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TOPIC

AI Applications in Characterizing and Enhancing Optical Fiber Performance

Presented and evaluated on: 10 / 06 / 2025, by the jury composed of:

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بسم الله الرحمن الرحيم

Thanks

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إلى والدي

نبض قلبي الأول، وملهمي في كل لحظة. شكراً لك على دعمك المستمر، وكلماتك التي كانت وقوداً في أوقات التعب. كنتَ، وما زلت، قدوتي في الجدّ والاحتمال...

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رفيقات الدرب والمواقف، شاركتنّني الحلم، والضغط، والتعب، والضحك. شكراً , ربى آية, نسرين, سكينة,اكرام لكنَّ على المساندة التي لن تُنسى...

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رحاب نرجس

Index

Thanks……I
الاهداء……..II
اهداء……...…III
Index……....IV
list of figures…….....VI
List of tables…….....VIII
List of abbreviations……IX
General Introduction……X
Chapter1: Photonic crystal fiber 3
1.1.Introduction……..4
1.2.Historical background……..4
1.3.Photonic crystals……...5
1.3.1.Definition.....5
1.3.2.Types of photonic crystals 6
1.3.3.Main photonic crystal parameters.....7
1.4.Optical fiber……..8
1.4.1.Definition.....8
1.4.2.Structure and function 8
1.4.3.Applications.....8
1.5.Photonic -crystal fiber……..…….9
1.5.1.Structure and Light guidance mechanisms.....9
1.5.2.Parameters of photonic crystal fibers 10
1.5.3.Fabrication techniques.....10
1.5.4.Applications of photonic crystal fibers.....10
1.6.Conclusion……..11
Chapter 2: Artificial intelligence(AI) technique for optical fiber characterization and enchancement.....12
2.1 Introduction……13
2.2 Review of AI techniques in fiber optics…….13
2.2.1.Machine learning in fiber optics.....14
2.2.2.Deep learning for fiber analysis.....16
2.2.3. Optimization algorithms.....19
2.3 AI knowledge cycle for optical fiber optimization…….20
2.3.1.Data acquisition and sources 20
2.3.2.Feature engineering and extraction.....20
2.3.3.Data quality and preprocessing.....20

2.4. AI applications in optical fiber technology……21
2.4.1 Photonic crystal fibers characterization 21
2.4.2 Performance optimization 22
2.4.3 Fault detection and monitoring.....23
2.4.4 AI for real-time diagnosis of Fiber networks.....23
2.5 Challenges and limitations……..23
2.6.Conclusion……..24
Chapter 3: Modeling and simulation of photonic crystal fiber……..26
3.1.Introduction ……27
3.2.PCF modeling using COMSOL Multiphysics……27
3.2.1.Description of the PCF structure 27
3.2.2.Extraction of optical properties 29
3.2.3.Results COMSOL.....30
3.3.Modeling photonic crystal fibers using ANNs……...35
3.3.1. Motivation for using ANNs as a surrogate model ……..35
3.4.Numerical results and computation runtimes……37
3.4.1.Effective index ($\boldsymbol{neff}$).....37
3.4.2. Effective mode area (A_eff)…….....38
3.4.3.Dispersion(D) 39
3.4.4.Confinement loss ($\boldsymbol{\alpha c}$) 40
3.5.Conclusion……..42
General Conclusion.....43
Appendix.....46
References.....51
Abstracts 56

List of Figures

Chapter 01

Figure 1. 1 summarizing the key milestones of photonic crystals fibers 5
Figure 1. 2 shows schematic views of variety of photonic crystals with dimensions ranging from 1 to 3. 7
Figure 1. 3 Optic fiber cables. 8

Chapter 02

Figure 2. 1 Analysis of optical signals using SVM algorithm 15
Figure 2. 2 Supervised Learning Workflow-Training with labeled Data to Predict known Categories 17
Figure 2. 3 Unsupervised Learning Workflow-Data Clustering Without Labeled Output 17
Figure 2. 4 Flowchart of Neural Network-Based Optical Fiber Fault Detection System 19

Chapter 03

Figure 3. 1 The hexagonal structure using COMSOL 28
Figure 3. 2 The mesh of the hexagonal structure. 29
Figure 3. 3 Simulation of mode analysis. 30
Figure 3. 4 Variation of effective index with wavelength for various values of pitch and diameter. 31
Figure 3. 5 Variation of dispersion with wavelength for various values of pitch and diameter 32
Figure 3. 6 Variation of birefringence with wavelength for various values of pitch and diameter. 33
Figure 3. 7 Variation of effective mode area with wavelength for various values of pitch and diameter 34
Figure 3. 8 Cross-section of a solid-core hexagonal PCF with five rings of air holes. 36
Figure 3. 9 ANN representation with one input layer (5 input nodes), three hidden layers (50 nodes in each layer), and one output layer (4 output nodes) 37
Figure 3. 10 The scatter plot of training dataset produced by ANN comparing $neff$ values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x). 38
Figure 3. 11 The scatter plot of training dataset produced by ANN comparing $Aeff$ values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x**)** 39
Figure 3. 12 The scatter plot of training dataset produced by ANN comparing Dispersion values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x**)** 40

Figure 3. 13 a. The scatter plot of training dataset produced by ANN comparing αc values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x).....41
Figure 3.13.b. Actual values of c from the in logarithm…….42

List of Table

Table 3.1: The parameters of the hexagonal structure ……28

List of abbreviations

FCFs: Photonic Crystal Fibers

AI: Artificial Intelligence

ML: Machine Learning

DL: Deep Learning

DNN: Deep Neural Network

ANN: Artificial Neural Network

GA: Genetic Algorithms

FEM: Finite Element Method

PSO: Particle Swarm Optimization

GBM: Gradient Boosting Machines

SVMs: Support Vector Machines

MLP: Multilayer Perceptron

PML: Perfectly Matched Layer

General Introduction

In the era of the digital revolution and the growing global demand for high-speed and efficient data transmission, optical fibers have emerged as a fundamental component of modern communication infrastructure. With their unique characteristics such as high bandwidth, low spectral loss, and immunity to electromagnetic interference-optical fibers have become the preferred medium for data transmission in telecommunication networks, sensing systems, and advanced photonic technologies. As modern applications demand increasingly complex performance specifications, enhancing the optical and structural properties of fibers becomes necessary, particularly in terms of dispersion control, spectral efficiency, propagation modes, and nonlinear effects.

Although traditional modeling and simulation techniques have advanced considerably, they often remain computationally intensive and time-consuming, especially when dealing with complex structures such as Photonic Crystal Fibers (PCFs). This has created a growing need to integrate Artificial Intelligence (AI) tools to accelerate the design and optimization process while maintaining high levels of precision and efficiency.

Recent years have witnessed rapid developments in AI technologies, particularly in Machine Learning (ML), Deep Learning (DL), and evolutionary algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). These techniques have demonstrated remarkable ability in handling complex, nonlinear design problems, predicting optical properties from limited datasets, and even replacing conventional numerical solvers through the use of surrogate models based on Artificial Neural Networks (ANNs).

This thesis aims to explore the application of AI in the characterization and enhancement of optical fiber performance by integrating intelligent learning techniques with advanced simulation tools such as COMSOL Multiphysics. It highlights the role of neural networks in predicting optical parameters, as well as the effectiveness of evolutionary optimization algorithms in tuning the geometric structure of optical fibers to achieve optimal performance. The significance of this study lies in demonstrating how AI can effectively contribute to the development of

next-generation optical fiber technologies by improving their performance, reliability, and adaptability across a wide range of scientific and industrial applications.

The script contains three chapters:

- The first chapter offers a comprehensive introduction to photonic crystals and photonic crystal fiber encompassing their characteristics and applications.
- The second chapter discusses the use of artificial intelligence techniques in analyzing and improving the performance of optical fibers, as well as the challenges faced this field.
- The third chapter focuses on the use of COMSOL Multiphysics and artificial Neural Networks for modeling and simulating PCFs.

Finally, our work will culminate in a comprehensive conclusion summarizing the findings obtained.

Chapter1:
Photonic crystal fiber

1.1. Introduction

PCFs, also known as microstructured or holey fibers, represent a significant innovation in optical fiber technology. Unlike conventional fibers that rely on total internal reflection within a uniform core, PCFs employ a periodic arrangement of microscopic air holes running along their length to guide light in unique and highly controllable ways. This structural versatility enables the design of fibers with tailored dispersion properties, endlessly single-mode behavior, high nonlinearity, and even light guidance in low-index cores or air. In recent years, PCFs have attracted considerable attention for their potential in a wide range of applications, including nonlinear optics, super continuum generation, sensing, and high-power laser delivery. This chapter provides a detailed overview of the principles, types, fabrication techniques, and emerging applications of photonic-crystal fibers, laying the foundation for understanding their role in advanced optical systems.

1.2. Historical background

The development of PCFs is rooted in the broader field of photonic crystals, a concept that emerged in the late 1980s. In 1987, Eli Yablonovitch and Sajeev John independently introduced the idea of periodic dielectric structures that could control the propagation of light by creating photonic band gaps—frequency ranges in which electromagnetic waves are forbidden to propagate. This marked a turning point in optics, opening the door to a new class of materials capable of manipulating light in much the same way that semiconductors control electron flow.

Inspired by this ground-breaking concept, researchers began exploring how similar principles could be applied to optical fibers. A major milestone came in 1996 when Philip Russell and his team at the University of Bath in the United Kingdom successfully fabricated the first photonic-crystal fiber. Using a technique known as *stack-and-draw*, they arranged silica capillaries in a regular pattern and drew them into a fiber with a microstructured cladding containing a periodic array of air holes. This innovation enabled novel light-guiding mechanisms, such as endlessly single-mode operation and highly controllable dispersion, which was not possible before in conventional step-index fibers.

The introduction of PCFs sparked a rapid wave of research and development. Throughout the early 2000s, new fiber designs were proposed, including hollow-core

PCFs guided by the photonic bandgap effect, which allow light to propagate through air rather than solid glass significantly reducing absorption and nonlinear effects. These advances expanded the utility of PCFs into new domains, including high-power laser transmission, nonlinear optics, and precision sensing.

Today, photonic-crystal fibers are recognized as a key technology in modern photonics. Their evolution continues with innovations in fabrication techniques, materials, and hybrid structures, paving the way for applications in telecommunications, biomedical diagnostics, environmental monitoring, and quantum technologies. The historical development of PCFs highlights the ongoing synergy between theoretical concepts and practical engineering in the pursuit of advanced optical systems.

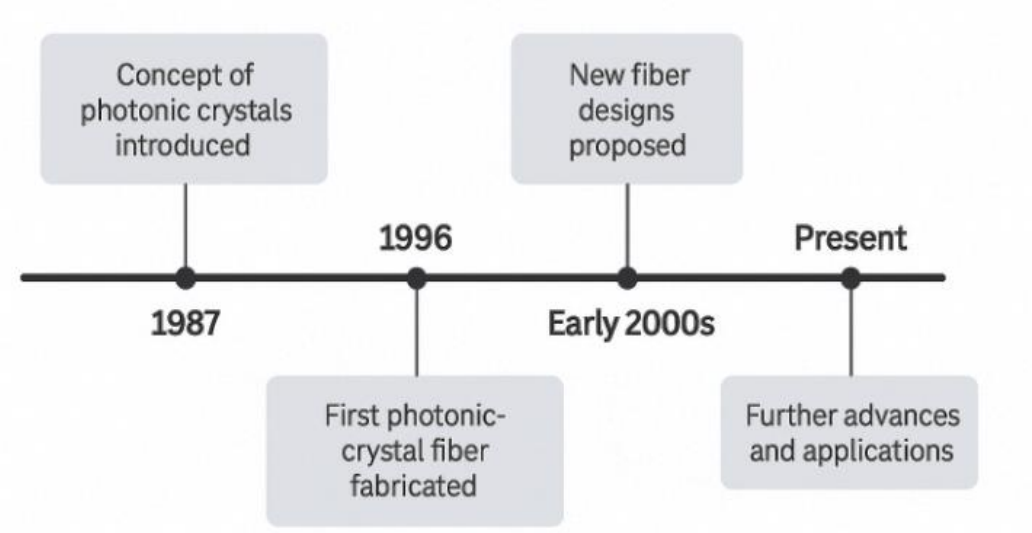


Figure 1. 1:summarizing the key milestones of photonic crystals fibers.

1.3. Photonic crystals

1.3.1. Definition

A photonic crystal is a special kind of material where the refractive index (which determines how light travels through a material) changes in a regular, repeating pattern. This pattern, called a lattice, has a spacing (called the lattice constant) that is about the same size as the wavelength of the light.

What makes photonic crystals unique is the **strong difference** in refractive index between the materials in the structure often more than double. This strong contrast

allows the crystal to **reflect, guide, or block certain wavelengths of light**, much like how a semiconductor controls the flow of electrons. Because of this, photonic crystals are used to **trap light, slow it down, or redirect it** in very precise ways. They are used in optical fibers, sensors, LEDs, and even in developing future optical computers.

Photonic crystals can indeed be classified based on the number of dimensions in which their refractive index is periodically varied.

1.3.2. Types of photonic crystals

Photonic crystals are grouped into **three types** based on how the periodic structure is arranged:

a. One-Dimensional (1D) Photonic Crystals

- **Periodicity** in one direction only.
- Example: A stack of alternating thin layers of two different materials (like dielectric mirrors or Bragg reflectors).
- **Application:** Mirrors in lasers, optical coatings.

b. Two-Dimensional (2D) Photonic Crystals

- **Periodicity** in two directions.
- Often made of a regular pattern of holes or rods arranged in a flat plane (like a honeycomb or square lattice).
- **Light moves freely in one direction**, but is controlled in the other two.
- **Application:** Optical waveguides, sensors, photonic chips.

c. Three-Dimensional (3D) Photonic Crystals

- **Periodicity** in all three directions.
- These are more complex to fabricate but can control light in **all directions**.
- **Application:** Advanced optical materials, full light control, potentially in future optical computers.

Understanding photonic crystal parameters is essential for designing and analyzing their optical properties.

