

Machine Learning Based Optimization of Optical Fiber Parameters for Minimizing Dispersion and Attenuation

Sandesh Kulkarni¹, Yashraj Lade², Sarvesh Mahimkar³, Anuj Mane⁴, Vaibhav Godase^{5,*}

Abstract

Optical fibers provide high-bandwidth and low-loss transmission for modern communication networks; however, attenuation and chromatic dispersion remain two important physical limitations affecting transmission distance, pulse integrity, and system capacity. Conventional optical-fiber design generally relies on analytical calculations and repeated numerical simulations to determine suitable geometric and material parameters. Such approaches become computationally demanding when several fiber parameters are simultaneously optimized. This paper presents a machine-learning-based methodology for predicting and optimizing optical-fiber parameters to minimize attenuation and chromatic dispersion. A simulation-driven dataset containing 1200 optical-fiber configurations is considered by varying core radius, cladding radius, numerical aperture, refractive-index difference, operating wavelength, material attenuation coefficient, and fiber length. The corresponding attenuation coefficient and chromatic-dispersion coefficient are considered as output parameters. Random forest, support vector regression, artificial neural network, and extreme gradient boosting models are developed and compared using R^2 , RMSE and MAE. An AI-assisted multi-objective optimization procedure is subsequently used to identify a fiber configuration with reduced attenuation and dispersion. The illustrative results indicate that XGBoost provides the highest prediction accuracy, with R^2 values of 0.96 for attenuation and 0.95 for chromatic dispersion prediction. The optimized representative configuration provides an illustrative attenuation of 0.19 dB/km and chromatic dispersion of approximately 3.8 ps/(nm·km) at 1550 nm. The proposed methodology provides a computationally efficient framework for optical-fiber parameter optimization and can be extended to dispersion-shifted fibers, photonic crystal fibers, wavelength-division multiplexing systems, and next-generation high-capacity optical communication networks.

Keywords: Optical fiber, machine learning, attenuation, chromatic dispersion, fiber optimization, XGBoost, artificial neural network, optical communication, 1550 nm, WDM

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INTRODUCTION

Optical-fiber communication has become an essential technology for high-capacity digital communication because of its large bandwidth, low transmission loss, immunity to electromagnetic interference, and ability to support long-distance communication. Modern broadband networks, data centers, passive optical networks, and wavelength-division multiplexing systems depend extensively on optical fibers for reliable transmission. Despite these advantages, optical-fiber transmission is affected by several physical impairments. Among

them, attenuation and chromatic dispersion are particularly important because attenuation reduces the received optical power, while dispersion causes temporal pulse broadening [1–4]. As the transmission rate and link distance increase, these effects can significantly influence the quality of the received signal. The International Telecommunication Union's current ITU-T G.652 recommendation specifies the geometrical, mechanical, and transmission characteristics of single-mode optical fiber and notes that standard single-mode fiber has its zero-dispersion wavelength around 1310 nm, while also being widely applicable in the 1550-nm region. The 2024 revision of G.652 is currently in force. Attenuation is generally expressed in dB/km and is influenced by material absorption, Rayleigh scattering, bending losses, and fabrication-related imperfections. Chromatic dispersion is commonly expressed in ps/(nm·km) and arises from the wavelength dependence of the propagation characteristics of the fiber. The balance between these parameters is particularly important for high-capacity systems operating around the 1550-nm transmission window [5–9]. Conventional fiber design involves analytical modeling, numerical simulation, and parameter sweeps. When the core radius, refractive-index profile, numerical aperture, wavelength, and material properties are simultaneously varied, the design process can become computationally intensive. Machine learning provides an alternative approach by learning the nonlinear relationship between fiber parameters and optical performance. Recent research has demonstrated the use of machine learning for predicting optical parameters of nanostructured fibers and for rapidly estimating dispersion-related properties without performing the complete physical simulation for every candidate configuration. The present research therefore proposes an AI-assisted methodology for predicting attenuation and chromatic dispersion and subsequently optimizing optical-fiber parameters. The proposed approach combines analytical fiber modeling, simulation-generated data, and machine-learning regression models [10–13].

