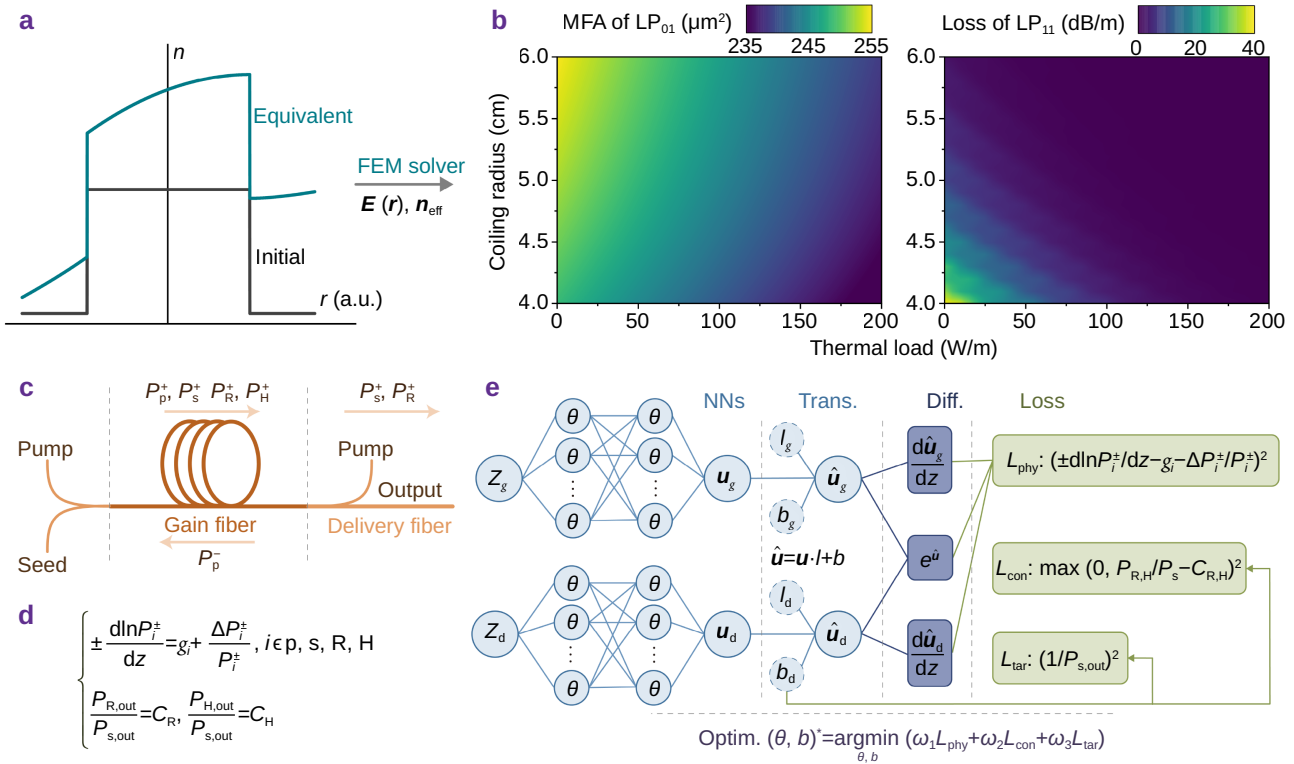


Fig. 3 | Coupled multiphysics model and physics-informed algorithm for high-power fiber amplifiers. (a) Comparison between the initial step-index profile and the equivalent RIP under coiling and thermal effects. $E(r)$ is the electric field distribution, and n_{eff} is the effective refractive index. (b) Parameter maps showing the MFA of the LP_{01} mode and the bending loss of the LP_{11} mode as functions of coiling radius and thermal load. (c) Schematic of the amplifier configuration comprising gain and delivery fibers, with superscripts + and - indicating forward and backward propagation directions. (d) Governing physical equations (transformed via logarithmic derivatives) and nonlinear boundary constraints (SRS and TMI thresholds). C_R and C_H define the permissible ratios of Raman and HOM components relative to the signal at the thresholds. (e) Architecture of the physics-informed algorithm. Two NNs output latent variables (u_g, u_d) over normalized positions (Z_g, Z_d). A transformation block (Trans.) enforces exact boundary conditions using prescribed functions l (vanishes at the boundaries) and b (strictly satisfies the boundary values) to ensure physically consistent predictions ($\hat{u}$). Automatic differentiation (Diff.) recovers the laser powers and calculates their derivatives to construct a composite objective function (Loss). The optimization process (Optim.) minimizes the physical loss (L_{phy}), the constraint loss (L_{con}), and the target loss (L_{tar}) simultaneously. The unknown boundary conditions are trainable variables, which are optimized directly in the logarithmic domain. This mathematical formulation implicitly exerts an exponential mapping, which structurally guarantees that the recovered physical power values remain strictly non-negative throughout the entire training process.

high-dimensional design space with enhanced efficiency, without sacrificing modeling fidelity.

Leveraging these dynamic modal properties, the longitudinal power evolution of distinct laser components can be accurately modeled by the power-balance equations (see Supplementary information Section for details):

$$\pm \frac{dP_i^\pm}{dz} = g_i(P_p^\pm, P_s^\pm, P_R^\pm, P_H^\pm)P_i^\pm + \Delta P_i^\pm, \quad (i \in p, s, R, H), \quad (2)$$

where P represents the laser power, and the subscripts p, s, R , and H denote the pump, signal, Raman, and HOM, respectively; the signs + and - indicate forward and backward propagation directions, and ΔP accounts for the distributed spontaneous noise for the Raman and HOM components. The effective gain coefficient g_i encompasses the rare-earth ion gain, Raman gain, mode-coupling gain, and various losses, all of which are modulated by the local-

ized mode perturbations discussed above.