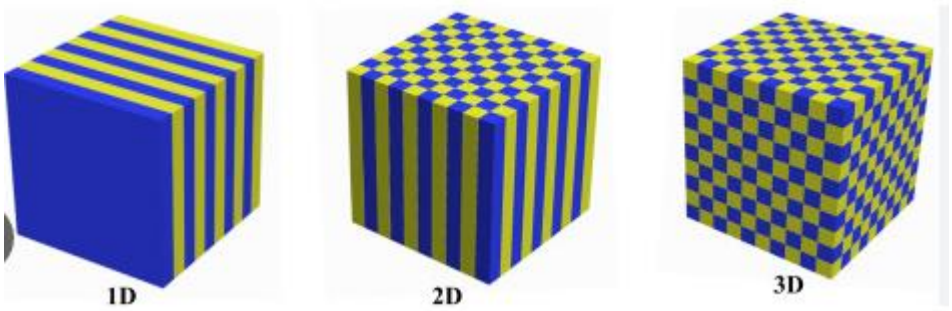


Figure 1.2: Shows schematic views of variety of photonic crystals with dimensions rranging from 1 to 3.

1.3.3. Main photonic crystal parameters

1. **Lattice constant (a)**

It is the distance between two repeating units in the crystal structure. It defines the periodicity and is usually on the order of the operating wavelength. Example: For visible light, *a* might be ~200–600 nm.

2. **Refractive index contrast**

The Refractive Index Contrast is the difference in refractive index between the materials in the structure. Then, high contrast (e.g., $n_1 = 1.5$, $n_2 = 3.5$) is essential for creating strong photonic bandgaps (regions where light cannot pass).

3. **Filling factor (f)**

It is the fraction of one material in a unit cell (e.g., how much space the holes or rods take up). It influences bandgap size and light propagation behavior.

4. **Photonic bandgap**

A range of wavelengths (or frequencies) where light cannot propagate through the crystal. The size and position of the bandgap depend on lattice constant, refractive index contrast, and geometry.

5. **Symmetry and Geometry**

The shape of the pattern (square, triangular, hexagonal, etc.) affects the **directionality** and **anisotropy** of the photonic bandgap. In 2D crystals: circular holes vs. rods, and their arrangement, matter a lot.

6. **Dimensionality (1D, 2D, 3D)**

As covered earlier, the number of periodic directions determines the control over light and design complexity.

1.4. Optical fiber

1.4.1. Definition

An optical fiber is a thin, flexible strand made of glass or plastic that transmits light signals over long distances. These fibers are designed to carry information in the form of light pulses, allowing for high-speed data transmission with minimal loss.

1.4.2. Structure and function

An optical fiber consists of three main components

1. **Core**: The innermost part where light travels. It's made of glass or plastic with a high refractive index.
2. **Cladding**: Surrounds the core and has a lower refractive index, causing light to reflect back into the core through a process called **total internal reflection**. This keeps the light confined within the core.
3. **Coating**: A protective outer layer that shields the fiber from physical damage and moisture.

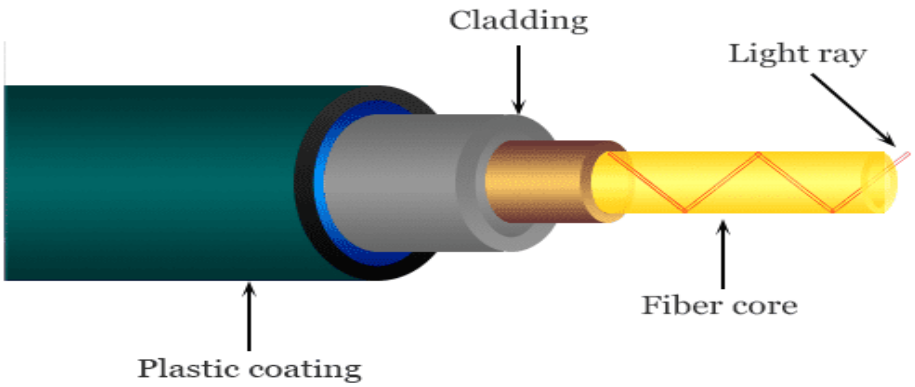


Figure 1.3: Optic fiber cables.

1.4.3. Applications

Optical fibers are widely used in various fields such as:

- **Telecommunications**: For internet, telephone, and television services.
- **Medical**: In devices like endoscopes for internal imaging.
- **Industrial**: For sensors and data transmission in harsh environments.
- **Military and Aerospace**: Due to their resistance to electromagnetic interference.

1.5. Photonic -crystal fiber

PCF is a specialized optical fiber that incorporates a microstructured arrangement of air holes running along its length. These air holes are typically organized in a periodic pattern around the fiber's core, forming a photonic crystal structure. This unique design allows PCFs to guide light in ways that differ from conventional optical fibers, offering enhanced control over light propagation.

1.5.1. Structure and light guidance mechanisms

PCFs are characterized by their cross-sectional structure, which consists of:

- **Core**: The central region where light is confined. Depending on the design, the core can be solid or hollow.
- **Cladding**: Surrounding the core, the cladding contains a periodic array of air holes that create the photonic crystal effect.

There are two primary mechanisms by which PCFs guide light:

1. **Index-Guiding PCFs**: These fibers have a solid core with a higher refractive index than the surrounding cladding. The periodic air holes in the cladding lower its average refractive index, enabling light confinement in the core through total internal reflection, similar to conventional fibers but with greater design flexibility.
2. **Photonic Bandgap (PBG) PCFs**: These fibers can have a hollow or lower-index core. Light is confined in the core not by total internal reflection but by the photonic bandgap effect, where certain wavelengths are prohibited from propagating in the cladding, thus trapping them in the core.

1.5.2. Parameters of photonic crystal fibers

Understanding PCFs involves several critical parameters:

a. **Lattice constant (Λ)**: The center-to-center distance between adjacent air holes in the cladding. It determines the periodicity of the photonic crystal structure.

b. **Air Hole diameter (d)**: The size of the air holes, which, along with Λ, influences the fiber's optical properties.

c. **d/Λ Ratio**: The ratio of air hole diameter to lattice constant. This dimensionless parameter is crucial in defining the fiber's guiding properties and the existence of photonic bandgaps.

d. **Refractive index contrast**: The difference in refractive index between the core and the cladding. In PCFs, this contrast is engineered through the air hole structure rather than material composition.

1.5.3. Fabrication Techniques

The production of PCFs typically involves:

1. **Preform fabrication**: Creating a large-scale model of the fiber's cross-sectional structure, often by stacking capillary tubes and rods to form the desired pattern of air holes.

2. **Fiber drawing**: Heating the preform and drawing it into a thin fiber while maintaining the relative dimensions of the structure, resulting in a fiber with the intended microstructure along its length.

1.5.4. Applications of photonic crystal fibers

PCFs offer unique properties that make them suitable for various advanced applications:

- **Supercontinuum generation**: Their high nonlinearity and tailored dispersion profiles enable the generation of broad-spectrum light sources used in spectroscopy and metrology.

- **High-Power Transmission**: Hollow-core PCFs can transmit high-power laser beams with reduced nonlinear effects and material damage.

- **Sensing**: The ability to fill the air holes with gases or liquids allows PCFs to function as sensitive detectors for environmental monitoring and biomedical applications.
- **Telecommunications**: PCFs can be designed to have low dispersion and loss characteristics, making them suitable for long-distance data transmission.

1.6. Conclusion

PCFs represent a significant advancement in fiber optics, offering unique and highly customizable properties that surpass the capabilities of conventional optical fibers. Their engineered microstructures allow precise control over light propagation, enabling tailored dispersion, enhanced nonlinearity, and specific polarization characteristics. These features make PCFs ideal for a wide range of advanced applications, including:

- **High-Power Lasers**: PCFs can handle high optical intensities, making them suitable for generating high-power femtosecond pulses and super continuum light source.
- **Telecommunications**: The ability to design PCFs with single-mode operation across broad wavelength ranges ensures excellent beam quality and reduced modal dispersion, benefiting high-speed data transmission.
- **Sensing**: PCFs' microstructured design allows for sensitive detection of gases and liquids, making them valuable in environmental monitoring and biomedical applications.
- **Nonlinear Optics**: The high nonlinearity of PCFs facilitates efficient super-continuum generation and other nonlinear optical processes, expanding their use in spectroscopy and ultrafast optics.

Their versatility and performance position PCFs as a key technology in both research and cutting-edge industrial applications, paving the way for future innovations in photonics.

Chapter 2:
Artificial Intelligence (AI) Technique for Optical Fiber Characterization and Enhancement

2.1. Introduction

In recent years, there has been a significant advancement in integrating AI technologies into the fields of photonics and optics fiber, leading to a paradigm shift in how optical systems are designed, optimized, and operated. Among AI technologies, ML has proven to be an effective tool in addressing the complexities of optical systems. It is employed in the design and optimization of photonic components such as waveguides, lasers, and photonic integrated circuits, accelerating development processes and enhancing performance accuracy beyond what traditional methods can achieve. [19]

In the field of fiber optics, the motivation for adopting AI arises from the increasing challenges associated with fiber characterization and performance optimization. The complexity introduced by nonlinear effects and dispersion, in addition to the vast amount of real-time data generated by modern optical networks, makes manual or purely analytical management insufficient. [20] Here, AI plays a key role by providing intelligent solutions, including automated fault detection, network behavior prediction, and dynamic resource optimization. These capabilities enhance network efficiency, reduce operational costs, and support scalability and adaptability in response to future technological evolution. [21]

2.2. Review of AI techniques in fiber optics

AI has become an essential and increasingly significant component in the field of optical fibers, playing a vital role in the development of communication systems, network management, and modern sensing technologies. The remarkable progress in AI techniques, particularly in ML and DL, has opened up broad opportunities to enhance the performance of optical fiber networks, making them smarter and more adaptive to dynamic changes. [22]

For instance, AI technologies can analyze massive volumes of data transmitted through optical networks in real time, enabling intelligent and rapid decision-making to optimize network performance, predict potential faults, and allocate resources more efficiently. [23]

2.2.1. Machine Learning in Fiber Optics

a. Brief overview of machine learning:

ML has become a transformative tool in the field of fiber optics, enabling smarter, more efficient, and predictive systems. Its integration into optical communication and sensing systems addresses key challenges such as performance optimization, fault detection, and data-driven network management.

ML is a prominent branch of AI that focuses on developing algorithms capable of learning from data and identifying patterns to make accurate decisions or predictions without explicit programming. In the field of optical fibers, ML serves as a powerful tool for processing complex data obtained from measurement and monitoring devices such as Optical Time Domain Reflectometers (OTDR) thereby enhancing fiber characterization, performance prediction, and intelligent fault detection. [24]

b. Types of machine learning

- **Supervised learning**

This type of learning relies on labeled data, where the input is associated with known outputs. It is widely used to train models that predict specific parameters such as dispersion, attenuation, or loss in optical fibers. Algorithms such as regression, neural networks, and support vector machines (SVMs) are commonly employed in this context. [25]

- **Unsupervised learning**

Used when labeled data is not available, this approach helps uncover hidden patterns or clusters in data. It is particularly useful for detecting unknown faults or analyzing signal distributions within the fiber. [26]

- **Semi-supervised learning**

This approach combines both supervised and unsupervised learning, often applied when only a small portion of data is labeled while the rest remains unlabeled. It is ideal in cases where labeled data is scarce or costly to obtain. [27]

c. Common Machine Learning algorithms and models in optical fiber characterization and enhancement

In optical fiber applications, a range of ML algorithms has proven effective for both characterizing fiber properties and enhancing network performance: [25]

- **Support Vector Machines (SVMs)**

SVMs are supervised learning models that find the optimal hyperplane maximizing the margin between different classes in the feature space. This characteristic makes them highly effective for classification tasks. For instance, in fiber optic testing, SVMs have demonstrated over 95% accuracy in distinguishing micro-bends from macro-bends based on Optical Time Domain Reflectometers trace patterns, effectively separating normal from faulty signals. An illustrative SVM example is shown in Figure 2-1.

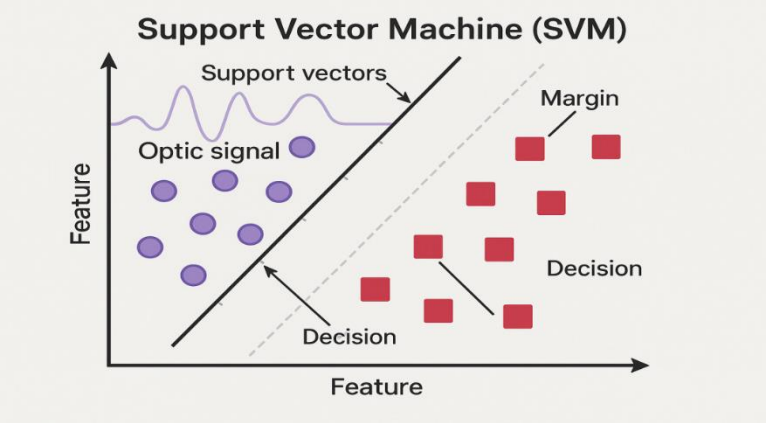


Figure 2. 1: Analysis of optical signals using SVM algorithm

- **Random Forests (RF)**

RF are ensemble learning methods that combine the predictions of numerous decision trees by averaging their outputs, which helps to reduce overfitting and improve robustness to noisy data. For example, in fiber optic parameter estimation, Random Forest regressors have been employed to predict attenuation and chromatic dispersion, achieving mean absolute errors below 0.1 dB/km. [25]

- **Gradient Boosting Machines (GBM)**

GBMs are iterative ensemble methods that sequentially build decision trees by fitting each new tree to the residual errors of the preceding ones, enhancing model accuracy progressively. For instance, GBMs have been successfully applied to forecast nonlinear impairment coefficients in optical systems, achieving relative errors below 5%. [29]

- **K-Nearest Neighbors (KNN)**

KNN is a non-parametric classification method that assigns a class to a test sample based on the majority class among its k nearest neighbors in the training dataset. Due

to its simplicity and effectiveness, KNN has been applied in fiber optic fault detection, achieving recall rates exceeding 90% for identifying fiber breaks. [25]

- **Gaussian Process Regression (GPR)**

GPR is a non-parametric, probabilistic modeling technique that delivers both predictive means and uncertainty estimates, facilitating risk-aware parameter estimation. In practical applications, GPR has been employed to model attenuation variability in optical fibers subject to temperature changes, with prediction intervals successfully encompassing 95% of observed measurements. [29]

- **Autoencoders**

Autoencoders are unsupervised neural networks designed to learn compact representations of input data by encoding and then reconstructing it, enabling the detection of anomalies through increased reconstruction errors. In optical fiber monitoring, autoencoders have been successfully applied to identify rare faults, such as micro-fractures, achieving precision rates above 85%. [30]