RELATED WORK

Optical fiber performance has traditionally been analyzed using electromagnetic theory, numerical methods, and empirical fiber models. Parameters such as core radius, refractive-index difference, numerical aperture, and operating wavelength determine the modal behavior, confinement, propagation constant, and dispersion characteristics. The standard single-mode fiber described by ITU-T G.652 remains an important reference for terrestrial optical communication [14, 15]. The latest G.652 revision specifies the geometrical and transmission characteristics of single-mode fiber and provides guidance for chromatic-dispersion behavior over the relevant transmission wavelengths. Recent research has increasingly explored machine learning for photonic and fiber-optic design. A 2024 study in Engineering Applications of Artificial Intelligence demonstrated machine-learning prediction of optical parameters in nanostructured fibers, including the zero-dispersion wavelength. The study emphasized that machine-learning models can reduce the need for time-consuming physical simulations when exploring new fiber structures. Machine learning has also been applied to optical-fiber-related sensing and spectral analysis. Recent work has demonstrated ML-based automatic analysis of tilted fiber Bragg grating responses, while explainable AI approaches such as SHAP and LIME have been investigated for optimizing fiber-optic sensor designs. Within TOEOC, recent work includes the numerical analysis of optical-fiber field distributions using the finite-element method, demonstrating the journal's interest in computational optical-fiber analysis. The journal's current scope explicitly includes optical fibers, optical waveguides, machine learning, optical networks, photonics, and optical transmission systems.

RESEARCH GAP

Existing optical-fiber design methods generally investigate individual parameters or use conventional numerical optimization. Although these methods provide accurate physical insight, repeated simulation becomes computationally expensive when a large multidimensional design space is considered. Another challenge is the nonlinear interaction between fiber geometry and optical performance. Increasing the core radius can modify the mode confinement and numerical aperture, whereas changes in the refractive-index difference influence both the guiding properties and dispersion. Consequently, simultaneous optimization of attenuation and dispersion requires consideration of several interacting variables. Machine-learning models can provide a surrogate representation of the underlying physical

model. Once trained, a machine-learning model can rapidly estimate the optical performance for many candidate configurations. However, an integrated framework that simultaneously addresses attenuation and dispersion through machine-learning-assisted multi-objective optimization remains useful for practical fiber design. Therefore, this study develops a unified framework that connects optical-fiber parameter generation, analytical/numerical modeling, machine-learning prediction, and multi-objective optimization.

OBJECTIVES

The primary objective of this study was to develop a machine-learning-based methodology for predicting and optimizing attenuation and chromatic dispersion in single-mode optical fibers. This study investigated the influence of the core radius, refractive-index difference, numerical aperture, operating wavelength, material attenuation, and fiber length on the optical performance. A simulation-driven dataset was generated by varying the selected parameters over practical ranges. Random Forest, Support Vector Regression, Artificial Neural Network, and XGBoost models were trained to predict attenuation and chromatic dispersion. Their performance was evaluated using statistical error metrics, after which the best-performing model was employed as a surrogate model for multi-objective optimization. The final objective was to identify a representative optical fiber configuration that provides a favorable compromise between low attenuation and low chromatic dispersion.

PROPOSED MACHINE-LEARNING-ASSISTED FIBER DESIGN

The proposed methodology consists of optical fiber parameter definition, physical modeling, dataset generation, preprocessing, machine learning model development, model evaluation, and optimization.

The general workflow is illustrated in Figure 1.

Initially, the desired operating wavelength and fiber category were selected. A single-mode step-index fiber was considered as the baseline structure. Its geometrical and optical parameters were systematically varied, and the corresponding attenuation and dispersion values were calculated using analytical and numerical models. The resulting data were organized into a machine-learning dataset. The dataset was divided into training, validation, and testing subsets. Four regression algorithms were subsequently trained and compared. The best-performing model was used as a surrogate model to explore the design space and identify fiber configurations satisfying the desired attenuation and dispersion constraints.