To tackle those nonlinear equations that implicitly define the maximum signal power, we reformulate the optimization as a differentiable learning task using a physics-informed algorithm. Drawing on the strengths of physics-informed neural networks (PINNs)²⁶, our algorithm incorporates the power-balance equations and a customized loss reconstruction, ensuring that the optimization process remains self-supervised and strictly bounded by the underlying physics. Since gain and delivery fibers involve distinct laser interactions, they are treated separately (Fig. 3(c)). Solving the power-balance equations directly with standard PINNs is intractable due to the computational complexity of the gain coefficient and the numerical stiffness introduced by sharp spatial variations in the gP product. To alleviate the latter issue, we divided both sides by P_i to transform the power-balance equations in terms of the log-derivative

(Fig. 3(d))²⁷. The effective gain coefficients depend solely on the powers of all laser components at that specific longitudinal position. Thus, they could be pre-calculated to construct a surrogate model that maps gain coefficients across diverse power combinations, thereby dramatically accelerating training (See *Methods* for more details on the surrogate model). Figure 3(e) illustrates the architecture of the physics-informed algorithm. The efficacy of the algorithm relies on a composite loss function that respects physical laws, satisfies competing threshold constraints, and simultaneously maximizes the target output power (See *Methods* for more details on the algorithm). Furthermore, treating the parameters of interest as trainable variables enables flexible initialization and joint optimization.

2.2 Execution of the optimization framework

To demonstrate the framework's applicability, we evaluate a

bidirectionally pumped fiber amplifier using a commercial gain fiber as an illustrative example. The execution workflow comprises four key stages that advance systematically from the extraction of fundamental fiber parameters to comprehensive system-level optimization. First, the cross-sectional RIP (Δn) of the gain fiber is measured at room temperature, revealing a non-uniform, center-depressed core structure (Fig. 4(a)). The average core numerical aperture (NA) is approximately 0.062, matching that of the step-index fiber shown in Fig. 3(a). Second, this practical RIP is incorporated into the calculations of transverse mode parameters. As shown in Fig. 4(b), both the MFA of the LP₀₁ mode and the bending loss of the LP₁₁ mode are significantly altered by the thermal load, with the latter also exhibiting a strong dependence on the coiling radius. Notably, a comparison between Fig. 4(b) and Fig. 3(b) validates that fibers with similar core NAs but different RIPs can exhibit markedly different modal properties. Third, a