2.2.2. Deep Learning for fiber analysis

a. Brief overview of deep learning

DL is an advanced subfield of ML, itself a branch of AI, that focuses on algorithms inspired by the architecture and functioning of the human brain, specifically through deep ANNs. These networks are capable of learning and generalizing from large and complex datasets by autonomously extracting relevant features without the need for manual feature engineering. This ability to effectively handle high-dimensional and nonlinear data makes DL especially well-suited for fiber optics applications, where signal behaviors and physical properties frequently demonstrate intricate nonlinear patterns that are difficult to capture with conventional methods [31]

b. Types of deep learning models

- **Supervised deep learning**

This approach involves training neural networks on datasets where the input data is paired with known, labeled outputs. By learning from these examples, the model can accurately predict outcomes for new, unseen data. In fiber optics, supervised DL is especially useful for estimating parameters like attenuation, dispersion, and signal loss. [32]

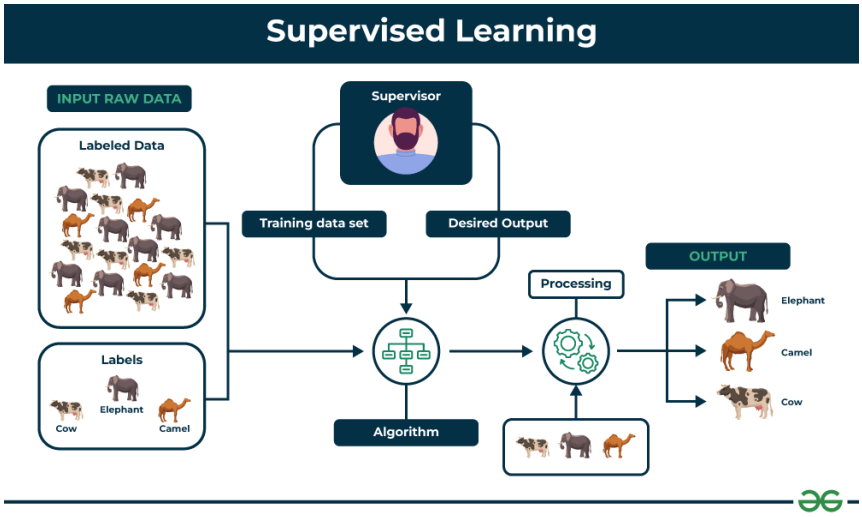


Figure 2. 2: Supervised Learning Workflow-Training with labeled Data to Predict known Categories.

- **Unsupervised deep learning**

Unlike supervised learning, this approach operates without labeled data, enabling the model to identify underlying patterns or groupings within the input data autonomously. In the context of optical fiber systems, unsupervised DL can be employed to cluster similar signal patterns or to detect unusual behaviors and anomalies in the network. [33]

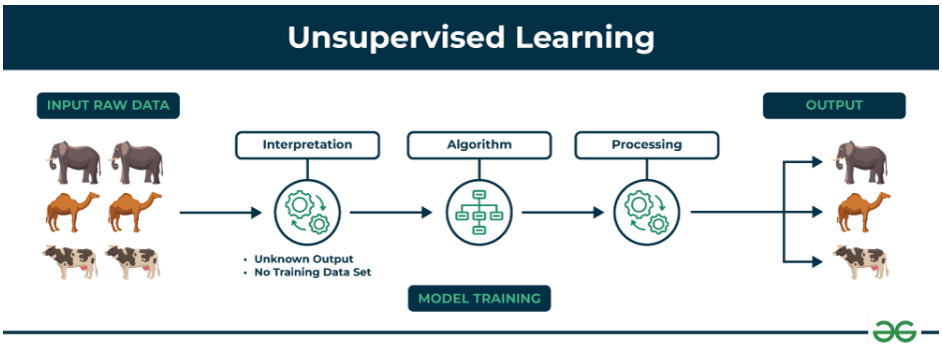


Figure 2. 3: Unsupervised Learning Workflow-Data Clustering Without Labeled Output.

c. Deep learning models used in this study

This study utilizes a combination of DL models-namely ANNs, Deep Neural Networks (DNN), and Recurrent Neural Networks (RNN)-to predict key optical fiber parameters such as dispersion coefficient, confinement loss and effective index. The DNN architecture, featuring multiple hidden layers, effectively models the complex

nonlinear and high-dimensional relationships typical of optical fiber systems, enabling precise parameter estimation in challenging propagation environments. [34]

ANNs serve as foundational models that learn mappings between input features and output metrics, while DNNs extend this capability by capturing deeper hierarchical features for improved accuracy. RNNs, with their inherent ability to process sequential and time-dependent data, are particularly useful for analyzing temporal dynamics and signal evolution within optical fibers.

Training for these models is primarily supervised, using labeled datasets containing fiber characteristics (e.g., geometry, refractive index profiles) and corresponding performance measurements. This approach ensures the networks can accurately approximate the relationships between structural inputs and their physical effects [34].

By integrating these diverse DL architectures, the study aims to enhance the robustness and scope of fiber optic parameter prediction. A detailed explanation of each model follows:

- **Artificial Neural Networks**

Feedforward ANNs are composed of interconnected layers of nodes (neurons) that process input data by passing signals through weighted connections and applying nonlinear activation functions. These networks typically include an input layer, which receives raw data features such as launch power, wavelength, and fiber length; one or more hidden layers, where the input signals are transformed and combined to capture complex, nonlinear relationships; and an output layer that generates predictions like Optical Signal-to-Noise Ratio or Bit Error Rate. By training on both simulated and experimental datasets, ANNs effectively learn the intricate mappings between input parameters and fiber performance metrics. This approach has demonstrated high accuracy, with reported correlation coefficients exceeding 0.98 between predicted and measured values, underscoring the efficacy of ANNs in optical fiber parameter estimation [28]. Figure 2.2 provides a detailed representation of these elements and their connections.

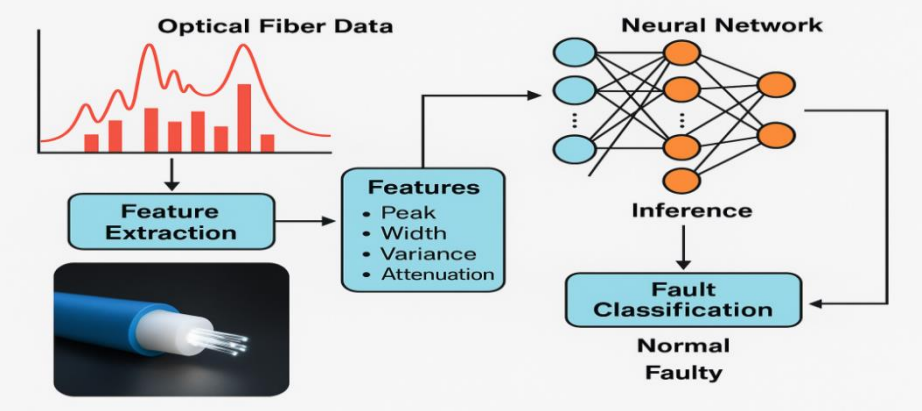


Figure 2. 4 Flowchart of Neural Network-Based Optical Fiber Fault Detection System.

- **DNNs**
- **RNNs**

2.2.3. Optimization algorithms

Optimization algorithms are essential tools for improving optical fiber performance, especially when addressing complex design challenges involving multiple objectives or extensive parameter spaces. These algorithms enable the fine-tuning of fiber physical and structural characteristics—such as refractive index profiles, core dimensions, air hole sizes, and spacing—to meet specific targets like minimizing signal loss, reducing dispersion, or maximizing bandwidth efficiency.

- **Genetic Algorithms (GA)**

Genetic Algorithms are inspired by the process of natural evolution and genetics. They begin with a randomly generated population of candidate solutions, called individuals, which evolve over successive generations. Key operations in GA include selection of the fittest individuals, crossover (recombination) of solution traits, and mutation to introduce variability. A fitness function evaluates each solution's quality to guide the evolutionary process toward optimal designs. In optical fiber engineering, GA has proven effective for optimizing PCF structures by adjusting parameters such as air hole diameter and spacing to tailor properties like zero dispersion wavelengths or enhanced birefringence. [37]

- **Particle Swarm Optimization (PSO)**

Particle Swarm Optimization draws inspiration from the collective movement patterns observed in flocks of birds or schools of fish. In PSO, a swarm of particles explores

the search space, where each particle represents a candidate solution. Particles adjust their trajectories based on their own best-known position and the best position discovered by the entire swarm, enabling efficient convergence toward optimal solutions. PSO is widely recognized for its fast convergence speed and has been effectively applied to optimize fiber parameters, identifying configurations that minimize dispersion or loss at targeted wavelengths. [37]

- **Applications of optimization in fiber design and parameter tuning**

Optimization methods like GA and PSO are employed in various fiber optics research areas, including:

- **Geometrical design of photonic crystal fibers** to achieve specific optical behaviors such as low-loss transmission windows and broadband zero dispersion. [37]
- **Automated tuning of simulation model parameters** to reduce manual adjustment, accelerate design cycles, and improve prediction accuracy. [37]
- **Creation of hybrid optimization strategies** that combine GA and PSO or integrate these algorithms with ML models, aiming to speed up the search process and enhance the reliability of performance predictions. [37]

  The synergy between advanced optimization algorithms and photonic design is paving the way for more rapid, efficient, and intelligent development of optical fibers, ultimately supporting the evolution of high-capacity, next-generation communication networks.

2.3. AI knowledge cycle for optical fiber optimization

AI applications in optical fiber optimization depend on a well-defined knowledge cycle that ensures efficient data handling, precise modeling, and continual system enhancement. This cycle consists of several key stages, each contributing to the development of intelligent and adaptive fiber optic networks.

2.3.1. Data acquisition and sources

The cornerstone of any AI-driven system is the availability of high-quality data. In optical fiber networks, data is gathered using various sensing and diagnostic instruments, including Optical Time Domain Reflectometers (OTDRs), Optical Spectrum Analyzers, and fiber Bragg grating sensors. These tools provide detailed measurements related to parameters such as signal attenuation, dispersion, loss events,

temperature fluctuations, and strain, which serve as essential inputs for AI models. [38]

2.3.2. Feature engineering and extraction

After data collection, the next step is to identify and extract the most informative features. Feature engineering is critical for converting raw sensor data into structured and meaningful representations tailored for ML algorithms. Examples of extracted features include signal peak amplitudes, rise and fall times, or specific spectral components. The success and accuracy of AI models heavily rely on selecting and engineering features that best capture the underlying fiber performance characteristics or anomalies. [39]

2.3.3. Data quality and preprocessing

Before training AI models, ensuring the dataset's integrity through preprocessing is crucial. This phase involves noise filtering, normalization, handling missing or corrupted data, and applying necessary data transformations. Effective preprocessing mitigates potential biases and inconsistencies, enhancing the model's robustness and preventing overfitting. Consequently, well-preprocessed data enables the AI system to generalize effectively and maintain reliable performance when encountering new, unseen data. [40]

2.4. AI applications in optical fiber technology

AI is transforming optical fiber technology by enabling enhanced design processes, performance optimization, and real-time system monitoring. Within the realm of PCFs, AI offers significant advances in characterization, design efficiency, and fault management.

2.4.1. Photonic crystal fibers characterization

PCF provide sophisticated control over light propagation but present challenges due to their complex structures and sensitivity to defects. Traditional characterization techniques are often computationally intensive and time-consuming. AI approaches deliver faster, more accurate, and automated solutions for property prediction, defect identification, and intelligent fiber design, greatly improving PCF reliability and development speed. [41]

- **Mode profile prediction**

A ML method employing Convolutional Neural Networks (CNNs) has been developed to rapidly estimate the mode profiles of PCFs. This technique predicts field intensity distributions for fundamental and higher-order modes by analyzing structural parameters such as hole diameter, pitch, and ring count. Compared to conventional numerical methods like the Finite Element Method (FEM) or Finite Difference Time Domain, this approach offers substantial speed improvements while maintaining high accuracy, facilitating rapid optimization and integration of optical devices within PCFs. [41]

- **Dispersion prediction**

SVM with radial basis function kernels have been applied to forecast chromatic dispersion and other optical properties of PCFs. This approach leverages fiber structural and material characteristics to generate accurate dispersion curves over various wavelengths much faster than conventional simulations. Such efficiency supports the design of dispersion-flattened or highly dispersive fibers for targeted applications. [42]

- **Birefringence prediction**

ANN have been used to predict birefringence in PCFs, including phase and group birefringence as well as beat length, without being limited by structural asymmetries or stress-inducing elements like elliptical holes. By incorporating diverse material and geometric parameters, these models closely replicate results from numerical simulations, enabling effective fiber designs for polarization-maintaining applications and polarization-sensitive sensors [43].

2.4.2. Performance optimization

Advancements in fiber optics require innovative design and optimization strategies to maximize performance for modern communication systems.

- **Enhancing transmission characteristics**

DL models enable holistic optimization of communication channels by learning the complex, nonlinear interactions across the transmission path. These models can develop novel modulation and coding schemes optimized for the optical fiber environment, improving bandwidth utilization while mitigating signal degradation caused by noise, dispersion, and nonlinear effects. Their adaptive capabilities allow

real-time response to changing channel conditions, enhancing spectral efficiency and transmission reliability. [44]

- **AI-driven design of fiber geometries**

ML techniques, particularly CNNs, facilitate the efficient design of PCF geometries by accurately predicting optical properties from structural parameters. Trained on large simulated datasets, these models bypass the need for slow numerical simulations, supporting inverse design workflows that rapidly optimize fiber structures for telecommunications, sensing, and nonlinear optics applications [41].

2.4.3. Fault detection and monitoring

AI enhances fiber optic network reliability by enabling real-time anomaly detection and fault prediction. These capabilities allow for proactive maintenance, reducing service disruptions and improving overall network stability.