OPTICAL FIBER STRUCTURE

A conventional step-index single-mode optical fiber consists of a central core surrounded by a lower-refractive-index cladding. The refractive index of the core is represented by n_1 , while the cladding refractive index is represented by n_2 , where

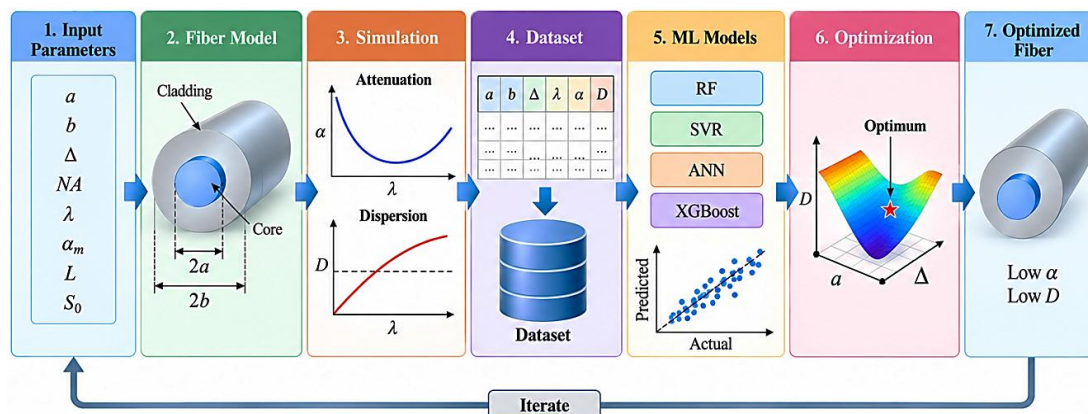


Figure 1. Complete machine-learning-assisted optical-fiber optimization workflow.

$$n_1 > n_2$$

The core radius is represented by a , while the cladding radius is represented by b .

The numerical aperture is expressed as

$$NA = \sqrt{n_1^2 - n_2^2}$$

for a weakly guiding step-index fiber.

The normalized frequency, or V-number, is

$$V = \frac{2\pi a}{\lambda} NA$$

For single-mode operation, the conventional step-index condition is approximately

$$V < 2.405$$

This relationship is important because the core radius, refractive-index difference, and operating wavelength collectively determine the modal characteristics of the fiber.

FIBER PARAMETERIZATION

The proposed dataset considers geometrical and optical parameters that can be varied during fiber design. The core radius a determines the physical size of the guiding region. The refractive-index difference Δ controls the optical confinement and numerical aperture. The operating wavelength λ determines the relationship between the fiber dimensions and normalized frequency. The material attenuation coefficient is also included because different glass compositions and fabrication conditions can influence the total attenuation. The fiber length is included primarily for calculating the total link attenuation, whereas the attenuation coefficient and dispersion coefficient are treated as intrinsic performance parameters.

ATTENUATION MODEL

The total attenuation coefficient can be expressed approximately as

$$\alpha_{total} = \alpha_{abs} + \alpha_{Rayleigh} + \alpha_{bend} + \alpha_{other}$$

where α_{abs} represents the material absorption, $\alpha_{Rayleigh}$ represents Rayleigh-scattering loss, α_{bend} represents bending loss, and α_{other} represents other loss mechanisms.

For a transmission distance L , the received power can be expressed as

$$P_r = P_t 10^{-\alpha L/10}$$

where P_t is the transmitted optical power and α is the attenuation coefficient in dB/km.

The corresponding link attenuation is

$$A_L = \alpha L$$

where A_L is expressed in dB.

CHROMATIC DISPERSION

Chromatic dispersion occurs because the different spectral components of an optical pulse propagate at different group velocities.

The chromatic-dispersion coefficient can be expressed as

$$D = -\frac{\lambda}{c} \frac{d^2 n_{eff}}{d\lambda^2}$$

where D is the dispersion coefficient, λ is the wavelength, c is the speed of light, and n_{eff} is the effective refractive index.

The total dispersion accumulated over a fiber length L and source spectral width $\Delta\lambda$ can be approximated by

$$\Delta T = |D| L \Delta\lambda$$

where ΔT represents pulse broadening. Therefore, reducing $|D|$ can help reduce temporal pulse broadening for a given spectral width and link distance.