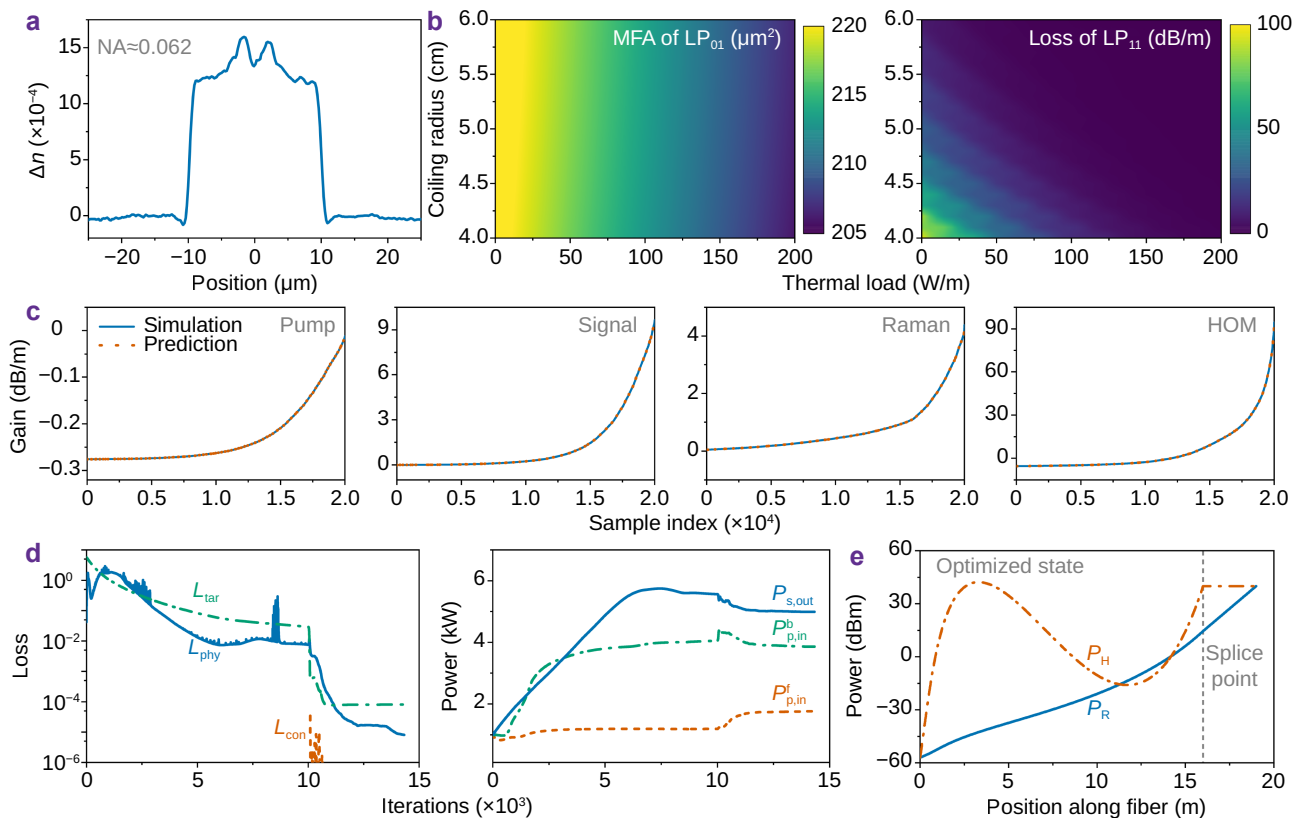


Fig. 4 | Execution workflow and performance of a high-power fiber amplifier. (a) Measured RIP (Δn) of the gain fiber at room temperature. (b) Calculated transverse mode properties. The heatmaps illustrate the MFA of the LP₀₁ mode and the bending loss of the LP₁₁ mode as functions of thermal load and coiling radius. (c) Validation of the trained surrogate model. The predicted gain coefficients for pump, signal, Raman, and HOM (LP₁₁ mode) are compared against rigorous numerical simulations. The x-axis represents 2×10^4 random parameter samples, sorted in ascending order of their ground-truth values for clarity. (d) Training process of the optimization framework. The left panel shows the steady convergence of the physical loss (L_{phy}), constraint loss (L_{con}), and target loss (L_{tar}) over iterations. The right panel tracks the evolution of forward/backward pump powers ($P_{\text{p,in}}^f$, $P_{\text{p,in}}^b$) and the signal output power ($P_{\text{s,out}}$). (e) Power distribution of Raman (P_R) and HOM (P_H) along the fiber at the final optimized state. The vertical dashed line at 16 m demarcates the splice point between the active gain fiber and the passive delivery fiber.

surrogate model is trained to predict all four gain coefficients using datasets (see Supplementary Fig. S1) generated from these transverse mode properties and system-level amplifier parameters. The model predictions show excellent agreement with rigorous numerical simulations (Fig. 4(c)). Among the evaluated parameters, the maximum L_2 error occurs in the HOM gain coefficient, which remains at a negligible level of 6.4×10^{-4} . Finally, system optimization is executed. The overall convergence results exhibit good consistency across multiple training restarts (see Supplementary Fig. S2). Figure 4(d) and 4(e) illustrate the typical optimization process and the final converged state. The physical loss, constraint loss, and target loss all demonstrate steady convergence, indicating that the algorithm robustly navigates toward the optimum. The optimized forward pump power $P_{\text{p,in}}^f$, backward pump power $P_{\text{p,in}}^b$, and output signal power $P_{\text{s,out}}$ converge to 1.76 kW, 3.86 kW, and 4.99 kW, respectively (Fig. 4(d)). Under these optimal conditions, the Raman power (P_R) increases gradually along the fiber. In contrast, the HOM power (P_H) exhibits a complex non-monotonic evolution within the 16-m gain fiber before stabilizing within the 3-m delivery fiber (Fig. 4(e)). This behavior is attributed to the shifting balance between the thermally induced mode-coupling gain and the bending-induced loss along the gain fiber. Consequently, this framework enables the direct determination of the maximum achievable output power and optimal pump configuration

under SRS and TMI constraints.

2.3 Optimal design and amplifier realization

In practical high-power fiber amplifiers, the achievable laser performance is determined by both the gain fibers and the seed lasers²⁸. To isolate the performance enhancements attributable to the gain fiber, we assume the seed laser characteristics remain constant. Experimentally, this corresponds to the phase-modulated single-frequency seed sources typically employed in high-power sub-nanometer-linewidth fiber amplifiers, which exhibit stable temporal intensity and good spectral preservation during amplification. Currently, the highest reported output power for this type of fiber amplifier stands at 7 kW²⁹. Our objective is to leverage the proposed multiphysics optimization framework to design a customized gain fiber and fiber amplifier capable of surpassing this record.

Following the execution workflow, we deploy the framework to determine the optimal geometric parameters of a customized gain fiber. Figure 5(a) maps the optimization landscape, showing the maximum achievable output power, optical-to-optical conversion efficiency, and required fiber length as functions of core NA (see Supplementary Fig. S3 for more details). A low NA (≤ 0.059) yields high output powers (≥ 8.3 kW) but suffers from lower efficiency. Conversely, a higher NA enhances efficiency but degrades