2.4.4. AI for real-time diagnosis of fiber networks

Predictive maintenance systems powered by AI continuously monitor the health of fiber optic infrastructure using sensor data and network performance metrics. By identifying early signs of degradation such as signal loss, physical damage, or connector faults AI models can forecast failure events and recommend timely interventions. This proactive approach minimizes unplanned outages, optimizes maintenance scheduling, reduces operational costs, and extends network lifespan, thereby ensuring uninterrupted service delivery to end-users. [45]

2.5. Challenges and limitations

Despite the considerable progress in AI applications, deploying these techniques within optical fiber systems remains hindered by several technical and practical obstacles. These challenges can be categorized as follows:

a. **Data-related issues**

A primary obstacle is the limited availability and quality of labeled datasets tailored to photonic applications. Acquiring high-fidelity data in optical systems often necessitates expensive instrumentation and carefully controlled laboratory environments. Additionally, variations in measurement conditions and environmental interference introduce noise and inconsistencies, which can degrade the training process and model performance. The absence of standardized datasets further

complicates the fair evaluation and comparison of different AI methodologies within this field. [46]

b. Technical barriers

The integration of sophisticated AI models, especially DL frameworks, into photonic platforms presents significant technical challenges. These models typically require substantial computational power for both training and real-time inference, resources that may be scarce in embedded or operational photonic systems. Moreover, the opaque, "black-box" nature of many AI algorithms, particularly DNNs raises concerns about transparency and interpretability. For safety-critical applications like fiber fault diagnosis or optical signal classification, it is crucial to understand the rationale behind AI decisions to foster trust and enable validation. [47, 48]

Generalization gaps:

A further limitation concerns the ability of AI models to generalize across different fiber types, configurations, or environmental conditions. Models trained on specific fiber designs or under controlled experimental settings often struggle when applied to new or varied scenarios, limiting their scalability and practical deployment. This issue often necessitates costly retraining or adaptation of models for each new application context. [49]

Overcoming these challenges demands close collaboration among experts in photonics, data science, and hardware engineering. Such interdisciplinary efforts are essential to develop AI solutions that are not only accurate but also interpretable, computationally efficient, and flexible enough to adapt to diverse operational conditions.

2.6. Conclusion

AI has become a pivotal force driving the digital transformation of optical fiber technology, providing sophisticated solutions to the complex challenges involved in characterizing and optimizing optical communication systems. This chapter has reviewed a variety of intelligent methods that effectively analyze fiber properties through ML, DL, and optimization algorithms.

- Initially, ML techniques were presented as versatile tools for processing data collected from fiber systems. Using supervised, unsupervised, and semi-supervised approaches, these models have significantly improved the

prediction of critical physical parameters such as dispersion and signal attenuation, thereby enhancing network reliability and overall performance.

- DL has further advanced the field by enabling the handling of complex, high-dimensional datasets. Architectures such as DNN and CNN excel at recognizing patterns within propagation data and optical signals, making them well suited for classification, prediction, and defect identification tasks. Emerging models like Generative Adversarial Networks also show promise in addressing training data scarcity by augmenting datasets.
- Optimization algorithms, including GA and PSO have demonstrated considerable effectiveness in the optimal design of fiber structures and fine-tuning of operational parameters. These methods explore vast solution spaces intelligently to identify configurations that maximize performance.
- The AI knowledge cycle, encompassing data acquisition, feature engineering, and preprocessing, was emphasized as a fundamental framework for developing accurate and robust AI models. The applications discussed span from PCF characterization to enhancing transmission capabilities and enabling proactive fault detection in real time.
- Despite these advancements, several challenges persist, including limited availability and quality of labeled data, the high computational demands of sophisticated models, and difficulties in ensuring model generalizability across different fiber types and environmental conditions. Addressing these issues remains crucial for unlocking the full potential of AI in optical fiber technology.

In summary, AI represents a strategic asset that substantially improves the precision and efficiency of optical fiber analysis, offering promising avenues for advancing fiber design, performance, and sustainable technological development in this critical field.

Chapter 3:
Modeling and simulation of photonic crystal fiber.

3.1. Introduction

PCFs, a class of microstructured optical fibers, have garnered significant attention due to their unique ability to control and manipulate light in ways traditional fibers cannot. Their design, which typically incorporates a periodic arrangement of air holes running along the fiber length, allows for tailored dispersion characteristics, high nonlinearity, and single-mode operation over a wide spectral range. To explore and optimize these properties, computational modeling and simulation are indispensable tools.

ML techniques are used to compute various optical properties including effective index, effective mode area, dispersion and confinement loss for a solid-core PCF. These ML algorithms based on artificial neural networks are able to make accurate predictions of the optical properties of PCF. In this chapter, we propose to use ML techniques for computing various optical properties of the PCF. We combine the finite element simulations and ANN for the quick and accurate computation.

3.2. PCF modeling using COMSOL Multiphysics

3.2.1. Description of the PCF structure

The proposed structure is illustrated in **Figure 3.1**, when we have modeled a hexagonal PCF structure in COMSOL Multiphysics, the following parameters and components are typically considered in simulating:

- **Core/Cladding geometry**

The core is usually formed by omitting the central air hole or by using a defect. A hexagonal lattice of air holes is defined, typically arranged in **6** fold symmetry, this Air holes are circular and embedded in a silica background.

- **Lattice parameters**

To define this structure we use the following parameters:

Table 3.1 The parameters of the hexagonal structure.

Name	Values	Description
Pitch	2[um]	ʌ
D	1.2[um]	Cladding diameter
t_pml	5.5*0.5*p[um]	Thickness of the perfectly match layer
PML	14.3[um]	The perfectly match layer
N	6	The number of repeated cllading air holes.

Materials using :

- ✓ **Silica material: Silica** is a key material in our structure, used to simulate the propagation of light through the photonic crystal fiber, its refractive index (~1.444 at 1.550 um) influences optical behavior, while its conductivity (~1.38 W/m·K) affects heat transfer.
- ✓ **Air:** In PCF simulations, air is used to create low-refractive-index regions around the silica core, enabling light confinement. Air is assigned a refractive index of $n = 1$ and applied to the air holes to accurately model the optical contrast in the structure.

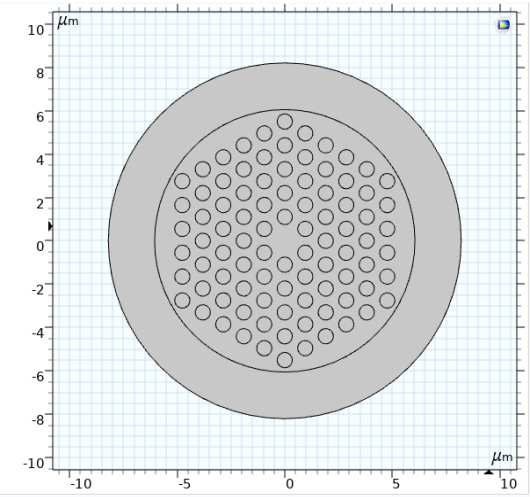


Figure 3.1: The hexagonal structure using COMSOL.

3.2.2. Extraction of optical properties

⇒ **Effective index (n_{eff}):** the effective index is extracted by modeling the optical structure and solving for the guided modes at specific wavelengths.

To calculate this index we use the equation:

$$n_{eff} = {\beta\lambda}/{2\pi} \qquad \textbf{3.1}$$

⇒ **Dispersion parameters(D):** simulations are performed over a range of wavelengths to obtain the effective index as a function of wavelength.

$$D = -2\pi c\beta\,{}^{2}/_{\lambda^2} \qquad \textbf{3.2}$$

The mesh of the structure is depicted in **Figure 3.2**, showing the division of the structure into small finite elements connected together to form a continuous network. Each finite element is characterized by a set of nodes or interpolation points, and the physical properties of the structure are assigned to these elements. This mesh is used to represent the design parameters and enable the search for optimal configurations by adjusting the shape, size, or position of the elements.

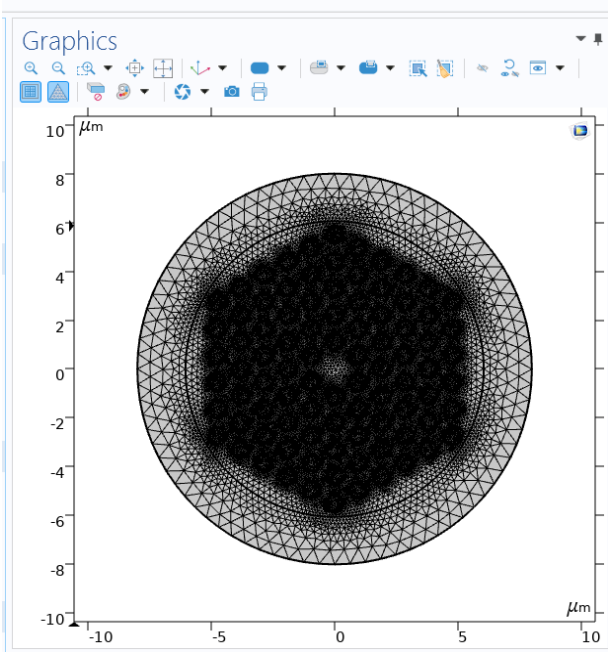


Figure 3.2: The mesh of hexagonal structure

In our simulation, we used the **Mode Analysis** study to investigate the guiding properties of the PCF. We assigned the appropriate material properties, with silica as the background and air for the holes. Using the **Electromagnetic Waves, Frequency Domain** interface, we set the frequency value to 1.55KHz. Then we were able to calculate the effective refractive indices and visualize the electric field distributions of the guided modes as shown in **Figure 3.3**

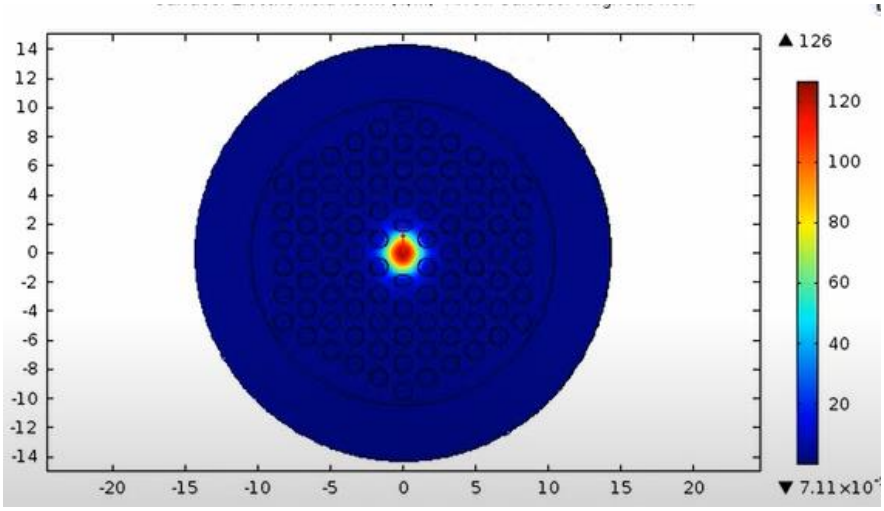


Figure 3. 1: Simulation of mode analysis.

3.2.3. Results of COMSOL

- **Effective index**

The **Effective mode index** in PCFs, denoted as $neff$, is defined as the equivalent refractive index that characterizes the propagation behavior of the electromagnetic wave within the fiber. It is typically calculated using numerical methods such as the FEM and depends on the precise geometrical configuration of the fiber, including air hole diameter and pitch. Its importance lies in serving as a fundamental parameter for understanding light guidance mechanisms within the fiber, and it is also essential for calculating key optical properties such as D and effective mode area, making it a critical tool for the design and performance analysis of advanced optical fibers.

The **figure3.4**. illustrates the variation of the e n_eff of the fu*n*damental mode as a function of wavelength for three different PCF configurations, simulated using COMSOL Multiphysics. The three configurations differ in Λ and d, as follows:

- Λ = 1.1 µm, d = 0.7 µm
- Λ = 0.7 µm, d = 0.45 µm
- Λ = 1.5 µm, d = 0.9 µm

The results clearly demonstrate that the behavior of the effective index is strongly influenced by the geometrical parameters of the fiber structure. While some configurations (Λ = 0.7 µm) exhibit sharp oscillations in $neff$ indicating high chromatic dispersion when (Λ = 1.5 µm) show more stable behavior, reflecting better mode αc lower D.

These findings highlight the critical role of geometric design in tailoring the optical characteristics of PCFs. Smaller pitch and diameter values may enhance nonlinear interactions, whereas larger values contribute to more stable mode guidance and efficient light transmission in broad-spectrum optical applications.

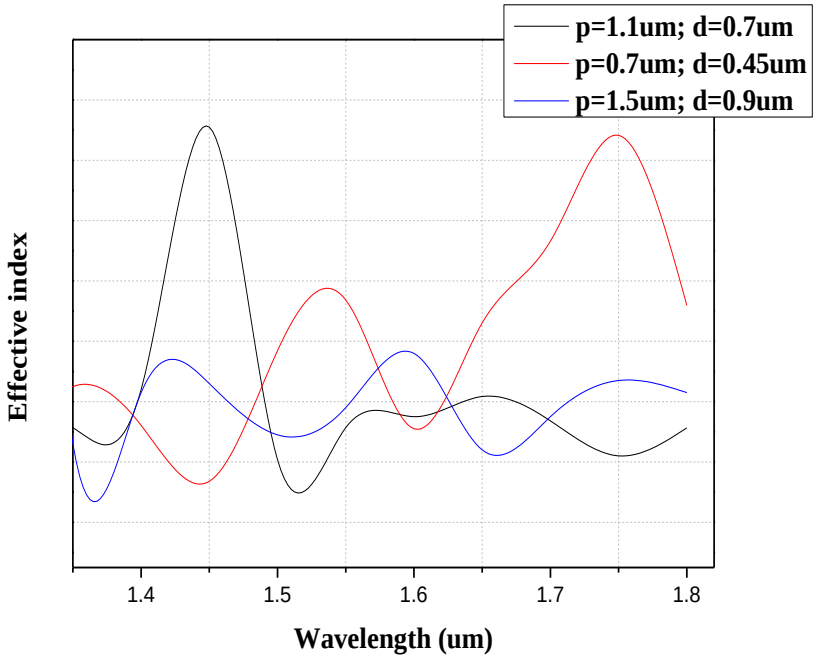


Figure 3. 2: Variation of effective index with wavelength for various values of pitch and diameter.

- **Dispersion**

Dispersion in photonic crystal fibers refers to the phenomenon that causes different spectral components of an optical pulse to propagate at different speeds, resulting in temporal broadening of the pulse as it travels through the fiber. Photonic crystal fibers are distinguished by their high ability to geometrically tailor dispersion properties more effectively than conventional fibers, thanks to their unique microstructured design.