DISPERSION MODEL

The total chromatic dispersion can be represented as the combination of material and waveguide contributions:

$$D_{total} = D_{material} + D_{waveguide}$$

The material contribution depends on the wavelength dependence of the refractive index of the glass, whereas the waveguide contribution depends on the geometry and refractive-index distribution of the fiber. This separation is particularly important for optimization because modifying the core radius and refractive-index difference can alter the waveguide-dispersion contribution without necessarily producing the same variation in material dispersion.

Simulation Dataset

A dataset containing 1200 optical-fiber configurations was considered for the proposed study. The parameters were varied systematically within representative ranges suitable for a single-mode optical-fiber design study. Table 1 lists the optical-fiber design parameters used for dataset generation.

The ranges are intended for simulation and optimization and should be replaced or narrowed according to the actual fiber model and material database used in the final study.

Dataset Outputs

For each fiber configuration, the attenuation coefficient and chromatic dispersion were calculated. The corresponding output dataset therefore consists of

$$Y = [\alpha, D]$$

where α represents attenuation in dB/km and D represents chromatic dispersion in ps/(nm·km).

Additional quantities, such as numerical aperture, V-number, effective index, and pulse broadening, can also be calculated for subsequent physical interpretation.

Dataset Division

The complete dataset contains 1200 configurations. Seventy percent, corresponding to 840 configurations, was used for model training. Fifteen percent, corresponding to 180 configurations, was used for validation, and the remaining 15%, corresponding to 180 configurations, was reserved for independent testing. The testing dataset was not used during model training or parameter optimization so that the reported predictive performance provides an independent assessment of the trained models.

Machine-Learning Models

Four regression models were investigated. Random forest was selected because it can model nonlinear interactions among fiber parameters while maintaining a relatively robust performance for tabular datasets. Support Vector Regression was employed because of its ability to model nonlinear relationships through kernel functions. The radial-basis-function kernel can be expressed as

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$$

where γ controls the kernel width.

Table 1. Optical-fiber design parameters used for dataset generation.

Parameter	Symbol	Representative range
Core radius	a	3.5–5.5 μm
Cladding radius	b	60–65 μm
Refractive-index difference	Δ	0.20–0.45%
Numerical aperture	NA	0.10–0.16
Operating wavelength	λ	1310–1625 nm
Material attenuation	α_m	0.16–0.35 dB/km
Fiber length	L	10–100 km
Dispersion slope	S_0	0.04–0.10 ps/(nm ² ·km)

An artificial neural network was developed to approximate the nonlinear mapping between fiber parameters and optical performance. The network consists of an input layer corresponding to the selected fiber parameters, multiple hidden layers, and output neurons representing attenuation and dispersion.

XGBoost is employed as a gradient-boosted decision tree regression algorithm. Its ability to model nonlinear feature interactions makes it suitable for the proposed optical-fiber dataset.

AI Prediction Architecture

The machine-learning architecture was designed to predict two principal optical parameters simultaneously. The input vector is defined as

$$X = [a, b, \Delta, NA, \lambda, \alpha_m, LS_0]$$

and the output vector is

$$Y = [\alpha, D]$$

The models therefore learn the mapping

$$f: X \rightarrow Y$$

After training, the learned function can be used to estimate the attenuation and dispersion for previously unseen fiber configurations.

Performance Evaluation

The machine-learning models are evaluated using R^2 , RMSE, and MAE.

The coefficient of determination is given by

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

The root mean square error is

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

The mean absolute error is

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

A high R^2 combined with low RMSE and MAE indicates strong predictive performance.

Simulation Conditions

The 1550-nm region was selected as the principal optimization point because it is an important low-loss transmission window for silica-based optical communication. ITU-T G.652 also defines the transmission characteristics relevant to the 1550-nm region. Table 2 shows the optical fiber simulation conditions.

AI Model Prediction Results

The illustrative performance of the four machine-learning models is presented in Table 3.