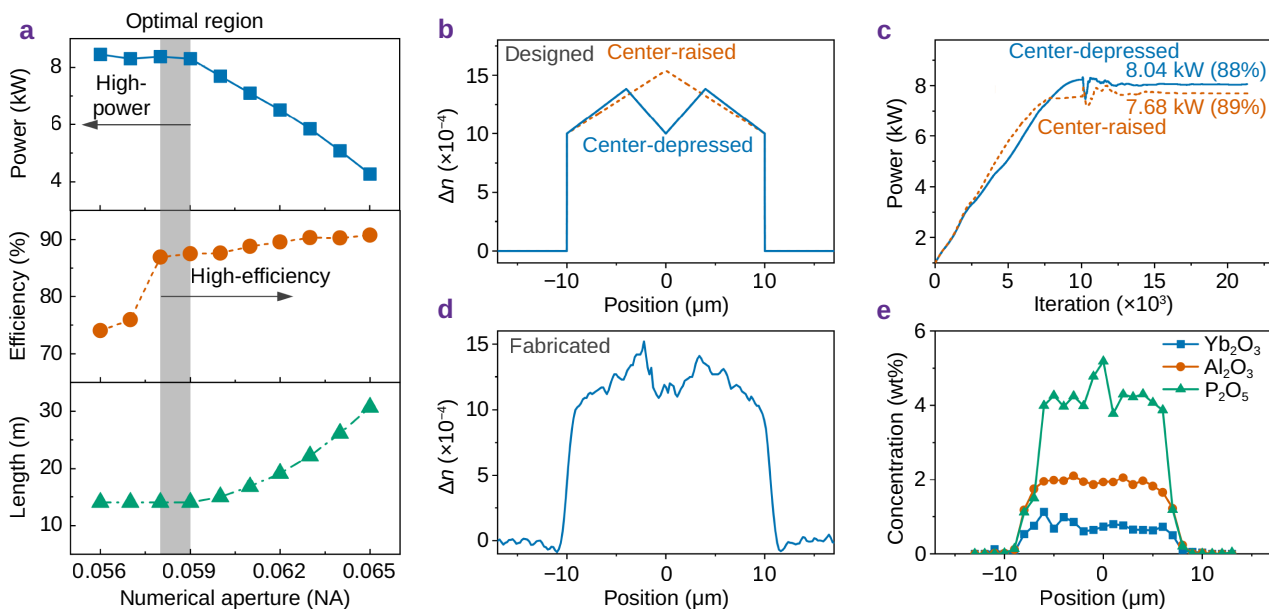


Fig. 5 | Optimization design and physical fabrication of the customized gain fiber. (a) Optimized results as functions of core NA, including the maximum achievable output power (top), optical-to-optical conversion efficiency (middle), and gain fiber length (bottom). The gray shaded area (NA: 0.058-0.059) denotes the optimal region for balanced high-power and high-efficiency operation. The maximum pump power at each end is set to 6.5 kW, and the minimum gain fiber length is set to 14 m in the optimization design. (b) Schematic representation of two practical RIPs at NA=0.0585: center-depressed and center-raised profiles. (c) Convergence curves for both designs. (d) Measured RIP of the fabricated gain fiber. (e) Radially resolved mass concentration (wt%) profiles of core dopants (Yb₂O₃, Al₂O₃, and P₂O₅), underpinning the physical origin of the customized RIP.

output power capacity due to the accelerated onset of the TMI. Our framework identifies a narrow optimal NA window between 0.058 and 0.059 that offers a synergistic trade-off between power and efficiency. Furthermore, we investigated how realistic fabrication deviations affect performance through two representative distributions, center-depressed and center-raised (Fig. 5(b)), at a median optimized NA of 0.0585. Notably, the center-depressed profile outperforms its counterpart, achieving an output power of 8.04 kW with an efficiency of 88% (Fig. 5(c)). We attribute this superiority to a dynamic thermal compensation effect. Under high-power operation, the thermally induced refractive index increase gradually flattens the initial central dip, thereby maintaining robust suppression of both SRS and TMI. In contrast, the center-raised fiber is limited to 7.68 kW with a slightly higher efficiency of 89%. Guided by these insights, we successfully fabricated a high-performance gain fiber. The measured RIP (Fig. 5(d)) confirms the accurate realization of the target center-depressed feature with an average NA of approximately 0.0585. Electron probe micro-analysis (EPMA) confirms the precise radial control of key dopants (Fig. 5(e)). Based on the measured actual RIP, our framework predicts an impressive achievable output power of 7.85 kW at 89% efficiency (see Supplementary Fig. S4).

Building upon the optimal design and the successfully fabricated gain fiber, we constructed a bidirectionally pumped high-power fiber amplifier (Fig. 6(a)) (See *Methods* for more details on the setup and measurements). The output signal grows almost linearly with the total injected pump, transitioning from pure forward pumping to bidirec-

tional pumping (Fig. 6(b)). A maximum output of 7.68 kW is achieved at the pump level of 9.16 kW, yielding an excellent overall optical-to-optical conversion efficiency of 84%. At the maximum output, the signal (centered at 1066 nm) maintains a 3-dB spectral linewidth of just 0.5 nm, alongside a Raman suppression ratio of 28.6 dB (Fig. 6(c)). Meanwhile, the signal exhibits excellent temporal stability, indicated by a normalized standard deviation (NSD) of merely 0.7% over a 100-ms window. The corresponding radio-frequency (RF) spectrum shows no characteristic TMI peaks (Fig. 6(d)). When the signal power scales from 7.59 kW to 7.68 kW, the RF spectrum of the signal laser remains almost unchanged, while a further increase in the signal power to a transient 7.76 kW immediately triggers a pronounced low-frequency noise enhancement below 10 kHz, clearly marking the onset of the TMI effect and demonstrating that the true TMI threshold of this system is precisely bounded between 7.68 kW and 7.76 kW (see Supplementary Fig. S5). The beam quality factors are measured to be $M_x^2=1.44$ and $M_y^2=1.49$ (Fig. 6(e)), demonstrating excellent beam quality. The concurrent absence of spectral degradation, temporal fluctuations, and RF peaks indicates effective mitigation of SRS and TMI. Both the output power and the efficiency are close to the predicted results. This customized amplifier not only substantiates our optimization framework but also establishes a new performance benchmark for high-beam-quality, sub-nanometer-linewidth fiber amplifiers (see Supplementary Table S2 for recent progress of high-power sub-nanometer-linewidth fiber lasers).