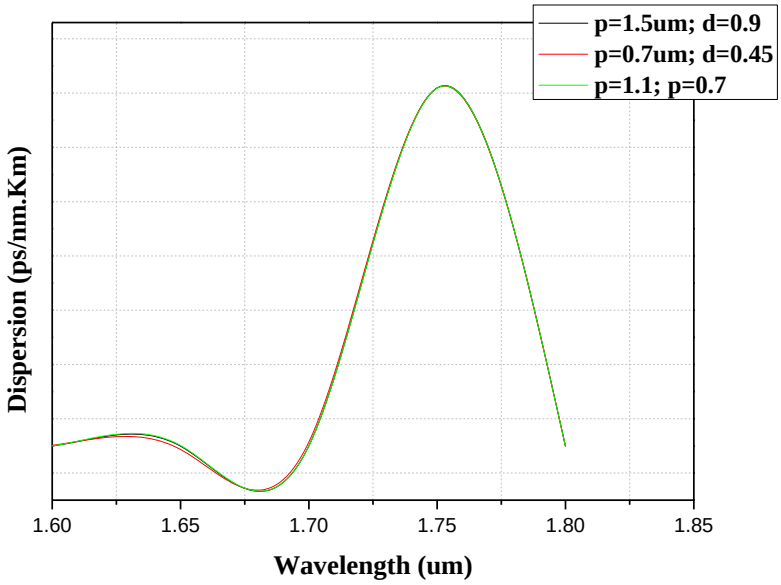


Figure 3. 3: Variation of dispersion with wavelength for various values of pitch and diameter.

- **Birefringence (B)**

Birefringence in PCFs refers to the **difference in effective refractive indices** experienced by two orthogonal polarization modes propagating through the fiber. This phenomenon arises due to structural asymmetries in the fiber's microstructured cladding such as unequal air hole sizes, non-circular core shapes, or asymmetrically arranged air holes which break the symmetry between the polarization axes (typically the x- and y-directions). In mathematical terms, birefringence B is defined as:

$$B=|neff,x-neff,y|$$

where $neff,x$ and $neff,y$ are the effective refractive indices of the modes polarized along the x- and y-axes, respectively.

High birefringence in PCFs is particularly desirable in applications that require **polarization-maintaining behavior**, such as fiber-optic sensors, coherent communication systems, and nonlinear optics, because it helps to preserve the state of polarization over long distances by suppressing mode coupling.

As the **figure 3.6** shows

Birefringence (B) generally decreases with increasing wavelength due to reduced interaction between the optical field and structural asymmetries.

The exact behavior depends on the PCF design and air hole arrangement.

Therefore, the spectral behavior of B(λ) must be carefully studied when designing fibers for polarization-sensitive applications such as sensing or coherent optical communication systems

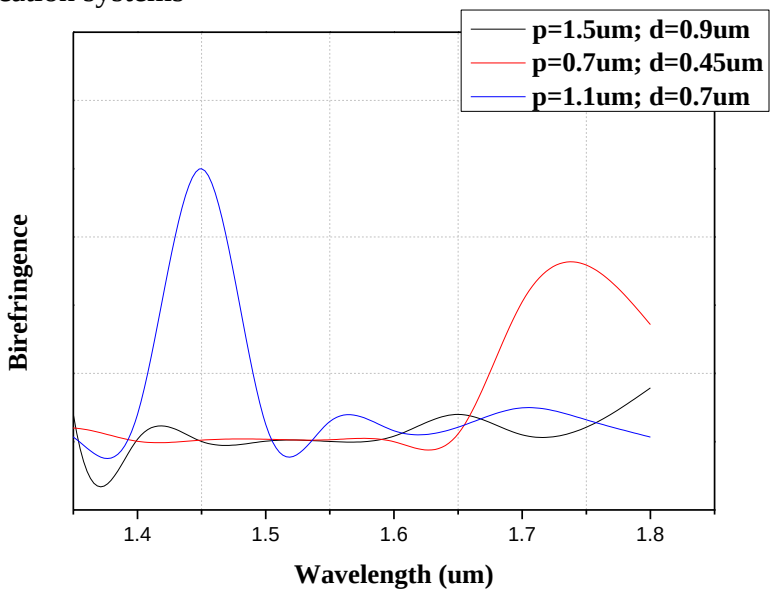


Figure 3. 4 : Variation of birefringence with wavelength for various values of pitch and diameter.

- **Effective mode area**

The effective mode area is a measure of the spatial extent of the electromagnetic field within the optical fiber and is used to determine the degree of energy confinement in the core compared to the cladding. A_eff is of great importance in optical fiber design, as it influences nonlinear phenomena such as self-phase modulation and frequency shift, in addition to affecting signal transmission

efficiency. Generally, fibers with smaller effective mode areas have a higher capability to induce nonlinear effects, while those with larger A_eff reduce such effects and are preferred for high-power signal transmission

Figure3.7 illustrates the relationship between the A_eff and the wavelength for three different PCF structures, which vary in their geometric parameters—namely the pitch (p or ʌ) and the air hole diameter (d). The results show that the effective mode area decreases with increasing wavelength until it reaches a relatively stable state, indicating that the electromagnetic field becomes more confined within the fiber core as the wavelength increases. The blue curve exhibits the highest A_eff values due to its larger structural dimensions, while the black curve shows the lowest values, reflecting a stronger confinement of light within the core. This analysis highlights the critical role of the fiber's geometric design in controlling A_eff properties, enabling the customization of fibers to meet specific application requirements, such as enhancing nonlinear performance or minimizing optical interference.

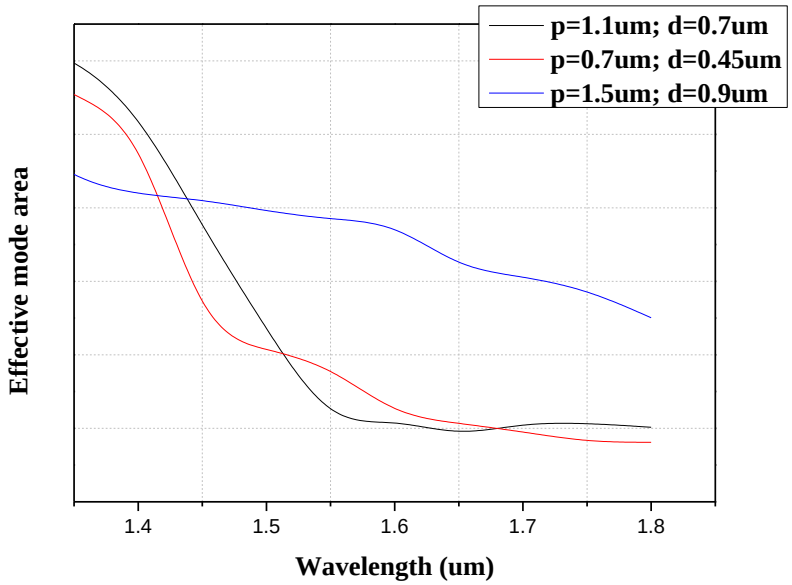


Figure 3. 5 Variation of effective mode area with wavelength for various values of pitch and diameter.

3.3. Modeling photonic crystal fibers using ANNs

3.3.1. Motivation for using ANNs as a surrogate model

Numerical modeling methods such as the FEM using COMSOL Multiphysics are accurate but computationally intensive, especially when exploring a wide design space for PCFs. ANNs serve as an efficient alternative by approximating the input–output relationships of complex physical systems quickly and effectively. Once trained, the ANN can predict key optical properties like $neff$ and chromatic dispersion for different design configurations almost instantly. This capability is particularly important in iterative design, real-time optimization, and sensitivity analysis applications, where repeated simulations using COMSOL would be time-prohibitive. Here, we propose the use of ML techniques to calculate various optical properties of PCFs. We combine finite element simulations with ANNs to perform fast and accurate calculations. We use a simple feedforward Multilayer Perceptron (MLP) model that can be quickly trained to estimate $neff$, $Aeff$, D, and confinement loss (αc) values for the PCF structure.

- **PCF modeling with ANN**

The ANN/MLP architecture parameters are introduced in this section along with the PCF type that is used for generating the dataset.The first step of the training procedure of an ANN model is to have a finite and appropriate labeled dataset. This initially generated dataset plays a crucial role for any ANN model. The accuracy of the model depends upon how well the dataset is aligned to the problem to be solved. Variant PCFs were simulated by changing some geometric property values and their optical properties were calculated. In our case, set of PCF geometric data including diameter of holes (d), separation between center of two adjacent holes (pitch, ʌ), refractive index of core (n_c), wavelength (λ), and number of rings (Nr) of a solid-core PCF (as shown in fig.3.4) were taken as input variables of the labeled dataset. [50]

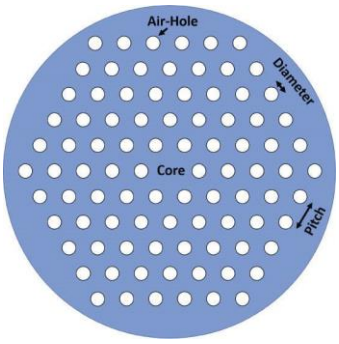


Figure 3. 6: Cross-section of a solid-core hexagonal PCF with five rings of air holes.

Subsequently, n_{eff}, A_eff, D, and α_c values were calculated using Lumerical Mode Solutions for more than 1000 samples, which were considered as the output variables of the labeled training dataset. A_eff, D, and c values can be defined by using the following equations.

$$A_eff(\mu m^2) = \frac{((\int\int |E(x,y)|^2 dxdy)^2}{\int\int |E(x,y)|^4 dxdy} \quad (3.3)$$

$$D = \frac{-\lambda}{c}\frac{Re(n_{eff})}{d\,\lambda^2} \text{ps/km.nm} \quad (3.4)$$

$$\alpha_c = 8{,}856 \times \frac{2\pi}{\lambda} \times \text{Im}(n_{eff}) \times 10^4 \text{dB/cm} \quad (3.5)$$

In this study, an ANN based on a MLP architecture was employed to predict optical fiber parameters. The model consisted of three fully connected hidden layers, each containing 50 neurons. The Rectified Linear Unit (ReLU) was used as the activation function due to its superior performance compared to Sigmoid and Tanh functions, and the Adam optimizer was selected for training due to its efficiency with large datasets.

A validation set comprising 10% of the training data was used to avoid overfitting and to objectively tune model parameters (weights and biases). The Mean Squared Error (MSE) was calculated after each training epoch to measure prediction accuracy, and backpropagation was applied to iteratively update the weights. The number of training epochs was determined based on MSE convergence to an

acceptable level.

This architecture was selected based on prior experience and empirical evaluations

reported in previous studies. [51] The selected structure proved sufficient to achieve

stable MSE while maintaining low computational cost.

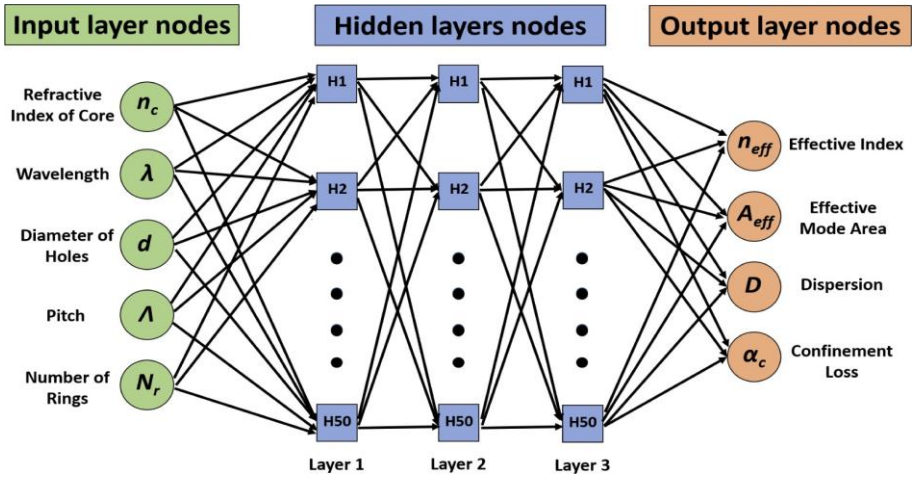


Figure 3. 7 :ANN representation with one input layer (5 input nodes), three hidden layers (50 nodes in each layer), and one output layer (4 output nodes).

3.4. Numerical results and computation runtimes

3.4.1. Effective index (n_{eff})

The performance of the ANN model in predicting the effective refractive index (n_eff) was evaluated by comparing its predicted values with the actual values obtained using the FEM. **Figure 3.10** illustrates a scatter plot showing the relationship between the predicted and true values, where the horizontal axis represents the true values and the vertical axis corresponds to the ANN predictions.

The points in the plot represent the model's performance across training, validation, and testing datasets. The proximity of these points to the line y = x reflects the prediction accuracy, where this line denotes perfect agreement between the actual and predicted values.

Remarkably, the model demonstrated excellent performance after only 50 training epochs, achieving a very low MSE. This indicates that the model efficiently learned the complex relationship between the design inputs and the effective refractive index within a relatively short training time.

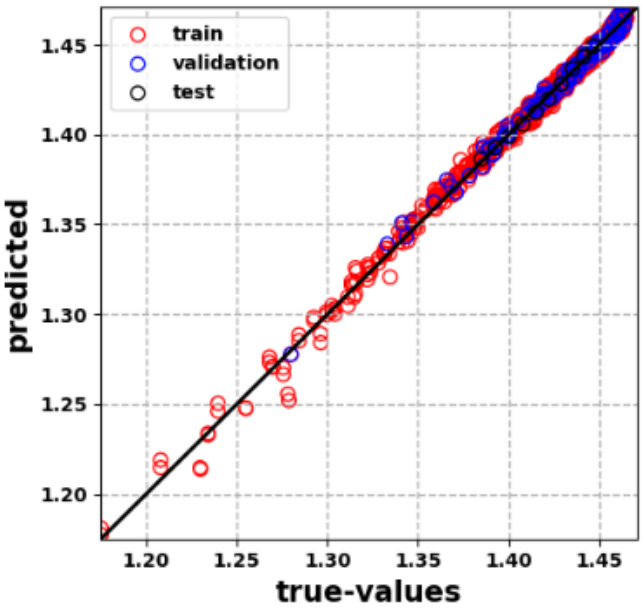


Figure 3. 8: The scatter plot of training dataset produced by ANN comparing $neff$ values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x).