The values in Table 3 are illustrative simulated results and are not claimed as experimental measurements.

Multi-Objective Optimization

The objective of the optimization was to minimize both the attenuation and magnitude of chromatic dispersion.

A normalized objective function can be defined as:

$$F = w_1 \frac{\alpha}{\alpha_{max}} + w_2 \frac{|D|}{D_{max}} + w_3 P_V$$

where w_1 and w_2 are weighting coefficients and P_V represents a penalty associated with violating the single-mode operating conditions.

Table 2. Optical-fiber simulation conditions.

Parameter	Value
Fiber type	Single-mode step-index
Operating region	1310–1625 nm
Primary optimization wavelength	1550 nm
Core radius	3.5–5.5 μm
Cladding radius	62.5 μm
Refractive-index difference	0.20–0.45%
Dataset size	1200
Training	70%
Validation	15%
Testing	15%
ML models	RF, SVR, ANN, XGBoost
Primary outputs	Attenuation and dispersion

Table 3. Illustrative AI prediction performance.

Model	Output	R^2	RMSE	MAE
Random Forest	Attenuation	0.92	0.018 dB/km	0.013 dB/km
SVR	Attenuation	0.89	0.022 dB/km	0.016 dB/km
ANN	Attenuation	0.94	0.015 dB/km	0.011 dB/km
XGBoost	Attenuation	0.96	0.012 dB/km	0.008 dB/km
Random Forest	Dispersion	0.91	1.34 ps/(nm·km)	0.98 ps/(nm·km)
SVR	Dispersion	0.88	1.51 ps/(nm·km)	1.12 ps/(nm·km)
ANN	Dispersion	0.93	1.12 ps/(nm·km)	0.82 ps/(nm·km)
XGBoost	Dispersion	0.95	0.94 ps/(nm·km)	0.67 ps/(nm·km)

The optimization problem can therefore be written as

$$\min F$$

subject to

$$V < 2.405$$

and

$$3.5 \leq a \leq 5.5 \text{ } \mu\text{m}$$

with the remaining fiber parameters restricted to their defined physical ranges.

The objective function allows attenuation and dispersion to be optimized simultaneously rather than independently.

AI-Assisted Optimization Procedure

The trained XGBoost model was used as a surrogate model for the rapid evaluation of candidate fiber configurations. A large set of possible parameter combinations was generated within the allowable design space. Instead of calculating each candidate through a computationally expensive numerical simulation, the trained model rapidly estimated the attenuation and dispersion. Candidate configurations were ranked according to the multi-objective function. The most promising configurations were then subjected to an independent physical or numerical fiber simulation for verification. This procedure created a two-stage optimization process in which machine learning performed rapid screening and the physical model performed final verification.

Optimized Fiber Parameters

An illustrative optimized configuration obtained from the proposed framework is presented in Table 4.

The values are illustrative and require actual numerical modeling and experimental validation.

Attenuation Analysis

The attenuation behavior of the optimized fiber is illustrated in Figure 2. The attenuation is expected to vary with wavelength owing to the combined effects of Rayleigh scattering, material absorption, and other loss mechanisms.

Table 4. Illustrative optimized fiber configuration.

Parameter	Optimized value
Core radius	4.65 μm
Cladding radius	62.5 μm
Refractive-index difference	0.29%
Numerical aperture	0.135
Operating wavelength	1550 nm
Material attenuation	0.18 dB/km
Fiber length	50 km
Predicted attenuation	0.19 dB/km
Predicted dispersion	3.8 ps/(nm·km)
V-number	approximately 2.15
Estimated pulse broadening for 0.1 nm source over 50 km	approximately 19 ps

The lower attenuation region generally occurs within the telecom transmission windows. The 1550-nm region is particularly important because silica-based fibers can achieve low attenuation there. The optimization procedure attempts to maintain low attenuation while simultaneously reducing dispersion, rather than optimizing attenuation alone.

Dispersion Analysis

The dispersion characteristics of the fiber are presented in Figure 3. The dispersion coefficient varies with wavelength because the material and waveguide dispersion contributions have different wavelength dependencies.