The discrepancy between the experimentally measured

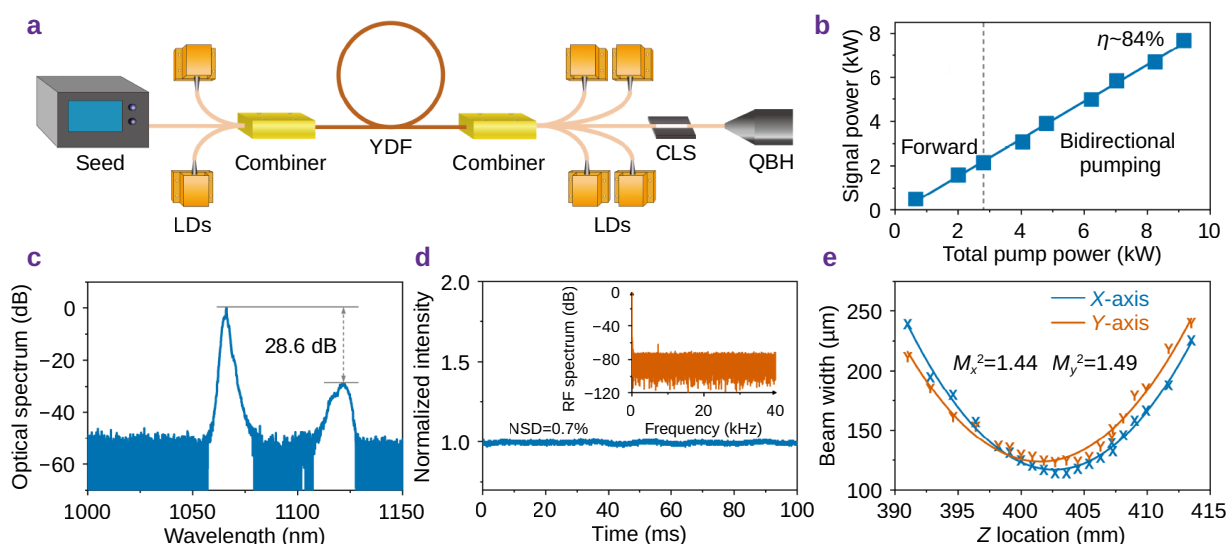


Fig. 6 | Experimental demonstration and performance of the optimized high-power fiber amplifier. (a) Schematic diagram of the bidirectionally pumped fiber amplifier. It comprises the seed, pump laser diodes (LDs), pump-signal combiners, custom-fabricated ytterbium-doped fiber (YDF), a cladding light stripper (CLS), and a quartz block holder (QBH). (b) Signal output power as a function of total pump power. The vertical dotted line indicates where backward pumping is introduced in addition to the existing forward pumping. (c–e) Characteristics of the signal laser at the maximum output power: (c) normalized spectrum, (d) temporal intensity trace over a 100-ms duration (inset: corresponding RF spectrum), (e) beam quality measurement along the X and Y axes.

output power (7.68 kW) and the idealized design value (8.04 kW) primarily arises from two physical aspects. First, a measurable structural deviation exists between the RIP of the fabricated gain fiber and the mathematically idealized design; incorporating the experimentally measured RIP into the framework refined the predicted output power from 8.04 kW to 7.85 kW. Furthermore, parametric sensitivity sweeps indicate that as the background loss coefficients of the pump or signal lights increase from 5 dB/km to 100 dB/km, the predicted maximum output power further degrades to 7.65 kW and 7.36 kW, respectively (see Supplementary Fig. S6). Therefore, the experimentally realized output power of 7.68 kW is both physically consistent and well within the expected tolerances of real-world fabrication imperfections.

To further verify the generality and robust predictive capability of the proposed framework beyond a single-point design configuration, we have also tested it against two independent fiber amplifiers operating at distinct power levels, namely 6 kW and 7 kW. These two narrow-linewidth fiber amplifiers utilize bidirectionally pumped configurations but feature structurally distinct gain fiber designs optimized for their respective power scales. The excellent agreement between the physical measurements and numerical predictions across both 6-kW and 7-kW power scales further demonstrates the robust predictive reliability of our framework (see Supplementary Figs. S7 and S8).

3 Discussion

Scientific machine learning (SciML) is revolutionizing science and engineering by combining data-driven efficiency with mechanistic rigor^{30–34}. However, in data-scarce domains such as high-power fiber laser design, the efficacy of SciML critically depends on the predictive fidelity of the underlying physical models. Historically, theoretical studies in this field have prioritized model development while overlooking a crucial reality: governing parameters are not static, but evolve dynamically under real-world operating conditions. Consequently, while existing models are invaluable for qualitative exploration, their parametric rigidity severely limits their utility in precision engineering. This study introduces a dynamic characterization of gain fiber properties to enhance the reliability of the physical model, thereby providing the high-fidelity mechanistic foundation required for SciML applications in fiber lasers. Building on this mechanistic foundation, our physics-informed, surrogate-assisted algorithm successfully navigates the non-convex design space of fiber lasers. By utilizing a surrogate model to map all gain coefficients and a physics-informed architecture to optimize the composite loss function, this algorithm bypasses the computational bottlenecks of traditional numerical solvers, enabling the efficient design of high-power fiber amplifiers.

Despite these promising results, several persistent challenges inherent to SciML must be acknowledged. First, the

convergence and stability of physics-informed algorithms often scale poorly with the dimensionality of the design space³⁵. Second, while we have successfully established the dynamic characterization of the gain fiber, the complex physical interplay with other components remains critical in high-power fiber amplifiers^{36–38}. To overcome these high-dimensional and systemic bottlenecks, subsequent research must pursue a deep integration of data and physics, including system-wide full-element modeling that incorporates all key optical modules, extensive digital characterization datasets for diverse components, and efficient data-physics fusion algorithms to realize autonomous laser design platforms.

4 Conclusion

In summary, this study presents an integrated data-physics fusion framework for the efficient and predictive design of high-power fiber amplifiers. By integrating a coupled multi-physics model with a physics-informed, surrogate-assisted optimization algorithm, the proposed approach addresses the parametric rigidity and computational bottlenecks of traditional numerical solvers. Guided by the framework's optimal predictions (an NA of 0.0585 with a center-depressed RIP), we fabricated a customized gain fiber and constructed a corresponding fiber amplifier. The resulting system delivered a record-breaking output power of 7.68 kW with an 84% optical-to-optical efficiency and excellent beam quality ($M^2 < 1.5$), representing the highest reported output power for sub-nanometer-linewidth fiber lasers to date.

This remarkable performance demonstrates the predictive superiority and practical engineering value of our framework. Future work will expand this methodology into a full-element integrated model, bolstered by comprehensive databases for diverse optical modules. Ultimately, this paradigm shift toward autonomous Laser Agents will pave the way for unlocking previously inaccessible performance regimes and accelerating the realization of fully functional digital twins for next-generation photonic systems.

5 Methods

5.1 Equivalent RIP and FEM simulation

To investigate the dependence of modal properties on coiling radii and thermal loads, an analytical model for the equivalent RIP was established. In this model, a uniformly distributed thermal load within the fiber core is assumed, which is a widely adopted and reasonable approximation for heavily pumped, double-clad fibers^{39,40}. This approximation can greatly simplify the calculation of the temperature distribution, thereby enabling efficient parameter sweeps. By integrating the conformal mapping technique⁴¹ into this thermal condition, the equivalent RIPs, accounting for both the thermo-optic effect and the bend-induced elasto-optic effect,

are expressed as

$$n_{e,co}(r, \varphi) = \left[n_{i,co}(r, \varphi) + k_T \left(T_0 - T_r - \frac{Qr^2}{4\pi a^2 \kappa} \right) \right] \cdot \left(1 + \frac{r \cos \varphi}{R_{eff}} \right)$$