This optimal performance is attributed to the effective ANN architecture, which includes three hidden layers with 50 neurons each, and the use of the ReLU activation function along with the Adam optimizer. Both techniques proved to be highly effective in accelerating the learning process and ensuring model stability.

3.4.2. Effective mode area (A_eff)

A_eff plays a critical role in defining the waveguiding characteristics of PCFs. A small A_eff is advantageous for enhancing fiber nonlinearity, whereas a large A_eff supports high-power transmission. A previously trained ANN model was utilized to predict A_eff values for a solid-core PCF structure.

The performance of the ANN model in predicting the effective mode area A_eff was evaluated by comparing the predicted values with the actual values obtained from FEM simulations. **Figure 3.11** presents a dot plot showing the relationship between true values (x-axis) and predicted values (y-axis), where the colored dots represent training, validation, and testing datasets respectively.

The model demonstrated accurate and efficient performance after only **50 training epochs**, indicating its high capability to learn the nonlinear relationship between the design inputs and the effective mode area output within a relatively short time. The

accuracy of the model is assessed by how closely the data points align with the ideal regression line y=x, which signifies perfect agreement between actual and predicted values. As illustrated in the figure, most of the data points cluster along this ideal line, reflecting high prediction accuracy.

Although minor deviations are observed at higher A_eff values (greater than 4.5), the overall performance remains robust across the entire range. This effective performance can be attributed to the chosen network architecture, which consists of three hidden layers with 50 neurons each, combined with the use of the ReLU activation function and the Adam optimizer-both of which are known for accelerating convergence and ensuring model stability.

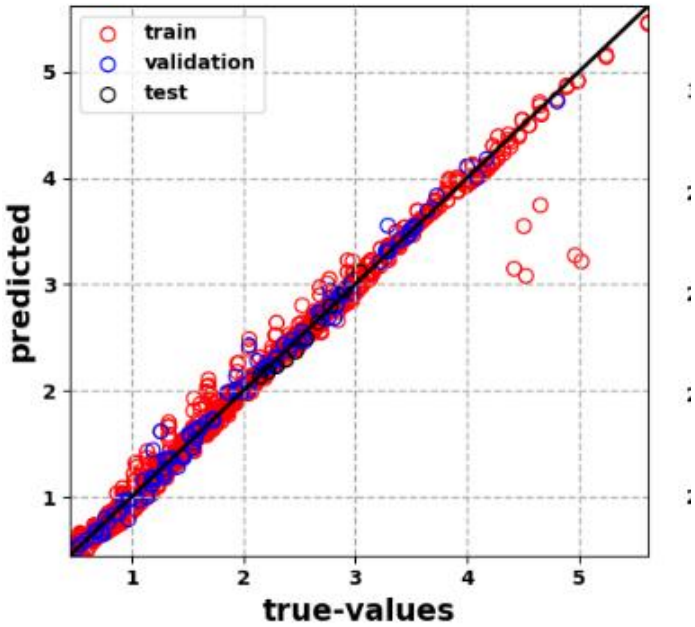


Figure 3. 9: The scatter plot of training dataset produced by ANN comparing $Aeff$ values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x**)**.

3.4.2. Dispersion(D)

The chromatic dispersion of a PCF is an important parameter for many applications, such as supercontinuum generation, and considered here next which may be calculated using Equation. (3.4).

The D depends on the second order derivative of neff with respect to λ the scatter plot showing training of the ANN model for dispersion is shown in **Figure. 3.12**.

The results demonstrate that the model performs relatively well, with most data points closely aligned along the ideal reference line y=x, indicating satisfactory predictive accuracy. However, some deviations are observed, particularly in the negative range (less than -600 ps/nm/km), suggesting a reduction in model accuracy in these regions. This discrepancy may be attributed to an imbalanced data distribution or the need to further refine the ANN architecture to better capture complex nonlinear relationships in those domains.

Overall, the model exhibits acceptable performance in predicting dispersion, with potential improvements achievable by enhancing the training data distribution or increasing the number of training epochs when necessary.

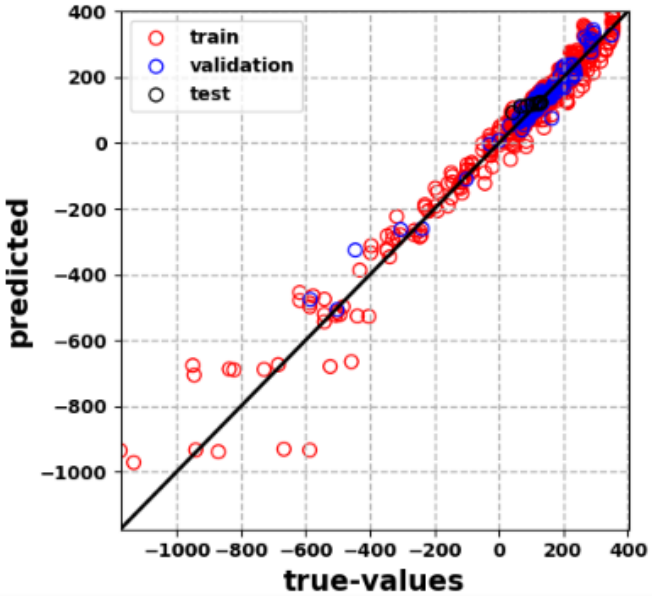


Figure 3. 10: The scatter plot of training dataset produced by ANN comparing *D*ispersion values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x**)**.

3.4.3. Confinement loss (αc)

All PCF suffers from confinement loss (αc) which depends on the imaginary part of the complex effective index, $neff$, and can be computed by using Equation. (3.5).

Figure .3.13.a presents the performance evaluation of the ANN model in predicting the values of αc by comparing the actual values with the predicted ones across the three datasets: training, validation, and testing. The graphical representation shows that the overall distribution of the data points does not follow the ideal diagonal line

(y = x), indicating a noticeable deviation between the predictions and the actual measurements, especially in the high-value range. This deviation is largely attributed to the clustering of data in the low-value range (less than 25 dB/km), which led to a model bias toward these values and a weak representation of higher values.

It is also evident that the model exhibits consistent performance across all datasets (train, validation, test), suggesting no apparent overfitting. However, this consistency reflects a general limitation in the model's learning capability (underfitting). Additionally, the random scatter of points in the higher value range indicates that the model lacks accurate representation in this region, which weakens the overall prediction accuracy and limits the model's generalization effectiveness.

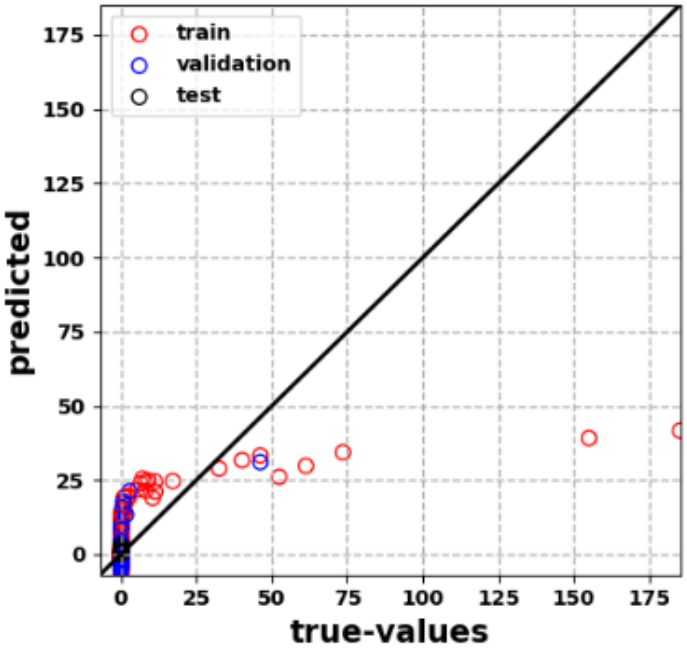


Figure 3. 11 a. The scatter plot of training dataset produced by ANN comparing αc values from the simulation(x-axis) and the ANN predictions(y-axis) along with the ideal linear model(y=x).

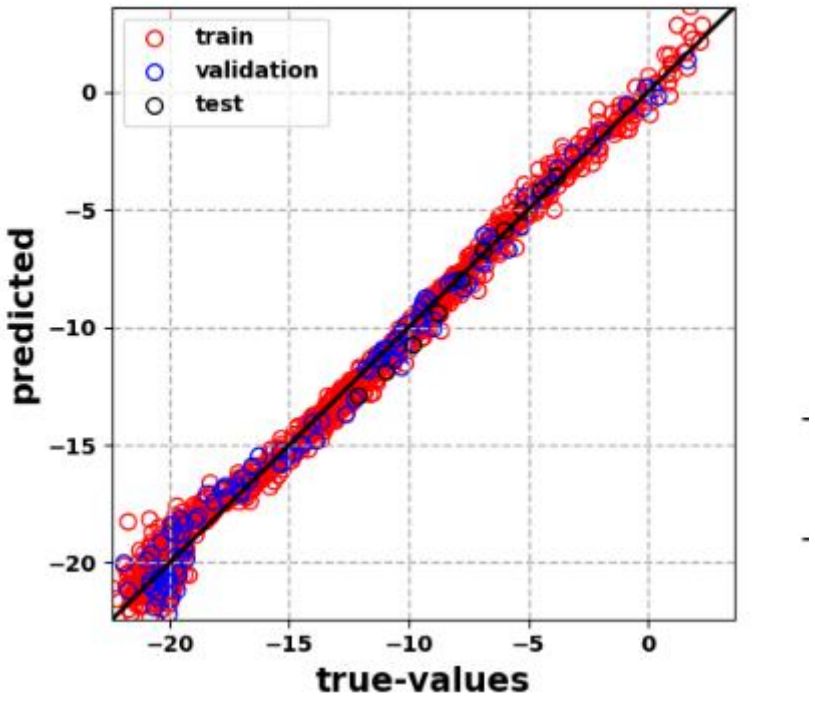


Figure 3.13.b. Actual values of c from the in logarithm.

The solution proposed to avoid this problem in our case was to take the logarithm of the Initially collected αc

3.5. Conclusion

this chapter, a comprehensive methodology was presented for the modeling and simulation of PCFs using the COMSOL Multiphysics environment. The focus was placed on analyzing key optical properties such as the n_eff, A_eff, D, αc. A large dataset was constructed based on simulation results by systematically varying the geometric structure of the fiber, including air hole diameter, pitch (Λ), and number of rings.

To enable rapid predictions and reduce computational time, an ANN was developed to serve as a surrogate model for simulating the fiber's properties. The training results showed that the ANN model's performance significantly improved with increased epochs and the use of refined datasets. The model's performance was assessed using metrics such as the MSE. Furthermore, the model demonstrated the ability to predict the optical characteristics of unseen fiber configurations, which highlights its robustness and efficiency.

The findings confirm that integrating numerical modeling with AI techniques, such as ANNs, offers a promising approach for accelerating the design and analysis of photonic crystal fibers while minimizing the time and cost associated with traditional simulations. This direction lays a solid foundation for advancing to more complex applications in the upcoming chapters, which will explore the use of DNNs and RNNs for advanced performance analysis of optical fiber

General Conclusion

AI has emerged as a transformative tool in the field of optical fiber technology, offering significant advancements in both the characterization and enhancement of fiber performance. Through techniques such as machine learning, deep learning, and data-driven modeling, AI enables real-time analysis, fault detection, and predictive maintenance, greatly improving the efficiency and reliability of optical communication systems. AI-driven optimization also enhances system design, allowing for better signal processing, noise reduction, and capacity management.

By leveraging vast datasets and learning from complex patterns, AI facilitates precise modeling of nonlinear behaviors and environmental impacts on fiber performance challenges that traditional methods struggle to address. Furthermore, intelligent control systems powered by AI contribute to dynamic bandwidth allocation, network reconfiguration, and automated quality monitoring.

This work includes:

- Chapter 1 provides an in-depth overview of photonic crystals, detailing their fundamental properties, structural characteristics, and a wide range of photonic applications.
- Chapter 2 explores the integration of AI methodologies in the analysis and optimization of optical fiber performance, while also addressing the key technical challenges and limitations within this domain.
- Chapter 3 presents a hybrid modeling approach that combines COMSOL Multiphysics simulations with Art ANNs to accurately model and predict the behavior of PCFs.

The results show that combining AI with numerical modeling speeds up fiber design and reduces cost. This approach also paves the way for more advanced applications using DNNs and RNNs for performance analysis.

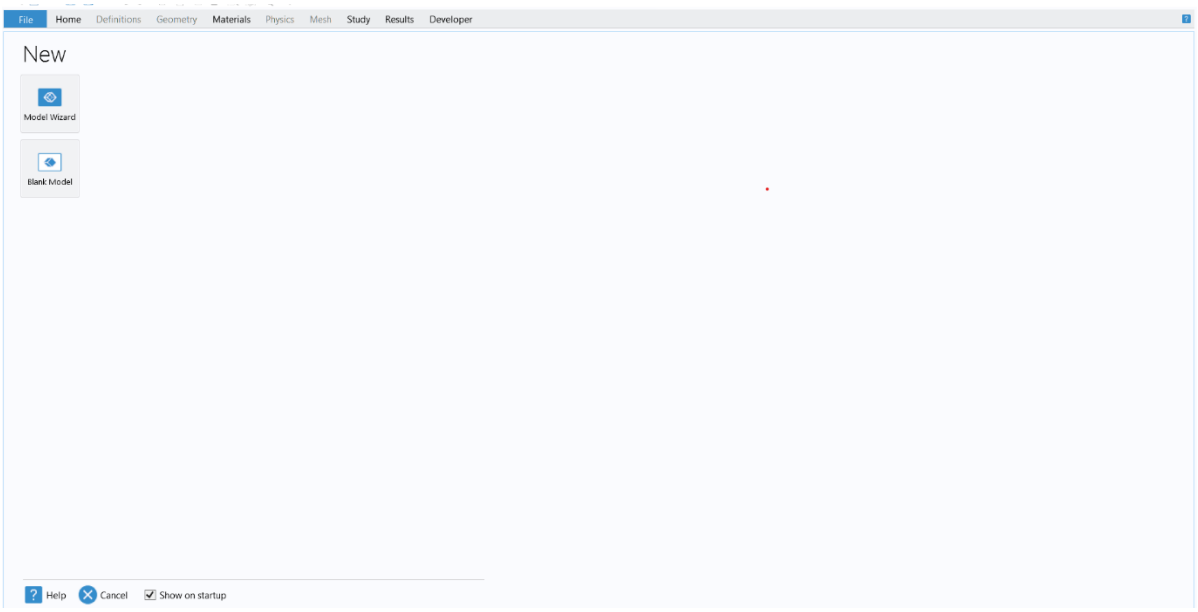
In summary, the integration of AI into optical fiber systems not only accelerates innovation in fiber design and diagnostics but also ensures higher performance, lower operational costs, and increased scalability, paving the way for the next generation of smart, adaptive optical networks.