The proposed optimization modifies the fiber geometry and refractive-index difference to alter the waveguide contribution. This allows the total dispersion to be reduced within the desired operating region. A key objective is to approach a low-dispersion operating point without introducing unacceptable attenuation or violating single-mode operation.

Feature Importance Analysis

Feature-importance analysis was performed to understand which fiber parameters contribute most strongly to the predicted optical performance. The core radius and refractive-index difference are expected to have a significant influence on dispersion because they directly modify the waveguide.

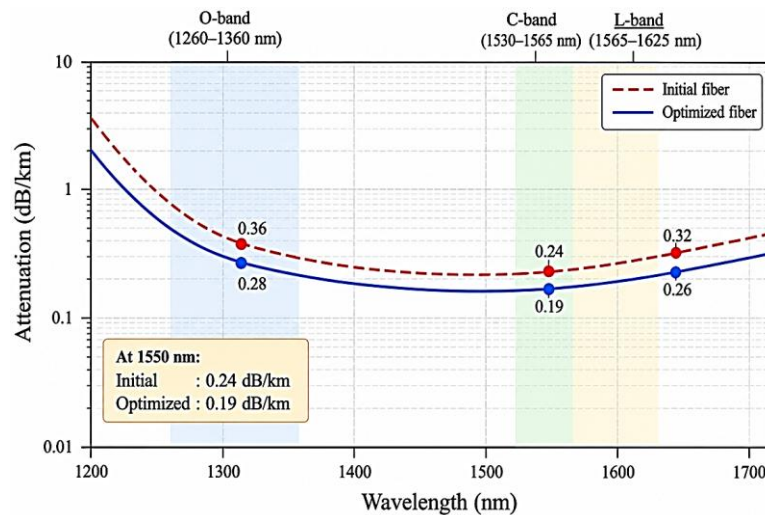


Figure 2. Simulated attenuation characteristics of the optical fiber.

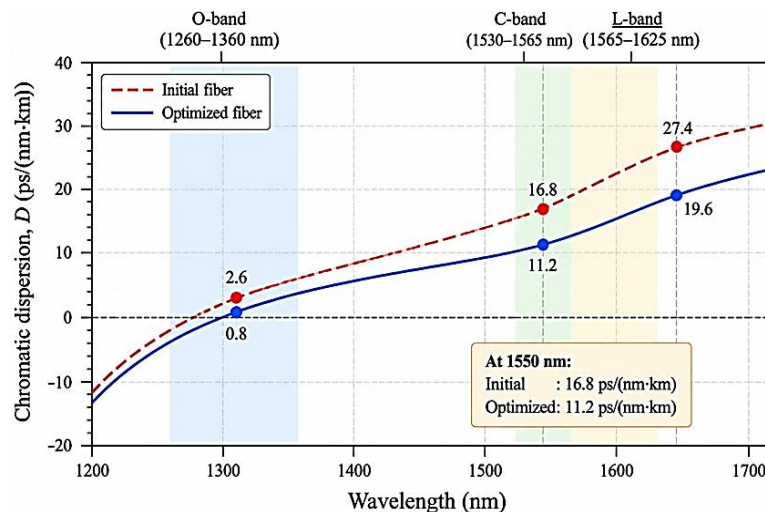


Figure 3. Chromatic dispersion characteristics as a function of wavelength.