$$n_{e,cl}(r, \varphi) = \left[n_{i,cl}(r, \varphi) + k_T \left(T_0 - T_r - \frac{Q}{4\pi \kappa} - \frac{Q}{2\pi \kappa} \ln \left(\frac{r}{a} \right) \right) \right] \left(1 + \frac{r \cos \varphi}{R_{eff}} \right), \quad (3)$$

where n_i and n_e denote the initial and equivalent indices, with the subscripts co and cl representing the core and cladding, respectively, the parameter k_T is the thermal-optic coefficient, T_0 is the peak temperature at the core center, T_r is the room temperature, Q is the thermal load (in W/m), a is the radius of the fiber core, and κ is the thermal conductivity of silica. The local polar coordinates relative to the bend plane are denoted by r and φ . The bending penalty is evaluated using the first-order approximation of conformal mapping, governed by the effective bend radius $R_{eff}=R_f R$, where R is the practical coiling radius, and R_f is the elasto-optic correction factor.

Physically, an increase in the thermal load Q induces a proportional rise in the absolute peak temperature T_0 . However, the modal parameters, such as the MFA and bending loss, are predominantly governed by the transverse index gradient rather than the absolute background index shift. Therefore, to isolate the impact of the index gradient and simplify the eigenvalue search space, the uniform temperature shift term (T_0-T_r) was mathematically treated as a constant background offset (fixed at 200 K, representative of typical high-power operation conditions) during the parameter sweeps. This decoupling strategy ensures the accurate extraction of gradient-dependent modal properties without compromising physical validity.

The modal properties were numerically resolved using the finite-element method (FEM) implemented in COMSOL Multiphysics 6.2. To calculate the bending loss, a perfectly matched layer (PML) with a thickness of $10\lambda_s$ was imposed at the outer boundary of the computational domain to extract the imaginary part of the effective refractive index. The cross-sectional computational domain was discretized using a heterogeneous unstructured triangular mesh. To precisely capture the core-cladding boundary and resolve the localized transverse modal fields, the mesh was highly refined at the dielectric interfaces with a minimum element size of 8.4 nm. Meanwhile, to maintain computational efficiency without compromising accuracy, the maximum cladding element size was set to 4.21 μm . The initial cladding index was 1.45 for ideal step-index fibers, and the measured RIP was interpolated into the model for practical fibers. The other physical and geometric parameters are summarized in Table 1.

Table 1 | Geometric and material parameters used in the FEM simulations.

Parameter	Symbol	Value
Wavelength	λ_s	1066 nm
Core radius	a	10 μm
Cladding radius	b	200 μm
Thermo-optic coefficient	k_T	$1.2 \times 10^{-5} \text{ K}^{-1}$
Thermal conductivity	κ	$1.38 \text{ W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$
Elasto-optic correction factor	R_f	1.28
Peak temperature rise	T_0-T_r	200 K

5.2 Surrogate model

The surrogate model maps the powers of the four laser components (inputs) to their corresponding gain coefficients (outputs). The ground truth for the gain coefficients was rigorously computed using analytical expressions (see Supplementary Section) combined with the modal dataset. To cover the parameter space across multiple orders of magnitude, we generated 100000 distinct power combinations using Latin hypercube sampling in a logarithmic space. The sampling bounds were defined by the practical operational limits: 10 W to 10^4 W for the pump and signal powers, 10^{-10} W to 100 W for the Raman power, and 10^{-9} W to 100 W for the HOM power. All input laser powers were log-transformed to facilitate network convergence.

The surrogate model is constructed as a fully connected NN with two hidden layers of 100 neurons each, using the hyperbolic tangent (Tanh) activation function to ensure continuous, differentiable outputs. The dataset was randomly partitioned into 80000 samples for training and 20000 for testing. The network was optimized by minimizing the mean squared error (MSE) loss function. To achieve both rapid convergence and high precision, we employed a two-stage optimization strategy. Initially, the Adam optimizer was used for 5000 iterations with a learning rate of 1×10^{-3} to explore a broad parameter space. Subsequently, we transitioned to the L-BFGS algorithm to fine-tune the model weights and locate the exact local minimum. The L-BFGS optimizer was configured with a learning rate of 1.0, a history size of 50, a maximum of 50000 iterations and evaluations, and tight tolerances for gradient (1×10^{-6}) and step size ($\sim 2.2 \times 10^{-16}$). The test dataset confirmed the surrogate model's accuracy, yielding a mean relative error of less than 2×10^{-6} . The surrogate model and the physics-informed algorithm were implemented in PyTorch and trained on an NVIDIA RTX 5090D GPU.

5.3 Physics-informed algorithm

The physics-informed algorithm comprises two independent feedforward NNs dedicated to modeling the gain and

delivery fibers, respectively. The key difference between the two NNs lies in their network dimensionality and the loss functions governed by different physical equations. For the gain fiber NN, the model must resolve complex multi-physics interactions among four coupled optical fields: the pump light, FM signal, Raman Stokes light, and HOM signal. Consequently, this NN incorporates four inputs and four outputs corresponding to these four state variables. For the delivery fiber NN, the powers of the pump light and HOM signal remain almost constant; thus, only the nonlinear interactions between the FM signal and the Raman Stokes light need to be governed. Accordingly, this NN requires only two input and output channels. Meanwhile, they are connected in a sequential cascade, where the outputs of the gain fiber NN serve as the boundary inputs for the delivery fiber NN. Each hidden layer contains 100 neurons, and the activation function is Tanh. To ensure exact physical consistency, the boundary conditions are rigorously enforced as hard constraints via a transformation block⁴², embedding the initial states into the network outputs. Furthermore, a residual-based attention mechanism⁴³ is integrated into the architecture to adaptively process the multi-scale exponential evolution of the Raman and HOM powers.