Appendix

COMSOL Multiphasyc is a numerical simulation software based on the FEM and which encompasses all stages of the modelling process: from the definition of geometries, material properties and physics, describing specific phenomena, to the resolution and post-processing of models while ensuring precise and reliable results.

Creating a new model

You can configure a template guided by the template wizard or start from a blank template as shown in the figure below.



CREATE A TEMPLATE GUIDED BY THE TEMPLATE WIZARD

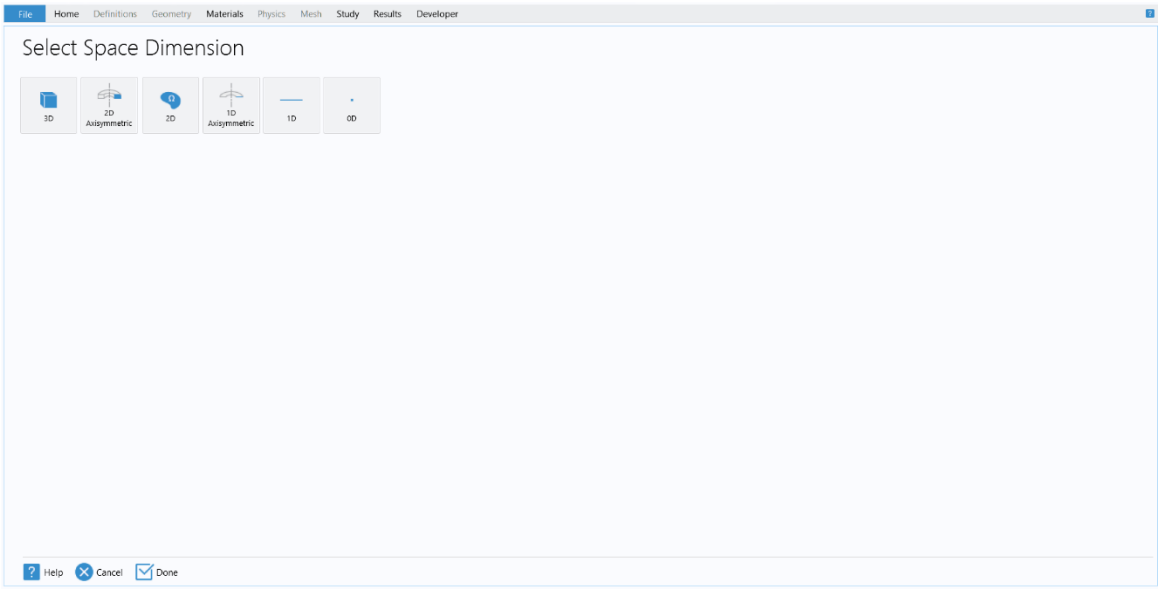
The model wizard will guide you in configuring the spatial dimension, physics and study type in a few steps:

- Start by selecting the space dimension for your model component:

  3D, 2D Axisymmetric, 2D, 1D Axisymmetric or 0D

- add one or more physical interfaces. These are organized into several branches of physics in order to facilitate their location.

- These branches do not correspond directly to the products. When products are added to your COMSOL Multiphasic Installation, one or more branches will be populated with additional physical interfaces.



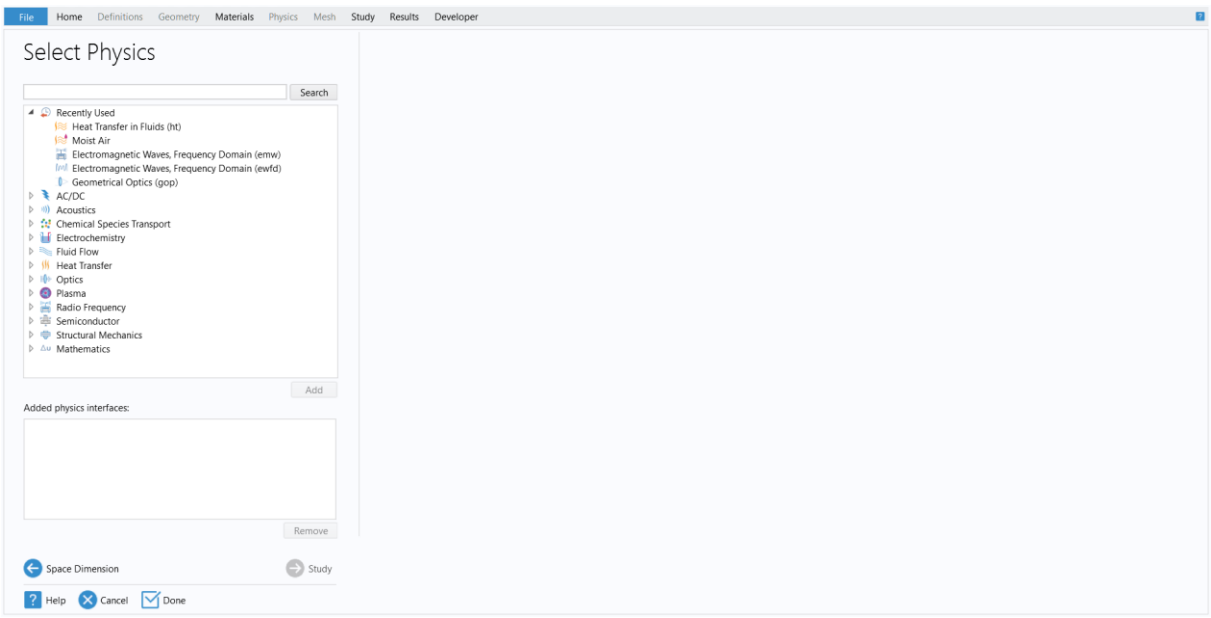
Select the study type that represents the solver or set of solvers that will be used for the calculation. Finally, click done. The desktop is now displayed with the template tree configured according to the choices you made in the template wizard.

CREATING A BLANK TEMPLATE

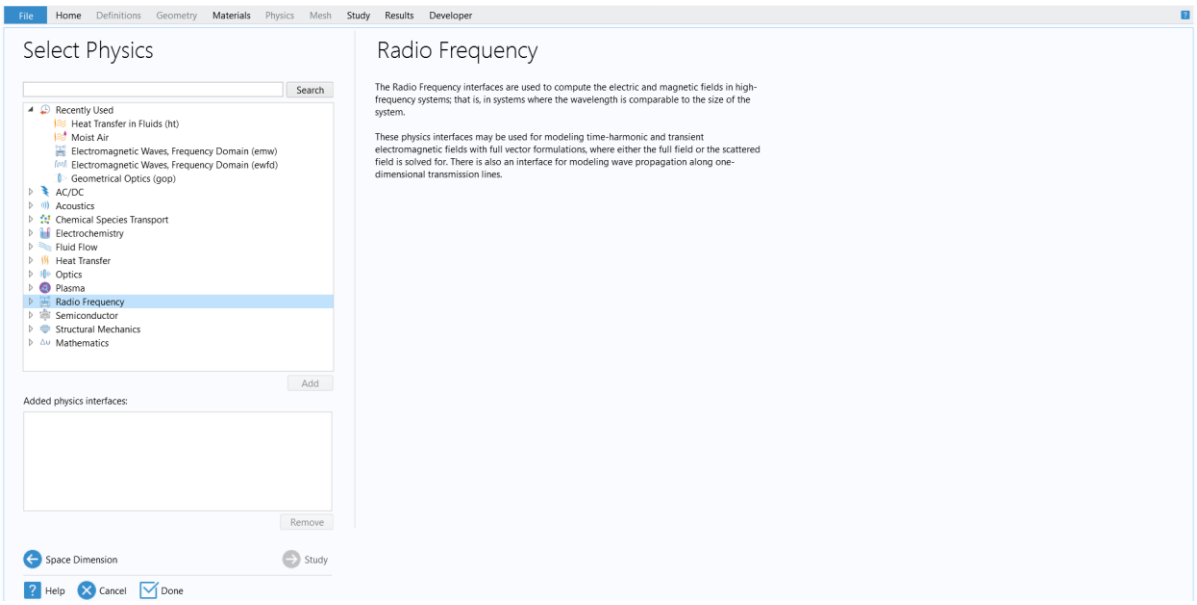
The Blank Model option will open the COMSOL Desktop interface without any

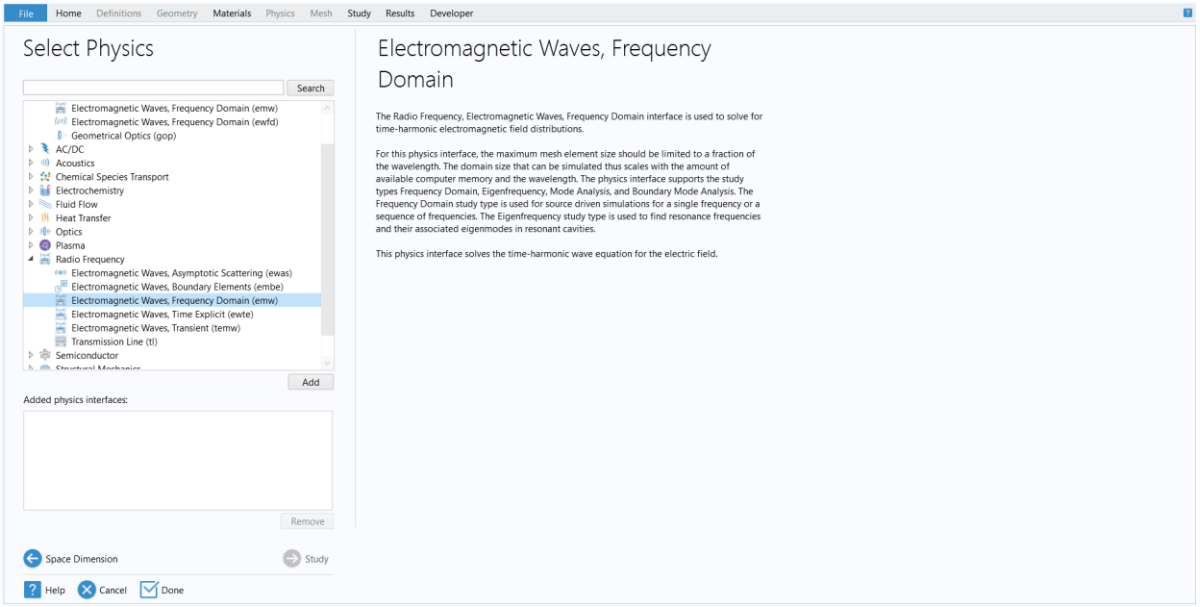
Component or study. You can right-click the model tree to add a component of a certain spatial dimension, physical interface, or study.

The following images show the method used to construct and simulate the photonic crystals.