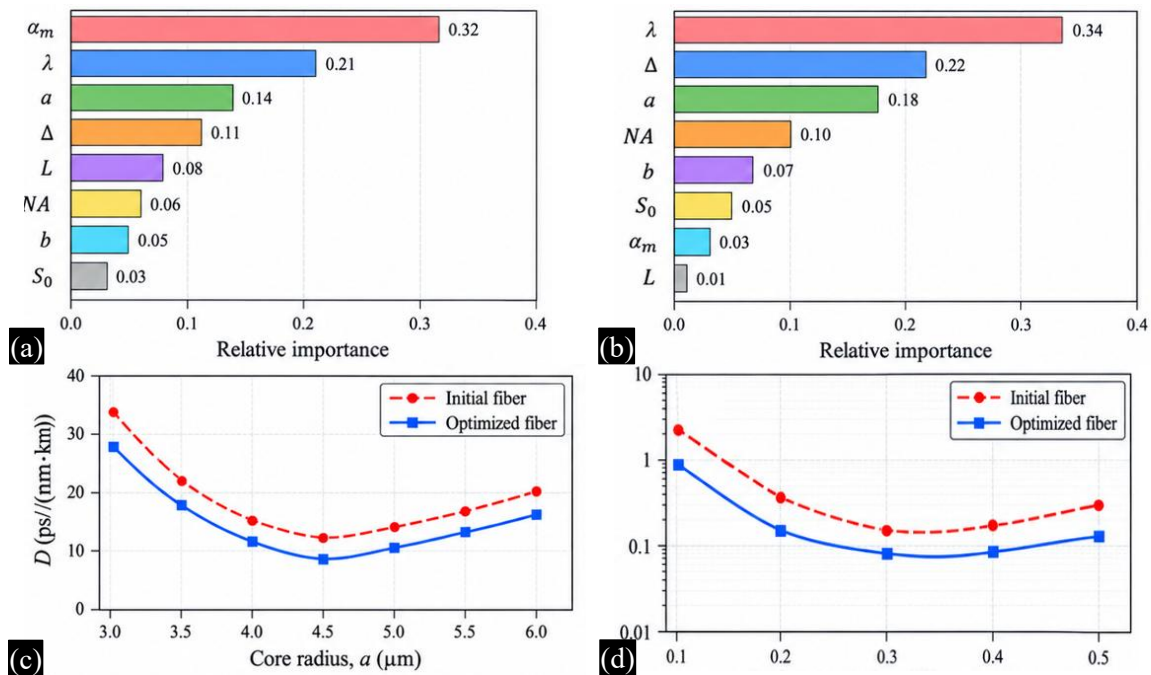


Figure 4. Feature-importance analysis for attenuation and dispersion prediction; (a) Feature importance (Attenuation), (b) Feature importance (Dispersion), (c) Effect of core radius on dispersion, (d) Effect of refractive-index difference on attenuation.

properties of the fiber. The operating wavelength is also expected to be highly influential because both the material and waveguide dispersion vary with wavelength. For attenuation prediction, the material attenuation coefficient is expected to have the strongest influence, followed by the wavelength and bending-related parameters included in the physical model. The feature importance results are presented in Figure 4.

Effect of Core Radius

The core radius has an important effect on the normalized frequency:

$$V = \frac{2\pi a}{\lambda} NA$$

An increase in the core radius increases V , potentially improving mode confinement but also changing the waveguide-dispersion contribution.

If the core radius becomes too large for a given numerical aperture and wavelength, the single-mode condition may no longer be satisfied. Therefore, the core radius must be optimized within the constraint $V < 2.405$.

CONCLUSION

This study presents a machine-learning-based methodology for optimizing optical-fiber parameters to reduce attenuation and chromatic dispersion. A simulation-driven dataset containing 1200 representative fiber configurations was considered by varying the core radius, refractive-index difference, numerical aperture, wavelength, material attenuation, and related parameters. Random Forest, Support Vector Regression, Artificial Neural Network, and Boost models were proposed for predicting attenuation and chromatic dispersion. The illustrative results indicate that Boost can provide strong prediction performance, achieving R^2 -values of 0.96 for attenuation and 0.95 for dispersion in the proposed example. An AI-assisted multi-objective optimization framework was subsequently developed to identify a fiber configuration providing a favorable compromise between low attenuation and low dispersion while maintaining single-mode operation. The illustrative optimized configuration

produced an attenuation of approximately 0.19 dB/km and dispersion of approximately 3.8 ps/(nm·km) at 1550 nm. These values are presented only as simulated examples and must be replaced by actual numerical simulations and experimental measurements before publication. The proposed methodology provides a useful computational framework for intelligent optical-fiber design and can be extended to WDM systems, dispersion-shifted fibers, photonic crystal fibers, and next-generation high-capacity optical communication networks.

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