The network parameters are optimized by minimizing a composite loss function, defined as $L_{\text{total}} = \omega_1 L_{\text{phy}} + \omega_2 L_{\text{con}} + \omega_3 L_{\text{tar}}$. The individual terms are formulated as follows: L_{phy} represents the physics-informed loss, derived from the power-balance equations. L_{con} serves as the penalty term for physical limits, handling the SRS and TMI constraints implemented via the Augmented Lagrangian Method. L_{tar} functions as the optimization objective designed to maximize the output power P_{out} . The weighting coefficients ω_1 and ω_2 were set to fixed values, while ω_3 was updated adaptively during training to reach the physically constrained state. The explicit expression for ω_3 is formulated as

$$\omega_3 = (P_{\text{R,out}}/P_{\text{s,out}} - C_{\text{R}})^2 + (P_{\text{H,out}}/P_{\text{s,out}} - C_{\text{H}})^2 + \omega_0, \quad (4)$$

where $P_{\text{R,out}}$ and $P_{\text{H,out}}$ represent the output powers of the Raman Stokes light and the HOM, respectively, and ω_0 serves as a fixed base weight.

The computational domain was discretized using Latin hypercube sampling, yielding 24000 collocation points (20000 for the gain fiber and 4,000 for the delivery fiber). Model optimization was performed using a standard two-stage training procedure: an Adam optimizer (learning rate: 1×10^{-3}) was used for the initial 10000 epochs to facilitate global exploration of the parameter space, followed by an L-BFGS optimizer to ensure precise numerical convergence. The training process was repeated 10 times with random restarts to verify the optimization's robustness and ensure the model consistently converged to the global optimum. The typical training time of the proposed framework is under 15 minutes, providing a significant efficiency advantage over traditional grid-search approaches that inherently

suffer from exponential scaling in execution time within high-dimensional parameter spaces. The detailed convergence curves and training times are provided in Supplementary Figs. S2 and S3.

5.4 Experimental setup and measurement

The high-power fiber amplifier was constructed based on a bidirectionally pumped MOPA configuration. The customized Yb-doped gain fiber (YDF) was fabricated via modified chemical vapor deposition (MCVD) integrated with chelate gas-phase deposition. The YDF features a core/cladding diameter of 20/400 μm with a core NA of approximately 0.0585. The fiber has a measured pump absorption coefficient of 1.2 dB/m at 976 nm, with an optimized total length of 14.0 m. To effectively suppress HOMs via bending loss, the YDF was coiled with a 4.7 cm radius. The seed laser is a typical phase-modulated single-frequency laser. Specifically, the primary output is generated by a low-noise single-frequency laser based on an ultra-short cavity (central wavelength: 1066 nm, output power: 40 mW). This single-frequency laser is externally modulated via a fiber-coupled LiNbO₃ electro-optic modulator, which is driven by a white-noise source and a radio-frequency amplifier to broaden the 3-dB linewidth to 0.6 nm. The laser power is subsequently boosted to approximately 50 W using a commercial pre-amplification module (Precilasers, China). The wavelength-stabilized 976 nm laser diodes (LDs) were coupled into the YDF via two custom-designed (6+1) $\times$ 1 pump-signal combiners, which exhibit a transmission efficiency of over 98% at both ends. The maximum available pump power at each end was 6.5 kW. The residual pump and cladding light were stripped by a cladding light stripper (CLS) before output. The amplified laser was delivered into free space via a quartz block holder (QBH) equipped with an anti-reflection-coated end cap. The entire amplifier system was mounted on a water-cooled platform maintained at 20 °C to mitigate thermal accumulation.

Before amplification, the YDF RIP was measured using a fiber index profiler (S14, Photon Kinetics). The output power was recorded by a water-cooled power meter. The optical spectrum was monitored with an optical spectrum analyzer (AQ6370D, Yokogawa) at a resolution of 0.04 nm. To diagnose TMI, a high-speed photodetector (Thorlabs PDA05CF2) coupled to a high-bandwidth digital oscilloscope (Tektronix MDO4104-6) was used to capture temporal intensity fluctuations and corresponding RF spectra. Furthermore, the beam quality factor (M^2) was evaluated using a camera-based beam profile system based on the ISO-standard D4 σ method.