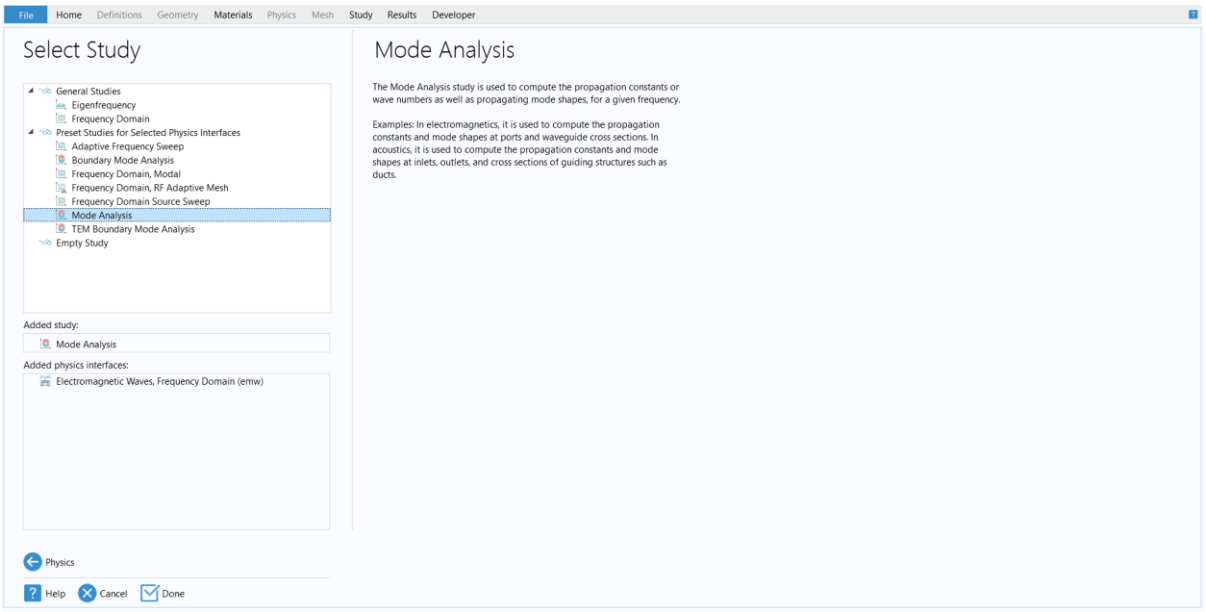


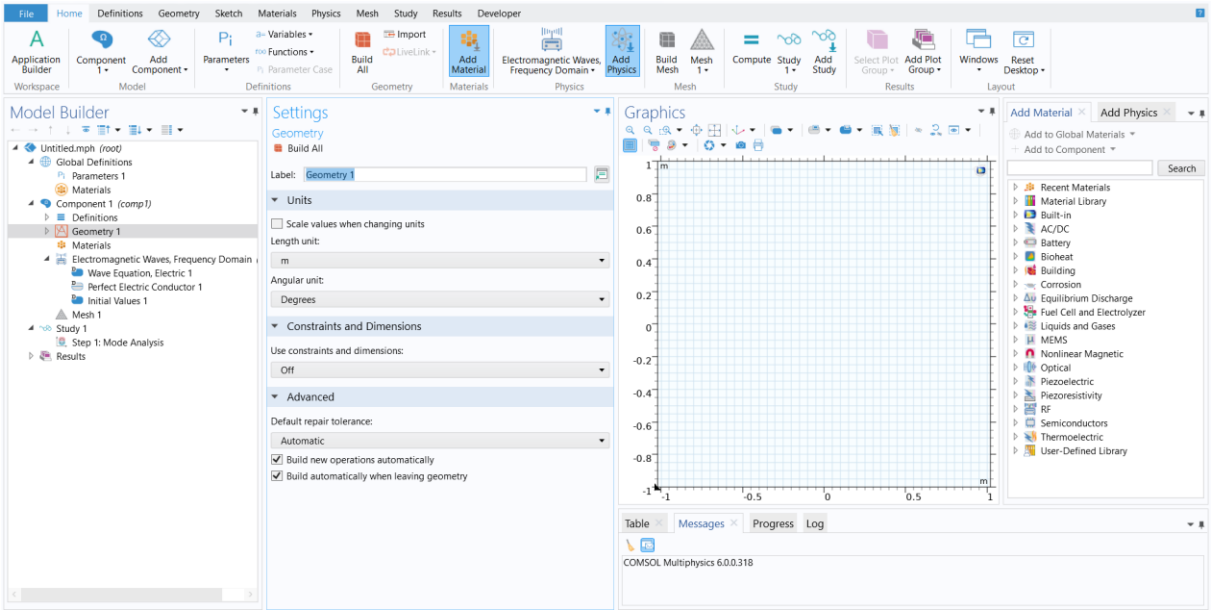
Appendix


File
Home
Definitions
Geometry
Materials
Physics
Mesh
Study
Results
Developer
Select Physics
Search
Recently Used
Heat Transfer in Fluids (ht)
Moist Air
Electromagnetic Waves, Frequency Domain (emw)
Electromagnetic Waves, Frequency Domain (ewfd)
Geometrical Optics (gop)
AC/DC
Acoustics
Chemical Species Transport
Electrochemistry
Fluid Flow
Heat Transfer
Optics
Plasma
Radio Frequency
Semiconductor
Structural Mechanics
Mathematics
Add
Added physics interfaces:
Remove
Space Dimension
Study
Help
Cancel
Done
Radio Frequency
The Radio Frequency interfaces are used to compute the electric and magnetic fields in high-frequency systems; that is, in systems where the wavelength is comparable to the size of the system.
These physics interfaces may be used for modeling time-harmonic and transient electromagnetic fields with full vector formulations, where either the full field or the scattered field is solved for. There is also an interface for modeling wave propagation along one-dimensional transmission lines.

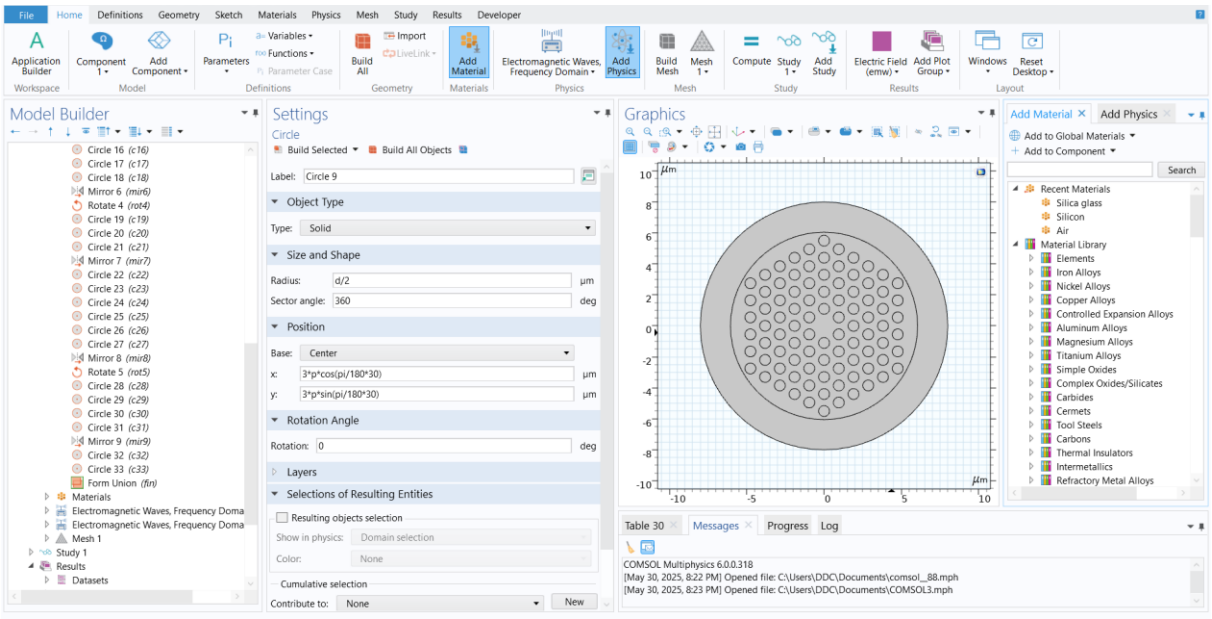

File
Home
Definitions
Geometry
Materials
Physics
Mesh
Study
Results
Developer
Select Physics
Search
Electromagnetic Waves, Frequency Domain (emw)
Electromagnetic Waves, Frequency Domain (ewfd)
Geometrical Optics (gop)
AC/DC
Acoustics
Chemical Species Transport
Electrochemistry
Fluid Flow
Heat Transfer
Optics
Plasma
Radio Frequency
Electromagnetic Waves, Asymptotic Scattering (ewas)
Electromagnetic Waves, Boundary Elements (embe)
Electromagnetic Waves, Frequency Domain (emw)
Electromagnetic Waves, Time Explicit (ewte)
Electromagnetic Waves, Transient (temw)
Transmission Line (tl)
Semiconductor
Add
Added physics interfaces:
Remove
Space Dimension
Study
Help
Cancel
Done
Electromagnetic Waves, Frequency Domain
The Radio Frequency, Electromagnetic Waves, Frequency Domain interface is used to solve for time-harmonic electromagnetic field distributions.
For this physics interface, the maximum mesh element size should be limited to a fraction of the wavelength. The domain size that can be simulated thus scales with the amount of available computer memory and the wavelength. The physics interface supports the study types Frequency Domain, Eigenfrequency, Mode Analysis, and Boundary Mode Analysis. The Frequency Domain study type is used for source driven simulations for a single frequency or a sequence of frequencies. The Eigenfrequency study type is used to find resonance frequencies and their associated eigenmodes in resonant cavities.
This physics interface solves the time-harmonic wave equation for the electric field.

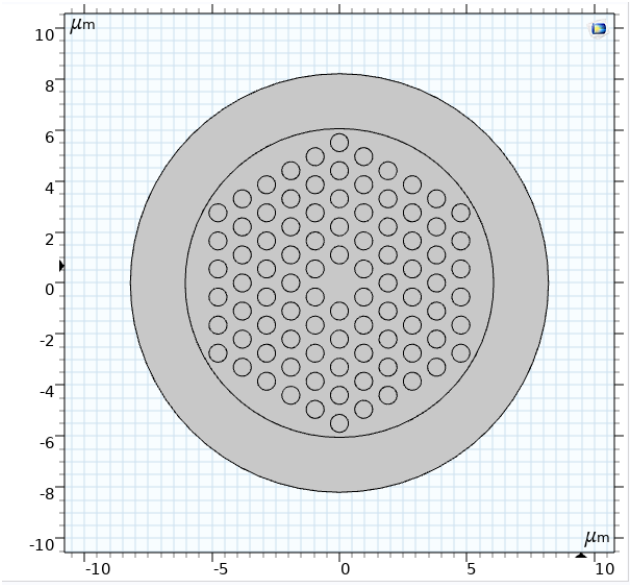
Appendix


File
Home
Definitions
Geometry
Materials
Physics
Mesh
Study
Results
Developer
Select Study
General Studies
Eigenfrequency
Frequency Domain
Preset Studies for Selected Physics Interfaces
Adaptive Frequency Sweep
Boundary Mode Analysis
Frequency Domain, Modal
Frequency Domain, RF Adaptive Mesh
Frequency Domain Source Sweep
Mode Analysis
TEM Boundary Mode Analysis
Empty Study
Added study:
Mode Analysis
Added physics interfaces:
Electromagnetic Waves, Frequency Domain (emw)
Physics
Help
Cancel
Done
Mode Analysis
The Mode Analysis study is used to compute the propagation constants or wave numbers as well as propagating mode shapes, for a given frequency.
Examples: In electromagnetics, it is used to compute the propagation constants and mode shapes at ports and waveguide cross sections. In acoustics, it is used to compute the propagation constants and mode shapes at inlets, outlets, and cross sections of guiding structures such as ducts.


File
Home
Definitions
Geometry
Sketch
Materials
Physics
Mesh
Study
Results
Developer
Application Builder
Component 1
Add Component
Parameters
Variables
Functions
Parameter Case
Build All
Import
LiveLink
Add Material
Electromagnetic Waves, Frequency Domain
Add Physics
Build Mesh
Mesh 1
Compute
Study 1
Add Study
Select Plot Group
Add Plot Group
Windows
Reset Desktop
Workspace
Model
Definitions
Geometry
Materials
Physics
Mesh
Study
Results
Layout
Model Builder
Untitled.mph (root)
Global Definitions
Parameters 1
Materials
Component 1 (comp1)
Definitions
Geometry 1
Materials
Electromagnetic Waves, Frequency Domain
Wave Equation, Electric 1
Perfect Electric Conductor 1
Initial Values 1
Mesh 1
Study 1
Step 1: Mode Analysis
Results
Settings
Geometry
Build All
Label: Geometry 1
Units
Scale values when changing units
Length unit:
m
Angular unit:
Degrees
Constraints and Dimensions
Use constraints and dimensions:
Off
Advanced
Default repair tolerance:
Automatic
Build new operations automatically
Build automatically when leaving geometry
Graphics
Add Material
Add Physics
Add to Global Materials
Add to Component
Search
Recent Materials
Material Library
Built-in
AC/DC
Battery
Bioheat
Building
Corrosion
Equilibrium Discharge
Fuel Cell and Electrolyzer
Liquids and Gases
MEMS
Nonlinear Magnetic
Optical
Piezoelectric
Piezoresistivity
RF
Semiconductors
Thermoelectric
User-Defined Library
Table
Messages
Progress
Log
COMSOL Multiphysics 6.0.0.318

Appendix


File
Home
Definitions
Geometry
Sketch
Materials
Physics
Mesh
Study
Results
Developer
Model Builder
Settings
Graphics
Circle
Build Selected
Build All Objects
Label: Circle 9
Object Type
Type: Solid
Size and Shape
Radius: d/2
Sector angle: 360
Position
Base: Center
x: 3*p*cos(pi/180*30)
y: 3*p*sin(pi/180*30)
Rotation Angle
Rotation: 0
Layers
Selections of Resulting Entities
Add Material
Add Physics
Table 30
Messages
Progress
Log
COMSOL Multiphysics 6.0.0.318
[May 30, 2025, 8:22 PM] Opened file: C:\Users\DDC\Documents\comsol__88.mph
[May 30, 2025, 8:23 PM] Opened file: C:\Users\DDC\Documents\COMSOL3.mph


μm
10
8
6
4
2
0
-2
-4
-6
-8
-10
-10
-5
0
5
10

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Hall– While older, it lays foundational theory for index contrast and waveguiding

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Abstract

Optical fibers are among the most important modern technologies in the field of communications, enabling high-speed and efficient data transmission over long distances with low signal loss and high immunity to electromagnetic interference. These fibers operate based on the principle of total internal reflection, transmitting light through a central core surrounded by a cladding with a lower refractive index.

In recent years, AI has played an increasingly significant role in enhancing the performance of optical fibers. Techniques such as machine learning and ANNs networks have contributed to data analysis, fault detection, performance prediction under various conditions, and the optimization of fiber design through accurate simulations and intelligent forecasting of optical properties. The integration of AI with optical fiber technologies represents a major step toward smarter, more flexible, and more efficient communication systems.

Résumé

Les fibres optiques représentent l'une des technologies modernes les plus importantes dans le domaine des télécommunications, permettant la transmission de données à haute vitesse et avec une grande efficacité sur de longues distances, tout en offrant une faible perte de signal et une forte immunité contre les interférences électromagnétiques. Ces fibres fonctionnent selon le principe de la réflexion totale interne, en transmettant la lumière à travers un cœur central entouré d'une gaine ayant un indice de réfraction inférieur.

Ces dernières années, l'intelligence artificielle a joué un rôle de plus en plus important dans l'amélioration des performances des fibres optiques. Des techniques telles que l'apprentissage automatique et les réseaux de neurones artificiels ont permis d'analyser les données, de détecter les défauts, de prédire les performances dans différentes conditions et d'optimiser la conception des fibres grâce à des simulations précises et à la prédiction intelligente des propriétés optiques. L'intégration de l'IA avec les technologies des fibres optiques constitue une avancée majeure vers des systèmes de communication plus intelligents, flexibles et efficaces.

ملخص

تُعد الألياف الضوئية من أهم التقنيات الحديثة في مجال الاتصالات، حيث تتيح نقل البيانات بسرعات عالية وبكفاءة كبيرة عبر مسافات طويلة، مع فقدان منخفض للإشارة ومناعة عالية ضد التداخل الكهرومغناطيسي. تعتمد هذه الألياف على مبدأ الانعكاس الكلي الداخلي لنقل الضوء عبر نواة مركزية محاطة بغلاف ذي معامل انكسار أقل.

في السنوات الأخيرة، لعب الذكاء الاصطناعي دورًا متزايد الأهمية في تطوير وتحسين أداء الألياف الضوئية. فقد ساهمت تقنيات مثل التعلم الآلي والشبكات العصبية الاصطناعية في تحليل بيانات القياس، واكتشاف الأعطال، وتوقع أداء النظام تحت ظروف مختلفة، بالإضافة إلى تحسين تصميم الألياف من خلال محاكاة دقيقة وتنبؤ ذكي بالخصائص البصرية. يُعتبر دمج الذكاء الاصطناعي مع تقنيات الألياف الضوئية خطوة مهمة نحو أنظمة اتصالات أكثر ذكاءً ومرونة وكفاءة.