References

1. Mourou G. Nobel lecture: extreme light physics and application. *Rev Mod Phys* **91**, 030501 (2019).

2. Dudley JM. Light, lasers, and the Nobel prize. *Adv Photonics* **2**, 050501 (2020).
3. Snitzer E. Optical maser action of Nd³⁺ in a barium crown glass. *Phys Rev Lett* **7**, 444–446 (1961).
4. Kao KC, Hockham GA. Dielectric-fibre surface waveguides for optical frequencies. *Proc Inst Electr Eng* **113**, 1151–1158 (1966).
5. Ramachandran S, Fini JM, Mermelstein M et al. Ultra-large effective-area, higher-order mode fibers: a new strategy for high-power lasers. *Laser Photonics Rev* **2**, 429–448 (2008).
6. Liu Y, Qiu ZR, Ji XR et al. A fully hybrid integrated erbium-based laser. *Nat Photonics* **18**, 829–835 (2024).
7. Han JL, Li MQ, Wu RB et al. High fiber-to-fiber net gain in erbium-doped thin film lithium niobate waveguide amplifier as an external gain chip. *Opto-Electron Sci* **4**, 250004 (2025).
8. Wang XR, Sun WQ, Sun XL. Passively Q-switched Nd: YAG waveguide vortex laser using Bi₂Se₃ saturable absorber. *Opto-Electron Eng* **53**, 260082 (2026).
9. Nilsson J, Payne DN. High-power fiber lasers. *Science* **332**, 921–922 (2011).
10. Jackson SD. Towards high-power mid-infrared emission from a fibre laser. *Nat Photonics* **6**, 423–431 (2012).
11. Jauregui C, Limpert J, Tünnermann A. High-power fibre lasers. *Nat Photonics* **7**, 861–867 (2013).
12. Richardson DJ, Nilsson J, Clarkson WA. High power fiber lasers: current status and future perspectives [invited]. *J Opt Soc Am B* **27**, B63–B92 (2010).
13. Dong L, Zervas MN. Past, present, and future of fiber lasers and amplifiers. *Opt Commun* **577**, 131419 (2025).
14. Rothe S, Chen CW, Ahmadi P et al. Wavefront shaping enables high-power multimode fiber amplifier with output focus. *Science* **390**, 173–177 (2025).
15. Dawson JW, Messerly MJ, Beach RJ et al. Analysis of the scalability of diffraction-limited fiber lasers and amplifiers to high average power. *Opt Express* **16**, 13240–13266 (2008).
16. Hejaz K, Shayganmanesh M, Rezaei-Nasirabad R et al. Modal instability induced by stimulated Raman scattering in high-power Yb-doped fiber amplifiers. *Opt Lett* **42**, 5274–5277 (2017).
17. Wen Y, Zhang C, Zhu Y et al. Origin of SBS-induced mode distortion in high power narrow linewidth fiber amplifiers. *Photonics Res* **13**, 1631–1636 (2025).
18. Molesky S, Lin ZN, Piggott AY et al. Inverse design in nanophotonics. *Nat Photonics* **12**, 659–670 (2018).
19. Zervas MN. Transverse mode instability, thermal lensing and power scaling in Yb³⁺-doped high-power fiber amplifiers. *Opt Express* **27**, 19019–19041 (2019).
20. Dong L, Ballato J, Kolis J. Power scaling limits of diffraction-limited fiber amplifiers considering transverse mode instability. *Opt Express* **31**, 6690–6703 (2023).
21. Zervas MN. Power scaling limits in high power fiber amplifiers due to transverse mode instability, thermal lensing, and fiber mechanical reliability. *Proc SPIE* **10512**, 1051205 (2018).
22. Ren S, Lai WC, Wang GJ et al. Experimental study on the impact of signal bandwidth on the transverse mode instability threshold of fiber amplifiers. *Opt Express* **30**, 7845–7853 (2022).
23. Zuo JX, Lin XC. High-power laser systems. *Laser Photonics Rev* **16**, 2100741 (2022).
24. Headley C, Agrawal GP. Noise characteristics and statistics of picosecond Stokes pulses generated in optical fibers through stimulated Raman scattering. *IEEE J Quantum Electron* **31**, 2058–2067 (1995).
25. Jauregui C, Stihler C, Limpert J. Transverse mode instability. *Adv Opt Photonics* **12**, 429–484 (2020).
26. Raissi M, Perdikaris P, Karniadakis GE. Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *J Comput Phys* **378**, 686–707 (2019).
27. Liu W, Cheng Z, Li J et al. Physics-informed neural networks for fiber laser amplification and its associated effects. *J Lightwave Technol* **44**, 4697–4706 (2026).
28. Liu W, Ma PF, Lv HB et al. General analysis of SRS-limited high-power fiber lasers and design strategy. *Opt Express* **24**, 26715–26721 (2016).
29. Ma PF, Yao TF, Liu W et al. A 7-kW narrow-linewidth fiber amplifier assisted by optimizing the refractive index of the large-mode-area active fiber. *High Power Laser Sci Eng* **12**, e67 (2024).
30. Carleo G, Cirac I, Cranmer K et al. Machine learning and the physical sciences. *Rev Mod Phys* **91**, 045002 (2019).
31. Karniadakis GE, Kevrekidis IG, Lu L et al. Physics-informed machine learning. *Nat Rev Phys* **3**, 422–440 (2021).
32. Wang HC, Fu TF, Du YQ et al. Scientific discovery in the age of artificial intelligence. *Nature* **620**, 47–60 (2023).
33. Momeni A, Rahmani B, Scellier B et al. Training of physical neural networks. *Nature* **645**, 53–61 (2025).
34. Ouyang WH, Shin Y, Liu SW et al. NOEM: efficient and scalable finite element method enabled by reusable neural operators. *Nat Comput Sci* **6**, 417–429 (2026).
35. Cuomo S, Di Cola VS, Giampaolo F et al. Scientific machine learning through physics-informed neural networks: where we are and what's next. *J Sci Comput* **92**, 88 (2022).
36. Wang M, Wang ZF, Liu L et al. Effective suppression of stimulated Raman scattering in half 10 kW tandem pumping fiber lasers using chirped and tilted fiber Bragg gratings. *Photonics Res* **7**, 167–171 (2019).
37. Stihler C, Jauregui C, Kholaf SE et al. Intensity noise as a driver for transverse mode instability in fiber amplifiers. *Photonix* **1**, 8 (2020).
38. Chen Q, Ren S, Liu W et al. Raman oscillation induced by weak internal reflections of fiber devices in high-power fiber amplifiers. *J Lightwave Technol* **42**, 859–864 (2024).
39. Brown DC, Hoffman HJ. Thermal, stress, and thermo-optic effects in high average power double-clad silica fiber lasers. *IEEE J Quantum Electron* **37**, 207–217 (2001).
40. Dong L. Transverse mode instability considering bend loss and heat load. *Opt Express* **31**, 20480–20488 (2023).
41. Schermer RT, Cole JH. Improved bend loss formula verified for optical fiber by simulation and experiment. *IEEE J Quantum Electron* **43**, 899–909 (2007).
42. Lu L, Pestourie R, Yao WJ et al. Physics-informed neural networks with hard constraints for inverse design. *SIAM J Sci Comput* **43**, B1105–B1132 (2021).
43. Anagnostopoulos SJ, Toscano JD, Stergiopoulos N et al. Residual-based attention in physics-informed neural networks. *Comput Methods Appl Mech Eng* **421**, 116805 (2024).

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Author contributions

All authors commented on the manuscript. P.M., Z.W., and J.C. conceived the idea and initiated the research. W.L. and Z.C. proposed the research methodology and performed the theoretical analysis. Z.P. fabricated the customized gain fiber. H.Y. and Y.C. constructed the experimental setup and performed experiments. W.L. wrote the manuscript with the input from all authors.

Competing interests

The authors declare no competing financial interests.

Supplementary information

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